Portfolio Structure, Real Estate Investment and the Performance of Defined Contribution Pension Funds

Doctor of Philosophy (PhD) in Real Estate and Planning

Henley Business School

Frank Kwakutse Ametefe

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DECLARATION

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

Name: Frank Kwakutse Ametefe

Date: 6th September, 2018

Signature:

ABSTRACT

With the growing importance of defined contribution (DC) pension funds around the world, concerns have arisen over their ability to provide adequate income replacement for members and the liquidity of their invesments. The first part of this thesis focuses on the illiquidity associated with real estate investments. The first chapter provides a discussion of liquidity within the context of DC pension funds. The second empirical chapter employs the tracking error optimisation procedure in the construction of portfolios that include direct real estate and selected liquid, publicly traded assets. We find that this helps to improve the performance of these blended portfolios. In the second part of this thesis, we look at various ways in which the real value of DC pension contributions can be preserved. The third empirical uses contemporary econometric approaches in the analysis of the dynamic relationship between asset returns and inflation/interest rate changes. Real estate and bonds were found to be a hedge against all the inflation/interest rates measures analysed. Some non-UK assets were also found to be a good hedge against selected benchmarks. The fourth empirical chapter of this PhD thesis examines the optimal allocation within portfolios designed to hedge against the various inflation and interest rate benchmarks. When the investment objective is to strictly track these benchmarks, bonds and real estate dominate the portfolios. Real estate, stocks and alternative assets receive significant allocations within the portfolios constructed to provide maximum risk adjusted returns relative to the minimum return benchmarks. We observe that the allocation to real estate reduced significantly following the global financial crisis period with bonds appearing to take its place. On the whole, this thesis contributes to the discussion on how best DC pension portfolios could be designed to comply with current investment regulations regarding liquidity and minimum returns requirements.

DEDICATION

I dedicate this thesis to the memory of my late father ***Mr. Johnson Kofi Ametewee*** (1947 – 2015)

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I wish to first of all say a big thank you to my supervisors Prof. Simon Andrew Stevenson and Dr. Steven Devaney for their guidance and support throughout this PhD research project. I owe the success of this research to them, not just for their promptness and meticulous guidance, but also for their concern for my welfare and my future. Thanks very much! This research has benefitted a lot from the insight of many players within the pension fund and asset management industry. I wish to specially thank Mr. Alex Moss of Consilia Capital and Mr. Adrian Benedict of Fidelity International.

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FRANK KWAKUTSE AMETEFE

LIST OF ABBREVIATIONS

ALM – Asset Liability Model

ARDL – Autoregressive Distributed Lag Model

CAPM – Capital Asset Pricing Model

CPI – Consumer Price Index

CVaR – Conditional Value at Risk

DB – Defined Benefit

DC – Defined Contribution

DCC – Dynamic Conditional Correlation

GARCH –Generalised Autoregressive Conditional Heteroskedasticity

GDP – Gross Domestic Product

GFC – Global Financial Crisis

HFRI – Hedge Fund Research Institute

IPD-UK – Investment Property Databank - United Kingdom

LIBOR – London Interbank Offered Rate

LPM – Lower Partial Moment

MAD – Mean Absolute Deviation

MAXDD – Maximum drawdown

PT – Modern Portfolio Theory

M-SD – Mean semi-deviation

MVA – Mean-variance analysis

NEST – National Employment Savings Trust

OECD – Organisation for Economic Cooperation and Development

ONS – Office of National Statistics

PPI – Producer Price Index

REITs – Real Estate Investment Trusts

RPI – Retail Price Index

S&P GSCI – Standard & Poor's Goldman Sachs Commodity Index

TAA – Tactical Asset Allocation

T-bill – Treasury bills

UBS – Union Bank of Switzerland

UCITS – Undertakings for collective investment in transferable securities

VaR – Value at Risk

VAR – Vector Autoregressive model

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CHAPTER ONE – INTRODUCTION

1.0 BACKGROUND OF THE THESIS

Pension funds represent pooled assets that are managed with the aim of supporting the income of members when they retire. Green and Robinson (2012) aver that a good pension is one that will pay an adequate and predictable stream of income in retirement, until death. A survey by Myers (2016) found that for many DC pension contributors, the most desirable outcomes are high investment returns, certainty, non-negative performance, low charges and immediate access (liquidity).

Over the years, there have been changes within the pension fund industry that have important significance not just for scheme members, but for financial markets, governments and society as a whole. Most significantly, traditional defined benefit (DB) pension plans have been losing their dominance in the occupational pension systems of many countries, with DC plans now accounting for the majority of invested assets in private sector occupational pension plans (Broadbent et al., 2006; Antolin et al., 2012). The main feature of a DC pension scheme is that during the pre-retirement phase, investment risk is borne by the individual member. Neither the fund nor the employer provides any guarantee as to the level of pension the member would receive at retirement.

Although the move to DC pensions offers a welcome relief to employers, it places a high degree of uncertainty on the retirement income of workers. DC pensions may make things easier for employers, but they achieve this by transferring risks to employees – risks that employees often do not understand and may not be able to deal with. For example, Tetlow & Crawford (2012) revealed that 59% of people aged between 50 and 64 with DC plans have never thought about the number of years in retirement they need to be able to finance. The consequences of this development is that many employees in the UK with DC pensions are currently saving too little for retirement and have very little understanding of the consequences of longevity risk – the risk that a pension plan will have to provide benefits to its members over a longer period than expected or the chance that a contributor might outlive his or her pension. Similarly, Ibbotson et al. (2007) estimate that married couples who are on DC pensions in the United States, had a 90% chance of outliving their assets at retirement. This compares with 3% of those with defined benefit plans.

National governments have focused closely on how to ensure that pension funds are managed in an appropriate way. This is because as pension plans fulfil their promises, the retiree population is more financially secure. Therefore, there is likely to be little or no need for social benefits to replace the loss of employee pensions (Ruloff, 2005). Following the 2008 Global Financial Crisis (GFC), there has been a lot of focus on managing risks owing to the unpredictable nature of markets and economies. Inflation risk in particular is of utmost importance to investors and portfolio managers as the scourge of rising prices could hurt returns across asset classes and erode the purchasing power of investors (Sweeting and Morris, 2011; Dessner et al., 2012; Antolin et al., 2012). Dessner et al. (2012) believe that negative real returns are not simply a product of high inflationary environments. Low inflationary environments accompanied by bear markets can also generate negative real returns. They believe that a diversified approach to portfolio construction, is best at providing a hedge against inflation. They also note that inflation protection strategies should be pursued without compromising other investment objectives such as liquidity, return and volatility target. This understanding, arguably, has informed the decision by many pension fund regulators to introduce minimum returns regulations in an attempt to protect the purchasing power of DC contributors as well as reassure and encourage more people to join occupational pension schemes.

Concerns have also been raised about how undiversified their portfolios are compared with their counterpart DB pension funds. Morales et al. (2017) found that pension fund investment a disproportionate amount of DC investment remain in short-term government bonds with very little investment in alternative assets. DCIF (2013) found that nearly 80% of DC default fund investment in the United Kingdom are in equities. This lack of diversification in DC fund portfolios has been attributed to the high emphasis that these funds place on liquidity (DCIF, 2017; Towers Watson, 2015). A Towers Watson (2015) analysis shows that DC members may receive as much as 5% in additional pension benefit if their contributions were invested in a more diversified portfolio than there currently are. In order to deliver adequate investment services, DC portfolios need to become more diversified and must include significant allocations to long-term, illiquid investments.

Real estate has long been a popular investment among pension funds. Among other things, real estate delivers stable returns and has low correlation with the traditional asset classes, hence providing diversification benefits. Real estate returns are also known to keep up with inflation (Case et al. 2012; Booth, 2002; Brounen et al., 2010). However, due to the increased emphasis on liquidity by DC pension funds, real estate and other alternative assets are not seen as good candidates for DC pension funds. In order to attract DC pension funds, a number of asset managers such as Legal and General have created real estate investment vehicles to meet the liquidity requirements by DC funds. Most of these funds contain a significant amount of cash. This places a drag on the returns of property portfolios. Similar blended or replication products have been developed within the hedge fund and private equity markets. This practice has important implications for the risk and return of the illiquid asset portfolios (Towers Watson, 2015; Farrelly & Moss, 2014).

1.1 OBJECTIVES OF THE THESIS

The objectives of this thesis are twofold: One is to determine the optimal allocation within DC pension fund real estate portfolios given the liquidity requirements of these funds. The second objective is to determine the optimal allocation to real estate within multi-asset portfolios that have been designed to deliver on return objectives linked to selected inflation and risk-free interest rates.

Although real estate is widely considered to possess the ability to hedge against inflation it is also viewed as an illiquid asset when owned directly (Farrelly and Moss, 2014). In order to meet the liquidity requirements from DC pension funds, several real estate investment funds have been created by investment management firms. These funds, known as hybrid or blended real estate funds, combine direct real estate and liquid, publicly traded assets. Often, these funds are created using just one or two pre-specified assets and weights, without any formal optimisation procedures. In this thesis, we apply formal optimisation techniques to the design of these hybrid real estate portfolios that can produce property-like returns whiles maintaining an acceptable level of liquidity. This idea has also been applied to other illiquid assets, too, such as hedge funds and private equity. Specifically, the following research questions are addressed in this thesis:

1. How effective is real estate in the preservation of the purchasing power of DC investors' contributions.
2. How does real estate's ability to hedge against inflation compare to that of other alternative assets as well as the traditional asset classes.
3. What is the optimal allocation within portfolios designed to hedge against inflation and interest rates commonly used by DC pension fund regulators and trustees as minimum return or performance benchmarks?
4. How does the composition of these optimal inflation and interest rate hedging portfolios compare to the current allocation within DC and DB pension fund portfolios?
5. What is the optimal allocation within the portfolio of hybrid real estate funds designed to provide returns comparable to direct real estate returns whiles at the same time maintaining a level of liquidity acceptable to DC pension investors.

In the first part of this thesis, econometric approaches are used to analyse the interdependency between asset returns and selected inflation and interest rate benchmarks. This part of the thesis enables us to identify assets that exhibit a long-term relationship with selected inflation and interest rate benchmarks and so could serve as a hedge against inflation and interest rate changes.

The portfolio analysis part of this thesis is in two parts. One part considers the allocation within DC pension scheme portfolios and the role that real estate plays within these portfolios. The second part considers the allocation within the real estate portfolios themselves.

In constructing portfolios designed to hedge against inflation and interest rate changes, we explore the objective of minimising tracking error relative to the inflation and interest rate benchmarks. We also maximise the risk adjusted returns given the inflation and interest rate benchmarks. The vast majority of studies on the role of real estate within investment portfolios have employed the approach of Markowitz (1952). The typical Markowitz framework minimizes risk for a certain level of return or vice versa. The optimisation models employed in Chapter 7 use the mean-tracking error and semi-variance of tracking error as the measure of risk. The objective of maximizing risk-adjusted returns is also explored within the two frameworks. This part of the thesis follows a growing stream of studies that explicitly construct inflation hedging portfolios for institutional investors such as pension funds and life insurance companies who have minimum return promises tied to inflation and interest rate movements (e.g. Bruno & Chincarini, 2010; Bruno & Chincarini, 2011; Twomey et. al, 2011; Downing et al., 2012; Briere and Signori, 2012;   Crawford et al., 2013; Koniarski and Sebastian, 2015, Ogunc and Ogunc, 2016).

For the simulations in this thesis, we employ the perspective of a UK DC pension fund that aims to diversify across the traditional asset classes of stocks and bonds as well as alternative assets such as real estate, commodities, hedge fund and private equity. As discussed later in this thesis, UK DC pension funds currently allocate more than 80% of their funds to stocks and the remaining are invested in bonds and cash. By expanding the asset universe to include as many assets as possible, we show that the current allocation within DC pension funds is sub-optimal at best.

1.2 CONTRIBUTIONS OF THE THESIS

This thesis contributes to the real estate finance literature in three areas: inflation hedging, strategic asset allocation and liquidity risk management. The thesis proposes and implements a framework that enables DC pension funds and other institutional investors to construct portfolios that deliver returns in line with their selected against inflation and interest rate benchmark. An approach has also been suggested to enable these funds invest in direct real estate compromising their liquidity requirements.

Although several studies have analysed the inflation hedging ability of real estate to hedge against inflation before the recent financial crisis (2007-2008), very few studies have done so following the crisis. It is well noted that the behavior of most assets has changed following the financial crisis. The interdependency between various assets and macroeconomic variables has also been altered. This thesis provides new evidence on the interdependency between the returns of various assets and inflation and/or interest rate changes. The identification of assets which have the ability to provide a hedge against inflation and interest rate changes is particularly important with the increasing dominance of DC pension funds. These funds have the primary objective of protecting the capital value of members' contributions. In some jurisdictions, there are laws that compel these funds to deliver returns in line with selected inflation or interest rates.

This thesis also contributes to the limited literature on inflation hedging within a portfolio context. Naranjo and Ling (1997) noted that empirical studies that have examined the relationship between real estate returns and the macro-economy have been limited to the question of whether real estate returns are sensitive to various changes in macroeconomic variables such as inflation. Very few studies have explored this issue within a portfolio context. Dessner et al. (2012) concluded that, instead of selecting specific assets for the purpose of hedging against inflation, a diversified approach to portfolio construction provides a better alternative for providing a hedge against inflation. They note further that inflation protection strategies should also be pursued without compromising other investment objectives such as liquidity, return targets and volatility constraints.

To the best of our knowledge, this is the first study to analyse the optimal composition of hybrid/blended real estate portfolios. Currently, open-ended real estate funds use one or two predetermined liquid assets, mostly cash and/or listed real estate. The studies in this area have focused on analyzing the performance implications of the current mix of assets within open-ended funds that blend cash and listed real estate with direct real estate. The use of cash within property portfolios has been found to impose a drag on the returns of these funds whiles the use of listed real estate significantly distorts the return structure of these portfolios. In this thesis, we propose and use formal optimisation techniques to select the optimal mix of liquid assets that should make up the liquid-asset components of property portfolios. The composition of these portfolios would ensure liquidity is directly incorporated into the portfolio construction process. We show that an optimal combination of listed real estate, cash and bonds would be best for these funds. A direct output of this thesis is the creation of a number of blended real estate return series that can be used in the much the same way as other real estate return series.

In this thesis, we focus on the efficient design of DC pension portfolios especially those designed to serve as default funds. We simultaneously examine the issue of inflation and interest rate hedging as well as liquidity within the context of DC pension funds concerned with protecting their portfolios against losses in capital value. By considering the important issues of capital preservation and liquidity, this thesis provides qualitative and numerical results to guide policy on how to ensure that DC members retire with adequate capital replacement to support them. Clearly, if members receive retirement income that is sufficient, the burden on governments to care for retirees would be reduced. This study is timely as it is conducted at a time when the issue of capital preservation has led many regulators and pension trustees to provide or consider providing return guarantees on members' capital contribution in nominal or real terms.

1.3 CONTEXT OF THE THESIS

In this part, we provide an understanding of the key issues that underpin this thesis. We first provide a definition of the key terms used in this thesis. We also discuss two of the key issues that have dominated discussions among pension regulators, trustees and contributors – the need for capital preservation and liquidity. These two issues are underpin the empirical analysis conducted as part of this PhD study. Finally, we provide a motivation for the reasons (i) why defined contribution (DC) pension funds, in particular, form the basis of this study, (ii) why real estate assets are of particular interest and (iii) why the United Kingdom is used as the context for this study.

1.3.1 THE CHANGING PENSION LANDSCAPE

The two most common forms of pension schemes are Defined Benefit (DB) pension schemes and Defined Contribution pension schemes (DC) pension funds. In a Defined Benefit (DB) scheme, the scheme's rules set out a formula for the level of benefits that scheme members will receive on leaving the scheme through death, retirement or ceasing employment. In Defined Benefit (DB) pension schemes the pension benefits paid out are often linked either to the scheme member's final salary or to their average salary during the course of their career and their length of service. Eason et al. (2013) find that final salary arrangements are more common within DC pension funds in the UK. The employer bears investment risk and longevity risk so long as they are solvent.

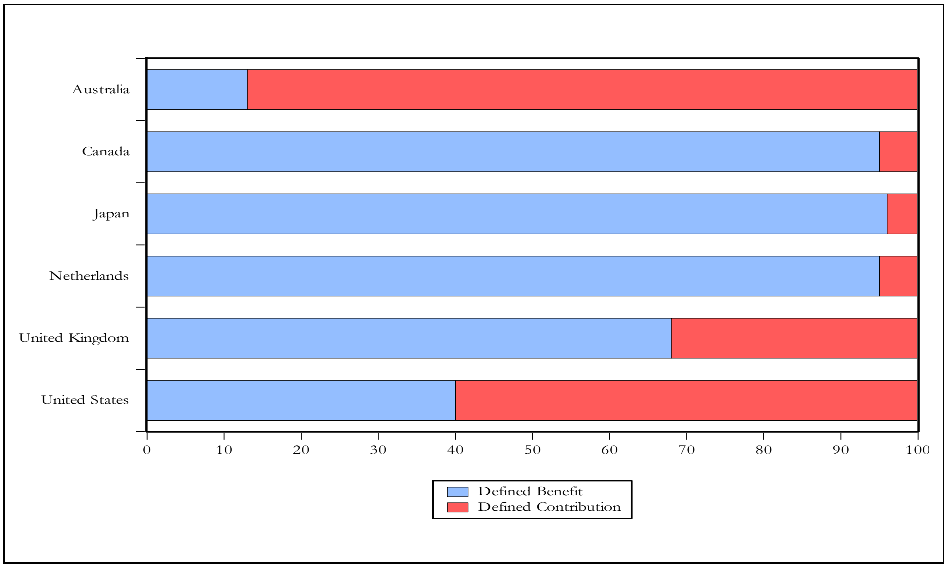
Within defined contribution (DC) pension funds, contribution rates are usually a fixed percentage of salary. These contributions are invested in a fund of the employee's choosing. DC pension funds could be trust-based or contract based.

The final pension paid out will be related to the returns on the assets in which members' funds are invested (after charges) and the way that the resulting pension pot is converted into a retirement income. If an annuity is taken, the annuity rate available at the time that the member retires will affect the member's final retirement income.

A more subtle difference between DB and DC pensions lie in the way each plan is managed. The assets within a DB pension fund are pooled together and managed as one big portfolio. The assets do not have to be split up until the benefits are actually paid out. This is made possible by the fact that the expectations of all the contributors in DB pension plans is defined in terms of their benefit. Within DC pension plans however, each individual's pension pot has to be tracked separately, as this is what determines what they get from the fund when they retire (Ezra et al., 2009).

Nearly all public sector schemes are Defined Benefit, as are the majority of large private sector schemes. However, most of the private sector schemes are closed to new entrants, and the majority of new private sector schemes are Defined Contribution (Carrera et al., 2012).

Figure 1(1) Defined Benefit – Defined Contribution Split



Source: Towers Watson Global Pension Study (2016)

Apart from pure DC and pure DB pension schemes, there are funds that have features of both DB and DC schemes. Eason et al. (2012) identify two of such funds within the UK, cash balance plans and DC funds with underpins. Cash balance plans require the employee to make DC-like contributions during the course of their employment. These contributions are credited with a fixed rate of return until the employee retires. If the accumulated contributions and the returns fall below the target amount, the employer makes up the difference. Similarly, in the event that the amount realised exceeds the promised or target amount, the employer retains the surplus. DC funds with underpins promise to pay the employee a guaranteed pension amount (as in a DB pension) or the accumulated amount within the DC fund, if the annuity that can be purchased with the accumulated amount within the DC fund is greater. Eason et al. (2012) noted that even though cash balance plans and DC funds with underpins have attributes of DC pension funds, they are classified as DB pension funds under UK statutory regulations.

One of the most significant changes that has occurred on the pension landscape globally is the move from Defined Benefit (DB) structures to Defined Contribution (DC) pension structures. A study by Towers Watson (2016) showed that the transition from DB to DC structures around the world has been at different rates in various countries. Whiles countries like Australia and the United States have DC pension funds dominating their occupational pension sector, DB pension funds still dominate in Japan, Canada and the Netherland. The UK still has DB pension funds having a larger asset under management than DC pension funds although it is expected that this would change once auto-enrolment is in full gear.

A number of factors have been attributed to the trend away from DB pension structures to DC pension structures. Turner and Hughes (2008) groups these factors into two: (i) the increasing cost of DB pensions to employers and (ii) changes in demand for defined benefit plans.

1.3.1.1 Changes in the Cost of Administering Defined Benefit Pensions

i. Changes in pension legislation

DB pension funds are governed by rules contained in pension legislation, regulation, and tax policy that over time have become increasingly complex and costly to administer. Broadbent et al. (2006) observe that these tax and regulatory restrictions have reduced the incentive for firms to sponsor DB plans, by increasing the cost of administering the plans, and by limiting firms' flexibility in providing benefits (e.g., by regulating funding and limiting the extent to which companies can target benefits to particular employees).

In the United States, the trend toward DC Pensions was preceded by important changes in pension regulations, beginning with ERISA and continuing through tax and pension regulations passed in the middle 1980's. Since many changes in pension regulation increase the relative cost of defined benefit plans and limit their effectiveness as devices for influencing retirement and productivity, it has been argued that the trend toward defined contribution pension plans largely reflects the effects of changing regulation (Clark et al., 1988). Some analysts have attributed the closures of DB pension plans in the U.K, to the increase in regulatory burden since the 1980s (Davis, 2004; Broadbent et al., 2006). The acceleration in DB pension plan closures in the U.K. since 2000 has been attributed primarily to the change in pension accounting towards market-based standards. Indeed, the increase in DB plan closures in the U.K. following the introduction of FRS 17 has led many observers to conclude that the reforms to pension accounting being considered in the U.S. and internationally will accelerate the trend away from DB pension plans due to the greater volatility in financial statements that the proposed reforms are expected to create. The Myners Report (2001) concluded that the shift to DC pensions in the UK is a result of numerous factors including increased labour mobility and cost but that regulatory changes such as the Minimum Funding Rule, the removal of the tax credit on dividends and the requirement to guarantee Limited Price Indexation have created disincentives for employers to offer DB plans. In Canada it is argued that over time the evolution of pension legislation, regulation and case law, particularly in the area of surplus ownership, have reduced the incentives for employers to sponsor DB pension plans (Armstrong & Selody, 2005).

In Australia, a change in pension legislation that introduced mandatory employer pensions was the main contributor to the massive shift from DB to DC pension plans. Prior to this, employer pension coverage was limited to a small share of the workforce, similar to the experience of other countries such as the U.K., Canada and the U.S. The transition to DC pension plans began with the introduction, in 1986, of award superannuation which required that part of an employee's pay increase would take the form of a superannuation payment. It accelerated markedly under the compulsory Superannuation Guarantee (SG) introduced by the Australian government in 1992. Under SG employers were required to make contributions (currently at 9% of earnings) on behalf of their employees.

ii. Investment risk

Investment risk relates to the chance that the expected return on an investment would not be realised. In defined benefit plans, the employer and employee may split the investment risk or the employer could assume all of the investment risk. Contribution rates to defined benefit plans will change over time to offset investment gains and losses. Furthermore, a defined benefit plan guarantees a set benefit level at retirement, ensuring that no individual plan participant's retirement income will be affected by short term changes in economic conditions (MeElreath et al, 2012).

Defined contribution plan participants on the other hand are solely responsible for their savings and investment performance. To illustrate the potential impact of changes in economic conditions on an individual, assume it is 2008 and a plan participant is expecting to retire in the near future. If this individual's portfolio were significantly exposed to equity markets, she would have experienced considerable losses over the course of the year. These losses, borne solely by the individual, would force her to delay retirement, or enter retirement with less available savings. Conversely, the pooled nature and long-term outlook of defined benefit plans allows the plans to provide benefits based on the previously mentioned benefit formula regardless of market fluctuations. Any short-term losses are absorbed by the defined benefit plan, and may be recovered through long-term investment returns and contributions.

Also, in DB schemes revaluation of accrued benefits and indexation of pensions in payment are key parts of scheme design. The value of the pension received and the cost of providing pensions may be affected by changes in price inflation. Wage inflation can also increase the cost of providing DB pensions. For ex-ample, if an active member of a final salary DB scheme receives a substantial increase in pay at the end of their career, this can disproportionately increase the cost of providing the resulting annual pension. The returns on bonds, equities and other assets in which a pension funds invests, would also affect their funding position. Where a scheme is in deficit, lower returns will increase the level of contributions required to close the deficit. Over the last decade, bond yields and equity returns have been volatile, and over the longer term the outlook for investment returns remains uncertain.

Broadbent et al. (2006) observed that the shift to DC scheme within the UK appears to be employer driven, and is largely due to pension underfunding and its persistence due to a decline in long-term interest rates. These they observe have reduced the incentive for employers to offer DB plans. Although the shift to DC plans shifts the investment risk to the participant, Ruloff (2005) maintains that the employer is also vulnerable. When the market turns down, the employer will suffer from low employee morale as DC assets deteriorate. At the same time, the plan sponsor might want to reduce staff. But with low account values, individuals eligible for retirement will be reluctant to leave, keeping payroll costs high. In addition, without a fully funded DB plan, the employer will not have the tools and the spare cash needed to encourage departures through an early retirement window. On the other hand, when the economy is good, the plan sponsor might want to increase staff. But at the same time, current employees might see sufficient DC funds as a good reason for them to retire. When this happens, the plan sponsor would not only be pressed to hire new employees to meet growing demands, but he will also need to replace retiring employees. Also, as participants make bad savings and investment decisions, they will be left without the means to pay for their retirement. Then taxpayers will need to make up for all of this difference.

iii. Increasing Life Expectancy

Longevity risk is the risk attached to the increasing life expectancy of pension plan participants, which can eventually translate into higher than expected pay-out-ratios for many pension funds. In a defined benefit plan, benefits are normally distributed in a lifetime annuity, or a series of monthly payments that lasts until death.

DB plans are implicit contracts in which the expected present value (discounted) of wages and pension payments must be at least equal to the expected present value (discounted) of wages a worker can earn in the spot market. As the workforce has aged, the costs of funding a DB plan have risen because the level of accrued benefits is higher and the post-retirement period has lengthened due to early retirements and increased longevity. Increases in life expectancy over the last 30 years due to medical advances and improved lifestyles have meant that people are living longer. For example, in the average life expectancy at age 65 in the UK in 1981 was estimated as being 14 years. In 2014 it was estimated to be over 21 years. Higher life expectancy increases the amount of money that DB schemes need to pay out because pensions have to be paid for longer (ONS, 2014).

In theory, increased life expectancy should not be a problem; firms forecast the postretirement payments and set the wage schedule and benefit parameters to keep the present discounted value of compensation equal to the productivity of the worker over the life of the contract. In practice, it may be difficult for firms to adjust compensation in response to shocks to forecasted values of longevity, benefit costs, or asset returns. Reasons for this difficulty include regulatory constraints, litigation risk, and the impact on employee morale. In addition, some evidence has suggested that workers value a dollar of DB pensions less than a dollar of wages (despite the tax preference for DB pensions), which may limit the ability of firms to substitute across types of compensation. Thus, increasing costs could give firms an incentive to terminate DB plans.

1.3.1.2 Changes in Demand for Defined Benefit Plans

The shift towards DC pensions does have some positive aspects, both for employees and for sponsor companies. Changes in employee characteristics have led to a change in their preference for defined contribution schemes. On the whole, employees have a preference for the portability which DC pension funds provide, all else being equal.

i. Employee mobility

Historically, the shift towards DC pension plans has largely been a response to changes in industrial structure and labour force composition that have given rise to an increasingly mobile workforce, DB plans, which are often not portable across employers, can penalize mobile workers since the expected pension benefit generally accrues only to employees who remain with the same employer throughout their career, DC plans avoid the accrual losses that can be associated with DB plans and provide mobile workers with much a more flexible means of managing their retirement savings (Broadbent et al., 2006).

Aaronson & Coronado (2005) explore the demand and supply factors contributing to the shift from DB to DC plans using data on pension coverage for 40 industries. Many of the factors they examine - and find to be statistically and economically important to the shift in pension coverage relate to increases in the mobility of workers between employers and in-and-out of the labour force. On the demand side, demographic trends in the labour force may have made the accrual risk of DB plans a more important consideration for workers. For instance, workers in dual-earner couples are likely to prefer pensions with benefits that are portable across employers because their employment decisions depend on the opportunities of their spouses. In addition, women with children may prefer the steady accrual in DC plans because family concerns are likely to affect their labour force participation and lead to greater-than-average job turnover, which is penalized significantly in back-loaded traditional DB benefit formulas. The authors further observe that labour markets in the U.S, seem to have become characterized by greater mobility, leading workers to derive less value from DB plans that traditionally have given disproportionate reward to long-tenured employees.

Although there are a range of opinions, the preponderance of the evidence in the U.S. suggests that worker mobility has increased over the past 30 years. Explanations include changes in the industry composition of employment, technological change, and changes in the demographic composition of the labour force toward workers with less stable labour supply. More mobile workers find DC plans relatively advantageous because benefits in these types of plans accrue more evenly through their career and are entirely portable should the worker separate from the sponsoring firm or leave the workforce for a period.

ii. Level of Unionisation

The overall trend toward defined benefit contribution plans may also reflect the changing composition of industry and work force. It is well known that defined benefit plans are more likely to be found in union firms, in large firms, and in certain industries such as manufacturing (Kotlikoff and Smith, 1983). To some extent, the trend toward defined contribution plans may simply reflect changes in the mix of jobs. Unions are more common within the manufacturing industry than service industry. Brown and Liu (2001) argue that a higher level of unionization in Canada relative to the U.S. is one factor supporting the persistence of DB pension plans. They also note that differences in pension regulation and tax policy have been important as well. This is likely a reflection of the fact that in Canada, the principal means of "freezing" a DB pension plan is to close the plan to new members while maintaining the DB plan for existing members. Many of the largest DB plans have been in manufacturing industries such as steel and auto production, and in other heavily unionized industries. As these industries have declined, the prevalence of DB plans has diminished.

Gustman and Steinmeier (1992) using data from IRS 5500 filings by pension administrators in the United States, found that at least half of the trend toward DC Pensions is due to a shifting employment mix toward firms with industry, size, and union status characteristics which have historically been associated with lower defined benefit plan rates. Not more than half of the trend can be attributed to a "stampede" by firms with given industry, size, and union status characteristics toward defined contribution pension coverage.

1.3.2 KEY ISSUES FACING PENSION FUNDS GLOBALLY

In this section, we discuss two of the main issues that underpin the empirical analysis that we undertake later in this thesis: (i) The demand for DC funds to guarantee a minimum amount of return to contributors (ii) The requirement that DC pension funds should provide a certain amount of liquidity within their portfolios.

1.3.2.1 Minimum Return Requirements

Many studies have attributed the negative feelings that people have about Defined Contribution pension schemes to the fear of losing even part of the nominal value of their accumulated contributions. It is therefore important that at least the accumulated contributions be guaranteed (e.g. Antolin et al., 2012; Merton, 2013, DWP, 2014).

Antolin et al. (2012) recommended that short of making minimum return guarantees mandatory, governments could require that at least one capital guarantee product is made available to members of all DC pension schemes as it is in Japan.

An alternative to return guarantees is the use of public pension stabilisers and old-age safety nets. The existence of these protective mechanisms minimises the share of retirement income that is exposed to market risk. However, public pension protection mechanisms often provide only partial protection especially for high net-worth individuals. Antolin et al. (2012) hold that these automatic stabilisers and old age safety nets are more valuable to retirees than return guarantees as automatic stabilisers guarantee a minimum level of retirement income as opposed to a minimum value of accumulated savings at retirement. Often, the decision to introduce minimum return guarantees depends on whether the public pension system provides adequate income replacement or not. Investment guarantees are more essential where much of retirement income come from DC pension plans.

Antolin et al. (2012) carried out a survey to determine the kinds of minimum return guarantees, if any, that exist in OECD countries. They found that several countries have regulations that require DC pension funds to promise a certain minimum amount of return on members' contributions. These guarantees are either absolute or relative to a certain benchmark.

Countries such as Czech Republic, Japan, Slovak Republic and Switzerland require DC plan providers or sponsors to offer absolute rate of return guarantees. Pension funds in the Czech Republic must guarantee the nominal value of contributions and must not realize a negative rate of return in any single year. Japanese DC pension plans must offer at least one capital guarantee product to members. In Slovakia, DC Pension funds must guarantee returns equal to or more than 0% every six months. The fund sponsor or provider is required to make up the difference if they fail to meet this requirement. Swiss DC pension funds have been required to provide different absolute returns over time. The rate was initially set at 4% in 1995 but has been reduced over time. Currently, the minimum return is linked to the returns on the 7-year Swiss Government bonds. This amount is usually credited to members' accounts and also applied when members switch plans or retire. To provide further certainty to DC contributors, the annuity conversion rate is also fixed.

Belgian and German pension funds also offer absolute return guarantees on contributions. However, given that these guarantees are the responsibility of the sponsoring employers and not the DC pension providers, these funds are classified as Defined Benefit by local laws and International Accounting Standards (IAS 19). Belgian pension funds must guarantee a minimum of 3.74% on employees' contribution and 3.25% on their own contributions. This rate is used to calculate what is due employees when they change plans or retire. German pension plans that have been established under the Riester reform in 2001 must guarantee a minimum return of 0% in nominal terms. Although most Riester pension funds are offered by pension providers, the guarantee is backed by the plan sponsor. Another type of German pension fund, Pensionskassen must guarantee at least 2.25% per annum. This rate is applied at retirement. Each year, the member's account is credited with this 2.25% or 90% of the fund's annual return, whichever is greater.

Countries that require DC pension funds to provide relative minimum returns that are linked to certain benchmarks include Chile, Denmark, Hungary, Poland and Slovenia. The Danish ATP which is the operator of the mandatory DC pension plan, guarantees a minimum return which the ATP sets itself in line with long-term interest rate movements. The minimum return required of DC pension fund in Chile depends on their equity exposure. The funds are grouped under options A, B, C, D and E. Funds A and B are funds with high equity exposure whiles C, D and E have a lower equity exposure. The funds with higher equity exposure (A and B) must provide minimum returns defined as the greater of 2% less than the average real rate of return over the previous 36-month period, and 50% of the weighted average rate of return. Funds C, D and E must produce minimum return that is set at the greater of 2% less than the average real rate of return over the previous 36-month period and 50% of the weighted average real rate of return. Hungary DC pension funds must not deliver returns less that are 15% less than the yield on Hungary Government bonds. Similarly, Slovenian DC pension schemes must guarantee a rate of return equal to 40% of the average annual interest rate on government bonds.

1.3.2.2 Pension Funds and Real Estate Investments

Pension funds play a key role within the financial markets of countries, owing to their huge asset base and long-term investment focus. The top 19 pension funds in the world control in excess of US$35 trillion dollars in assets and make up an amount equivalent to more than 80% of the GDP of these 19 countries (Towers Watson, 2015). The growth in pension funds as institutional investors has been attributed to their ability to pool risk and the unique tax advantages which they offer. Pension funds pool risk by diversifying their portfolio across a wide range of instruments whose returns are imperfectly or negatively correlated. International diversification also presents further opportunity for diversification as national trade cycles are not perfectly correlated. Risk pooling is made possible by the large asset base of pension funds which results in lower transaction costs and also makes them able to effectively invest in large indivisible assets whiles at the same time balancing the illiquidity of such investments. Investing through pension funds also offers some unique tax advantages to contributors. In particular, taxes are paid only at the time of receipt and not when returns are being earned. Often, most contributors will be in a lower tax bracket at retirement and so may lose very little of their investments. In many countries, pension contributions are tax deductible whiles in others, tax-free lump sum deductions are allowed. These benefits make investing through pension funds more tax efficient and could potentially result in higher returns for contributors.

Pension funds also represent very important investors in most financial markets, especially within the real estate market. The large capital base of many pension funds and their long-term investment horizon makes gives them the capacity to invest in projects, such as real estate, that require large amounts of funds to be invested over long periods. Similarly, real estate comprises the major wealth of most countries and is often cited as the bedrock of modern society. The real estate industry is a key driver of economic development in most countries and has both forward and backward linkages to other sectors within the economy. The industry gives both breadth and depth to modern financial systems and has recorded annual transaction volumes in excess of a trillion US dollars (Doling et al., 2013). It is estimated that the real estate industry contributed over €285 billion to the European economy in 2011. The industry also employs more than four million people (AREF, 2012). The forgoing discussion points to the symbiotic relationship between real estate and pension funds. A growth in one market often results in a growth in the other while a crisis in one market would lead to a disaster in the other. The recent financial crisis (2007 - 2008) for example demonstrated how critical the real estate industry is to financial markets and the global economy in general. Antolin et al. (2012) estimated that the 2007-2008 financial crisis which originated in the housing market led to investment losses of 20-25% or even higher in some cases, among pension funds.

However, an analysis of institutional real estate holdings shows that real estate investments have been volatile over the years. An annual survey by Pensions & Investments (2010) revealed that worldwide real estate asset under management by tax-exempted institutions peaked in June 2008 at US$1 trillion and plunged to US$677 billion in June 2010. Andonov et al. (2012) lament that despite this phenomenon, very little remains known about what determines the variations in real estate allocations by various institutional investors.

Although the issues discussed in this thesis are relevant to most, if not all, countries where DC pension funds have become the dominant form of retirement income provision, the simulations in the various empirical chapters are carried out from the perspective of a UK DC pension investors who desires to protect the real value of pension contributions as well as provide adequate liquidity within their portfolios. The UK also presents a flexible regulatory environment where Pension trustees can set their own objectives regarding issues like minimum returns, liquidity etc. This allows us to consider different scenarios when carrying out the simulations. For example, unlike most other OECD countries, the United Kingdom does not have a specified benchmark against which the performance of DC pension funds are evaluated. A review of the Statement of Investment Principles of Master trust pension funds in the UK shows that the trustees of the various funds have different inflation and interest rates against which they would hedge at least over the long run. These are examined later in more detail. The impact of what measure of inflation or interest rate is used within DC schemes is not straightforward especially as the rate only represents a floor and not what is actually paid to a DC contributor. Analysis in this thesis contributes to this discussion by showing whether the decision of DC trustees to adopt the RPI rate for example as a performance benchmark would result in better portfolio performance than another fund that adopts the CPI rate.

Using the UK as the context within which we situate our empirical studies also ensures that we have access to data on a wide array of traditional and alternative assets over an extended length of time. The United Kingdom is one of the biggest and most matured pension markets in the world and represents one of the countries where DC pension funds are expected to become the main source of income replacement for most retirees in the near future. Tetlow & Crawford (2012) observed that, within the UK, employer-provided defined benefit (DB) pension schemes are increasingly scarce in the private sector while the introduction of auto-enrolment in 2012 is expected to accelerate the move towards DC pension schemes.

It is important to note that by using UK the UK as our case study, we are not suggesting that all the various scenarios presented pertain only to the UK. Instead, we are conceptually testing whether the allocations are more sensitive to the inflation or interest rate benchmark being hedged against or the investment objective being pursued relative to a given benchmark. This approach is consistent with the approaches used by other studies on this subject (Munnell et al., 2009; Antolin et al., 2012; Grande and Visco, 2010, Scheuenstuhl et al., 2011). We will however provide enough background information on the various origin of the regulations and investment practices that form the basis of any analysis that we conduct in this thesis.

1.3.2.3 Pension Liquidity

Aside setting risk and return targets, there is an increasing emphasis on liquidity as a key objective among DC pension funds. Liquidity is a multi-faceted concept that requires further and closer definition if it is to be used meaningfully (Goodhart, 2008). In general, there are two kinds of liquidity (i) Funding liquidity (ii) Market/Asset liquidity. There are a number of measures that can be used to measure different aspects of liquidity. In Chapter 5, we provide a detailed review of these measures of liquidity.

A market is considered liquid at any point in time there are willing buyers and sellers in large numbers. One of the earliest definition of asset liquidity was provided by Keynes (1937): "An asset is liquid if it is more certainly realisable at short notice without loss". In this sense, cash is the most liquid asset as it can be used directly for economic transactions. Asset liquidity risk according to the Undertakings for Collective Investment in Transferable Securities (UCITs) is: "the risk that a position in the UCITS portfolio cannot be sold, liquidated or closed at limited cost in an adequately short time frame and that the ability of the UCITS to comply at any time with Regulation 104(1) is thereby compromised". Section 104 (1) which is referred to in this definition states simply that "Subject to Regulation 63(2), a UCITs shall redeem or repurchase at the request of the unit holder."

Timmermans (2009) groups market illiquidity into three. The first form of market illiquidity is the absence of a secondary market. For example, open-ended real estate funds are not normally traded on a secondary market. So are private equity funds which also lack a secondary market. These funds often undertake to redeem their shares occasionally. They may also arrange matched bargains between buyers and sellers. The second form of illiquidity occurs when a market that is otherwise liquid becoming illiquid when there are too many sellers for the number of buyers of a unit. When this happens, market makers withdraw from the market. A third form of illiquidity relates to markets that have limited liquidity. For example, hedge funds allow redemptions only occasionally, for example once every quarter, often with a notice period of one month.

Drehmann and Nikolaou (2008) define funding liquidity as "the ability to settle obligations with immediacy". Consequently, funding liquidity risk is the chance that an institution would not be able to meet or settle its obligations promptly. From the perspective of a pension fund, funding liquidity risk would mean that the fund cannot meet its financial obligations as and when they fall due or that they cannot meet these obligations without incurring significant losses.

Liquidity risk from the perspective of a pension fund relates to the risk that the fund cannot meet its financial obligations as and when they fall due or that they cannot meet these obligations without incurring significant losses. In comparing banks to life insurance companies and pension funds, Davis (1988) observed that the actual maturities of bank deposits are difficult to foresee and hence they require a relatively large amount of liquid assets to meet demand for these deposits. Pension funds and life insurance companies however have long-term assets and liabilities and as such face very little liquidity risk. Apart from early retirements (for pension funds) and early surrender (for life insurance companies), premature withdrawal requests are rare. Also, pension funds and life insurance companies receive a steady inflow of funds in the form of regular contributions (for pension funds) and premiums (for life insurance companies). Davis (1988) asserted that the main risks faced by pension funds and life insurance companies were actuarial and market risks. Actuarial risk relates to the risk that the death rate of beneficiaries differs from what was predicted while market risk is the risk that the accumulated assets would not provide the returns required to cover the pay-outs that were promised. Unexpected changes in earnings could also lead to contributions differing from what was initially estimated.

Clearly, the comparison of Davis (1988) was based on the situation within defined benefit pension schemes. For DC pension schemes, the obligations or outflows of pension funds can be classified into (i) the payout of benefits as a result of specified life events (ii) the transfer of funds when pension contributors are allowed to switch between providers or switch portfolios (Enrique et al., 2017). This means that the outflows of DC pension funds may be less predictable than what Davis (1988) suggested. A study by Australia's Prudential Regulation Authority (2008), for example, revealed that portability and the imminent retirement of a large cohort of DC members as well as illiquid investments resulted in a situation where Australian DC funds faced significant liquidity risk. Among the many suggestions put forward to help mitigate the increasing liquidity risk of DC pension schemes is the need for the funds to recognise that liquidity risk constitutes a material risk and must as such document appropriate measures to help them mitigate these risks. It is also important for the schemes to undertake a comprehensive liquidity stress test and for liquidity to be managed at the investment option level and not just at the whole fund level. Funds must also recognise that even otherwise liquid investments could become illiquid and remain that way for some time. Commenting on the UK situation, Porritt (2016) observed that the recently promulgated 'freedom and choice' legislation in the UK would make liquidity considerations even more complicated for UK DC pension funds. We provide a more detailed discussion of the 'freedom and choice' legislation and its implication in more detail in Chapter 2. Effectively, this legislation makes it possible for DC members who are 55 years old and above to withdraw their pension pots in a single go or in several tranches. This could potentially result in larger than expected outflows for DC pension funds. To mitigate this risk, Porritt (2016) recommends that funds need to examine the age profile and other characteristics of their members in order to determine how many of them are approaching the age of 55 and the proportion of them that are likely to make such early withdrawals. Those funds without the operational sophistication to hedge against liquidity risk must ensure that they have a large buffer to accommodate such capital calls.

The less predictable nature of outflows of DC pension schemes has important implications for the liquidity and the asset allocation within DC pension funds. Among other things, Morales et al. (2017) blame the lack of diversification within DC pension portfolios largely on the less predictable nature of outflows due to switching. Morales et al. (2017) studied the effect of switching on DC pension performance in a number of countries. They found that switching skews the portfolios of DC pension funds towards short-term instruments. They further found that as pension funds mature, they tend to decrease their investment in short-term assets and begin to invest in longer-term assets. Increased allocation to longer-term assets have also been due to a relaxation of restrictions on investments. Similarly, Musalem et al. (2012) analysed the returns of pension systems in 27 countries from 1990-2007. They found that that occupational schemes tend to generate returns than personal schemes. Additionally, closed schemes that do not allow members to switch often perform better than those that allow members to switch suppliers. The difference in performance was often due to an over-concentration of some funds investment in short-term securities such as government bonds and T-bills.

It is important to note that illiquidity may not always be a bad thing for investors. Investors who can tolerate some level of illiquidity are in a position to earn illiquidity premiums and thus record attractive earnings over time. For investors who are not seeking to exit a fund arrangements such as restricted liquidity, minimum holding period and exit fees could serve as a form of protection (Timmermans, 2009). Dusonchet (2006) found that hedge funds that offer less frequent redemptions tend to perform better than those that offer frequent redemptions.

Following the 2008 financial crisis, investment managers, regulatory agencies, pension trustees and consultants have increased their emphasis on liquidity. This increased emphasis also comes at a time that yields on liquid assets such as bonds has been at an all-time low. This means that, these investors and investment managers increase their allocation to less liquid assets in order to boost their returns. A comparison of the portfolios of DC and DB pension portfolios shows that DC funds are less diversified. DC pension funds are heavily invested in liquid assets such as stocks and bonds but not in alternative assets such as real estate, commodities, private equity, hedge funds etc (Aon, 2011; DCIF, 2013; Towers Watson, 2015; UBS, 2015; Schroders, 2016). The lack of diversification within DC pension funds has been largely attributed to the daily dealing requirement placed on DC pension funds

(DCIF, 2013; Blake et al., 1999). Towers Watson (2015) estimates that DC pension contributors could end up with about 5% in additional pension if these funds moved away from a reliance on liquid funds and rather include an optimal amount of alternative assets in their portfolios.

Although this practice of investing only in funds that provide daily pricing and liquidity is widespread among DC pension funds, some studies have concluded that there is no regulation that requires DC funds to restrict their investment to only liquid assets. For example, Ezra et al. (2009) found that the increased emphasis on liquidity within DC funds stems from the fact that DC pension funds were initially designed to provide a vehicle where contributors could move money from one investment vehicle to the other regularly. Mohammed (2015) attributed the move towards daily trading originated from competition between fund administrators who used the speed at which they are able to invest/disinvest as a measure of their efficiency. Towers Watson (2013) concluded that the daily liquidity requirement by DC pension funds is a result of ambiguities and perceived fiduciary concerns over such areas as liquidity, daily pricing, fees and reporting. In order to encourage investment in long-term investments, it is important for regulators to work to resolve these concerns.

Harrison et al. (2013) also call for a relaxation of the daily liquidity requirement to make it easier for these funds to attain optimal allocations. Another factor that has promoted the move towards daily liquidity requirements is the desire by regulators to promote flexibility in DC pension arrangements with a view to promoting competition. However, evidence available suggests that many pension fund contributors do not really make use of this increased flexibility, which unfortunately comes at a high cost. However, Mohammed (2015) concluded that immediate access to pension contributions is less of a priority DC members who are in the contributory phases.

In response to the liquidity requirements, many investment managers have developed products that would enable DC pension funds to gain access to real estate and other illiquid, long-term investments whiles at the same time satisfy their liquidity needs. In Chapter 2, we provide details of some of these products that have been developed for UK DC investors.

1.4 ORGANISATION OF THE THESIS

In this section, we set out the way in which the discussion within this thesis is organised. The current chapter (Chapter 1) presents a general introduction to this thesis. The first part of this chapter presents the objectives of the thesis and the motivation behind the studies that make up this thesis. The contributions of this thesis to the literature and the real estate investment industry are highlighted along with the limitations and areas for further research. The second part of Chapter One sets the stage for the discussions in this thesis. The main types of pension funds are first defined. We proceed to discuss some of the key changes that have occurred on the global pension landscape – particularly the shift from DB to DC pension structures. We end the chapter by introducing two of the key issues that are of concern to DC pension funds and that underpin the discussions in this thesis – the issue of capital preservation and liquidity.

Chapter Two builds on the context provided in Chapter One by presenting a more detailed discussion on the UK pension market. The chapter gives an overview of the UK pension system and the changes that have occurred over time. The accelerated move from DB to DC pensions following the introduction of Auto-enrolment is highlighted along with other changes introduced by the 2015 pension reforms. We carry out a review of the Statement of Investment Principles (SIPs) of various master trust pension funds in the UK. The goal of this review is to identify the objectives of these funds as regards promised outcomes and the management of liquidity within their investment portfolios. The chapter ends with a comparison of the portfolio composition of DB and DC pension funds in the UK and around the world. This analysis puts into perspective the calls from various quarters that DC pension funds need to become more diversified.

Chapter 3 reviews literature relevant to this study. The chapter focuses on role that real estate plays in the portfolios of pension funds and provides a builds a background to the analysis conducted later in the thesis. We review literature that demonstrates the range of optimisation and econometric approaches that have been used by various researchers in the analysis of the role real estate plays within investment portfolios. The range of findings from these studies are also highlighted.

Chapter 4 is the Data and Methodology Chapter. The first part of this chapter brings together all the issues relating to the data used in our empirical analysis – the sources of data, composition of the various return indices, issues with the various sources and the steps taken to address those issues. A section of the Data Chapter is devoted to the discussion of issues surrounding the use of appraisal based indices, specifically the IPD property index. The discussions point to the fact that, although they have their limitations, appraisal-based indices such as the IPD property portfolio indices do a good job of tracking the performance of the underlying markets. Once we complete a discussion on data used within this study, we proceed to develop a theoretical framework which provides a background to statistical, econometric and optimisation techniques employed in the various empirical chapters. We end the chapter by presenting some summary statistics on the various assets that form the basis of our empirical analysis. Measures taken to address concerns over the statistical properties of the various assets such as appraisal smoothing and stationarity are also outlined and the results of the data transformation techniques discussed.

The empirical analysis in this thesis can be thought of as being in two parts. The first part of this thesis looks at the illiquidity associated with real estate investments vis-à-vis the growing emphasis on liquidity by institutional investors, particularly, DC pension funds. The discussion here shows that real estate funds can be structured in a way that makes them an appropriate investment vehicle for DC pension funds to access the real estate market.

The liquidity part of this thesis is made up of two empirical chapters – Chapters 5 and 6. The first empirical chapter, Chapter 5, is largely exploratory. In this chapter, we discuss the concept of liquidity and how different aspects of liquidity are measured within the mainstream finance literature. Empirical applications of these measures of liquidity within the field of real estate are also discussed.

Chapter 6 focuses on hybrid or blended real estate funds which have become popular among DC pension funds as a way to access the direct real estate market whiles maintaining an acceptable level of liquidity. For an asset to be considered liquid enough for DC pension funds, it needs to be priced and traded on a daily basis. Blended/hybrid real estate products promise daily liquidity and dealing. To do this, these funds allocate a significant amount of their assets to liquid, publicly traded assets, often cash and listed real estate. Since these portfolios contain assets other than direct real estate, their returns, understandably, tend to deviate from the returns of the underlying property market. In Chapter 6, we apply formal optimisation techniques to the construction of hybrid/blended real estate funds that contain a certain proportion of direct real estate and some liquid, publicly traded assets. This is in contrast to the current practice of simply adding a certain amount of cash and/or listed real estate to a pre-specified percentage of direct real estate. The goal is to determine the optimal range and mix of assets that these funds need to hold in order to deliver property-like returns as much as possible. We employ the tracking error optimisation approach which is an extension of the Classic Markowitz optimisation framework. The extension is made to accommodate the needs of investors who wish to benchmark their performance against that of another portfolio. The benchmark portfolio for the optimisation in Chapter 6 is the IPD All Property portfolio. In order to gauge the ability of the various portfolios to produce out-of-sample performance that mimics the performance of the IPD direct property portfolio, we employ a variety of approaches including rolling tracking errors and dynamic conditional correlations estimated within a GARCH framework. We show that adding other liquid assets such as cash, general stocks and bonds of various maturities leads to improved tracking error and better performance within the hybrid real estate portfolios.

The analysis in the first part of this thesis shows that although liquidity is a major concern among DC pension funds, there are a number of ways that real estate portfolios can be put together to meet the daily liquidity needs of these funds. Once we confirm that real estate can be included in DC fund portfolios, we can proceed to analyse the inflation and interest rate hedging characteristics of real estate as well as other traditional and alternative assets which these funds invest in.

As discussed in the earlier chapters, inflation hedging is important for all investors but is particularly important for institutional investors such as DC pension funds who have return promises that are tied to inflation and interest rate changes. The second part of this thesis is dedicated to the identification of assets which have the ability to hedge against the inflation and interest rates which some UK master trust DC pension funds have adopted in their Statements of Investment Principles. In Chapter 7, we use a number of econometric models to analyse the ability of real estate assets to hedge against inflation and interest rate changes. The Autoregressive Distributed Lag (ARDL) approach to cointegration is used to determine the long-run inflation and interest rate hedging ability of the range of assets which DC pension funds invest in. This approach is preferred as it has the ability to handle cointegration relationship among variables irrespective of their order of integration. Similarly, the Toda and Yamamoto (1995) approach to testing for Granger causality is adopted to determine the short-run inflation hedging ability of the various assets. We carry out a sector-level analysis using a broad spectrum of asset sectors made up of real estate, stocks, bonds and alternative assets. We find that several assets provide a hedge against inflation but not interest rate benchmarks. Real estate in particular is a good hedge against inflation.

Although the analysis in Chapter 7 helps us to identify assets that can serve as an inflation or interest rate hedge the chapter does not consider the issue of optimal allocation within investment portfolios. In other words, the chapter does not address the issue of how to combine different assets within an investment portfolio to ensure that the purchasing power of these portfolios is preserved. In the penultimate chapter, we analyse the optimal allocation within portfolios designed to hedge against inflation and interest rate changes. We follow a growing stream of literature on inflation-hedging portfolio analysis and construct inflation and interest rate hedging portfolios using different inflation and interest rate measures. As in Chapter 6, this chapter also makes use of the tracking error optimisation model along with a semi-variance optimisation model. The risk-adjusted versions of the two models are also implemented i.e. Sharpe ratio for the model based on tracking error and Sortino ratio for the one that uses semi-variance as the measure of risk. In determining the role that real estate plays within the resulting portfolios, we run the analysis without any real estate series initially and then with different real estate vehicles. We also unsmooth the real estate series to determine whether the allocation to real estate is driven by the appraisal smoothing problem associated with real estate and other private market assets. The procedure of Geltner (2003) is used in unsmoothing the real estate series. This procedure and its implementation as well as its effect on real estate and the various private market series are also presented in this chapter. The results show that, for those portfolios constructed to purely hedge against inflation or interest rate changes, real estate and bonds, especially short-term bonds receive significant allocations. Real estate also receives significant allocations within portfolios optimised to maximise risk-adjusted returns.

The last chapter provides a summary of the various studies undertaken as part of this thesis. The implications of the findings of this study and some recommendations are also highlighted. We finish with a recap of the limitations of the various studies and an indication of some areas of future research that naturally arise from these limitations.

CHAPTER TWO – STYLISED FACTS ON THE UK PENSION MARKET

2.0 INTRODUCTION

In the second part of Chapter 1, we presented a general introduction to pension markets and how the global pension landscape has evolved over the years. This chapter is dedicated to the UK Pension Market. We provide an overview of the UK pension market and discuss the various changes that have occurred within the past few decades. We then turn our attention to the regulatory environment and investment activities of these funds – i.e. the investment regulations, allocations and their real estate investment activities.

2.1 AN OVERVIEW OF THE UK PENSION MARKET

This section looks at the key aspects of defined benefit and defined contribution pension arrangements within the UK. The changes that have occurred over the pension landscape over the past decade is reviewed. A survey by the Pensions Policy Institute (PPI, 2017) concluded that due to a combination of market, demographic and policy changes, retirees in the near future are more likely to retire with Defined Contribution Pension savings, live longer in retirement, receive state pension later and experience greater flexibility in accessing their pensions.

2.1.1 TYPES OF PENSIONS IN THE UNITED KINGDOM

The UK pension system is made up of a compulsory, redistributive state tier and a voluntary, non-redistributive private tier (Silcock et al. 2015). A new, single tier, state pension scheme has been introduced, effective April 2016, and replaces the basic and additional state pension arrangement that had been in existence. The pension amount for 2017/2018 is set at £159.35 per week for a single pensioner. To qualify, one has to make national insurance contributions for 35 years.

A second tier of pension within the UK is the occupational pension schemes which can be sponsored and managed by the employer or a third-party. These schemes can also be run and paid for by the government for the public sector or by private sector employers. A wide range of occupational pension arrangements currently exist in the United Kingdom. The PPI (2017) survey found that there are about, including DB and hybrid schemes, there are five types of pension arrangements in the United Kingdom. These include Defined Benefit Pensions, Individual DC Pensions, Group Personal Pensions, Occupational DC Pensions, Hybrid Pension Schemes.

Public sector schemes are defined as pension schemes run and paid for by the government for the benefit of government employees. Public sector schemes are statutory, formed and reformed through Acts of Parliament. The Armed Forces scheme can be amended only by primary legislation, which requires full Acts of Parliament. Other schemes can be amended by secondary legislation which is a speedier and less onerous procedure. Private sector schemes can be amended by the trustees and could be closed down by the sponsoring company.

There are 3 main differences in structure between public and private sector schemes. Firstly, Public sector schemes are - except for the Local Government scheme –unfunded. This means that pension benefits are paid out of current income as and when they become due. All approved private sector schemes and the Local Government scheme are funded (scheme members' pension rights should be covered by assets held under trust).

The first scheme for government employees was formalised by an Act of Parliament in 1810. The scheme was part of a government reform process to improve the efficiency of the Civil Service. Other state employees did not receive a pension scheme until much later. There are six main unfunded public sector pension schemes, the funded Local Government scheme and other quasi-public schemes.

There are seven public sector schemes with total active membership of around 5 million people, of different structures: Those centrally run and paid for directly by government departments and the locally run or 'branded' schemes where the regulations are set centrally but each scheme is separate and run by a local authority. There are also a number of much smaller schemes such as those for MPs, the Judiciary, Research Councils and the UK Atomic Energy Authority, with total active membership of around 31,000 people (Carrera et al., 2012).

Table 2(I) The Seven Main Public Sector Schemes

	Centrally run	Locally run
Unfunded	– NHS – Teachers – Armed Forces – Civil Service	– Police – Fire-fighters
Funded		– Local Government

Source: Carrera et al. (2012)

Private sector pension provision in the UK includes all non-state provided pension benefits. These pensions can take the form of Defined Benefit, Defined Contribution or hybrid schemes. Following the public sector, the first modern-style private sector schemes began to emerge in the early nineteenth century, mainly with large employers such as state chartered companies, utilities and railways.

In general, DC pension schemes can be organised as a Trust-Based scheme run by a board of trustees or could be offered as contract-based. Trust based DC pension schemes are set up by the employer. They are can either be administered by an in-house or third party pension administrator for groups of workers. An insurance company may provide part or all of the services. Master Trust pension funds create a platform which different companies can join in order to benefit from economies of scale. The Master Trust provider covers all the administration and compliance issues. Each employer however determines the contribution levels for themselves and their employees.

On the other hand, contract-based DC pension schemes are established by a contract between the individual employee and the service provider. There is no contractual relationship between the employer and the service provider. Even where there is a group policy, the scheme is still treated as a series of individual contracts.

2.1.2 FACTORS ACCOUNTING FOR THE GROWTH OF DC FUNDS IN THE UK

Another survey by the Pensions Policy Institute (PPI, 2012) found that four factors underpin the shift from defined benefit to defined contribution pensions in the United Kingdom. These factors include: (i) Increased life expectancy (ii) Investment risk (iii) Inflation (iv) Changes in regulation and legislation. The combined effects of these changes means has resulted in an increase in the contributions required to fund a typical final salary scheme from 11% in 1950 to 21% in 2012 (PPI, 2012).

Life expectancy in the United Kingdom has been on the ascendency due to medical advances and improvement in lifestyles. In 1981, the life expectancy in the UK at age 65 was 14 years. This figure has increased steadily over the years and currently stands at an average of over 20 years (ONS, 2016). Higher life expectancy means that DB pension schemes need to pay pension for a longer time, thus increasing cost. Some DB pension funds have resorted to transferring longevity risk to insurers with Buy-ins and Buy-outs reaching £40 billion in 2007.

Investment risk can be a major issue for DB pension funds as sponsors bear investment risk under defined benefit arrangements. Over the last decade, returns on stocks and bonds in the UK has been volatile, leading to concerns among DB plan sponsors that they will not be able to sustain benefit payments. In order to better match their liabilities, PPI (2012) found that DB pension funds have reduced their allocations to equities and increased their allocations to bonds.

Inflation is also an important issue for DB pension funds as the value of benefits beneficiaries receive under DB pension arrangements are affected by price inflation. In DB pension schemes, revaluation of accrued benefits and indexation of pensions in payments are essential parts of the scheme design. Although there is a cap on the mandatory indexation, this does not entirely eliminate inflationary risk for DB sponsors. Aside price inflation, wage inflation also poses a challenge for DB plan sponsors, especially for those who operate a final salary DB scheme. For example, if an active member on a DB scheme is given a huge pay rise shortly before retirement, the cost of providing pension for this individual would consequently be increased.

Several changes in pension regulation in the UK have resulted in an increase in the cost of DB pension funds and consequently their lack of attractiveness to sponsors. These regulations include changes in accounting standards for DB pension funds and changes in the standards for DB pension funding. Changes in taxation of pension funds and some EU regulations have also led to an increase in the cost of providing DB pensions.

2.2 CHANGES ON THE UK PENSION LANDSCAPE

2.2.1 AUTO-ENROLMENT

Defined benefit pensions have been in decline in the UK since the early 1960s. The membership of DB pension schemes reached an all-time high of 6 million in 1967 but has since been on the decline. Membership in DB pension schemes in the UK fell to 1.3 million in 2016 down from 1.6 million the year before (Ippolito, 1986; Turner and Beller, 1989). Turner and Hughes (2008) noted that the introduction of the Pensions Act 1990 acted as a catalyst for the move away from DB pension schemes towards DC pension schemes. The act prohibited the refund of contributions to members who change jobs and instead stipulated that these funds should be preserved and revalued in line with the lesser of the UK consumer price index and 4%. The act also established a minimum funding standard among other things. Whelan (2003) argues that the minimum funding standard increased the costs and resulted in a shift away from DB pension schemes.

Defined contribution schemes have however been experiencing growth. There was an acceleration in the growth of DC pension schemes in the early 1980s, both in terms of assets under management and their membership. Active membership of Defined Contribution pension schemes, which remained at around one million between 2008 and 2014 increased to 6.4million in 2016. (ONS, 2016). The main catalyst for the growth in DC pension funds in the UK is the introduction of Automatic Enrolment which is a staged process that requires employers to enroll qualifying employees into a workplace pension. The employees however have an option to opt out of the scheme. PPI (2017) estimates that over 8.3 million employees have been automatically enrolled by July 2017 with the opt-out rate averaging 9%.

Since the beginning of auto-enrolment, a number of Master Trust pension schemes have been set up in the UK. The biggest Master Trust pension scheme is the National Employment Savings Trust (NEST), which is a qualifying scheme established under the Pensions Act 2008, to help companies meet their obligations with the introduction of automatic enrolment. More than half (59%) of the employees enrolled under auto-enrolment have been enrolled into master trust schemes by March 2017. About 33% of enrolments have been into Contract based DC schemes. 4% were enrolled into DB pension schemes and Hybrid pension schemes. Less than 1% were enrolled under other trust-based DC pension arrangements.

When members join DC pension funds, they are placed in default funds unless they make an active choice to invest in a different fund. Over 99% of Master Trust DC pension members were found to be invested in the default fund in 2017 (PPI, 2017). Most of the default funds make us of life-cycle investment strategies. Life-cycle strategies typically make use of more volatile equity-based investments at the initial stages, when a member is further from retirement. As they get closer to retirement, the portfolio is shifted more to the use of fixed-income securities and cash as the member gets closer to retirement. Some of these funds start with less volatile assets to decrease the chance that members may stop contributing when they see a drastic loss in the value of their pension pots at an early stage.

2.2.2 FREEDOM AND CHOICE

Another significant change on the UK pension landscape is the introduction of the Freedom and Choice Legislation. This gives DC contributors greater flexibility in the way they can access their pension savings.

The introduction of the Taxation of Pension Act 2014, the Pension Act 2014 and other supporting legislations paved the way to what has become known as 'pensions freedoms'. Pension contributors can now draw from their pension pot as they wish after their 55th birthday. The only hindrance to how much they can withdraw is the rules of the particular DC pension scheme to which they belong. There are two main options are open to DC members: (i) Flexi-access drawdown and (ii) Uncrystallised funds pension lump sum.

Flexi-access drawdown (FAD) replaced capped drawdown from 6 April 2015. Any existing drawdown arrangement automatically changed to FAD on 6 April 2015. The plan holder could take 25% of the taken as tax free lump sum. This tax free cash is also known as pension commencement lump sum (PCLS). The remaining 75% stays invested in a drawdown fund. There is the opportunity to withdraw income amount from the fund by the individual, as they see fit. Any income withdrawal will be liable to taxable income- at the individual's highest marginal tax rate, which is 40% or 45% for higher earners.

The second option, uncrystallised funds pension lump sum, allows the DC contributor to withdraw a certain portion or all of his pension pot as a lump sum without first moving it into a drawdown fund. 25% of the amount is normally tax free and the remaining taxed as pension income.

The Taxation of Pension Act 2014 also made changes to how the amount remaining in a pension fund on the death of the DC member would be taxed. Under the old pension legislation, any remaining amount attracts a flat-rate tax of 55% whatever the age of the DC member at death. However, the new rules stipulate that no tax would be charged on pension benefits if the contributor dies after the age of 75. If the beneficiary DC contributor dies after the age of 75, the amount can be taxed at the marginal income tax rate of the beneficiary. The beneficiaries can also leave the funds in the fund and draw it over time as taxable income or pass it on to the next generation and so on.

The Pension Act 2014 introduced a new class of national insurance contributions which enable those who have reached the state pension age to contribute a lump sum that would enable them receive a top-up to their state pension of up to up to £25 per week. Men born before April 1951 and women born before April 1953 are eligible to make these contributions. The amount of lump sum that the retiree needs to pay in return for these top-up depends on their age. For example, a 65-year-old pensioner would need to pay £890 for a £1 a week top-up in state pension payment whiles a 75-year-old would need to pay £674 for the same amount of top-up.

The Pension Policy Institute (2017) survey shows that although the number of annuities purchased by retirees has been falling since 2009, the introduction of the Freedom and Choice has led to a fall in the number of annuities purchased. The number of annuities purchased peaked at 466,000 per quarter in 2009 but in 2017, only 20,000 annuities were purchased by retirees per quarter. On the other hand, the use of income drawdown contracts has been on the increase. The sale of income drawdown contracts doubled from 40,000 per quarter in 2014 to 80,000 per quarter in 2016. Although the number of initial lump-sum withdrawals increased from to 120,688 withdrawals in the second quarter of 2015, it has since fallen to an average of 59,000 withdrawals per quarter by the fourth quarter of 2016.

2.2.3 OTHER CHANGES

There are plans to increase the retirement age in the UK from age for both men and women is expected to increase to 66 in 2020 and further to 67 by 2028 and finally 68 by 2039. This means that people can expect to receive state pension later than is currently possible.

A number of regulatory changes have also been put in place following the introduction of the Automatic Enrolment. In 2015, contract based pension schemes are expected to set up Independent Governance Committees to ensure that these funds act in the best interests of members and that members receive value for money. Similarly, trust-based DC pension schemes are required to design default schemes that are in the best interest of contributors, ensure that financial transactions are prompt and accurate and that charges and costs are reasonable. The 2017 Pension Schemes Act also requires

2.2.4 PROPOSED CHANGES

In 2012, the UK Pension Minister Steve Webb called for pension providers to consider offering workers an affordable 'money-safe' guarantee that would ensure that that DC members would at least ensure that members would at least get back the nominal value of their accumulated contributions (i.e. individual contributions, employer contributions and tax relief). The Department of Works and Pension (DWP) announced in a 2014 press release that new pension reforms to the pension system were being considered by parliament. These reforms are aimed among other things to ensure that certainty would be brought back to pension savings by opening up new types of schemes which would remain affordable to employees but deliver better outcomes. In particular, a 'shared-risk' category would be given legal backing to encourage greater innovation in DC pension design.

On November 22nd 2012, the UK Department for Work and Pensions published 'Reinvigorating Workplace Pensions', in which it proposes the introduction of a new category of pensions in the UK market: defined-ambition (DA) pensions. Schouten and Robinson (2012) describe DA pensions as an attempt to reintroduce (or maintain) the concept of an employer bearing some risk on behalf of their employees. There are currently a number of different DA proposals around the world one of which is currently being implemented in the Netherlands. Schouten and Robinson (2012) describe the Netherland system as DA from DB (DA/DB) – that is, it is a modification of the DB pension system in which a pension fund continues to operate as before, but instead of promising to provide a pension based on average career salary, the employer promises to target a specific pension based on average career salary on the condition that employer contributions will not have to be raised in order to achieve this. Unlike DC, the employer is taking responsibility for trying to deliver a specified retirement outcome but, unlike DB, is not bound to deliver that outcome at all costs. As a result, companies no longer have the volatility and risk of DB pensions but at the same time employees receive more support and certainty than with most DC pensions. The second type of DA pension being proposed in the UK has been described Schouten and Robinson (2012) as DC plus pensions (DA/DC). These range from collective defined-contribution (CDC) pension plans to fairly straightforward money-back guarantees on DC investments. A DWP strategy paper (2014) lists essential features of a DA pension including bulk-purchased annuities, guaranteed returns on investment, and a separate employers' fund used to smooth returns of employees' funds through annual or terminal bonuses (a sort of partial CDC). CDC itself is not currently possible in the UK, but some forms of DA/DC pensions are in use, such as the cash balance pension provided to employees by UK supermarket chain Morrisons.

2.3 INVESTMENT REGULATION OF UK DC PENSION SCHEMES

2.3.1 MYNERS PRINCIPLES FOR INSTITUTIONAL INVESTMENT DECISION-MAKING

Although there are few regulatory constraints within the UK for DC pension funds in particular, the investment activities of pension funds in the UK are expected to be in conformity with a set of principles and best practices published by the Pension Regulator. These principles are drawn largely from the Myners (2001) Principles for Institutional Investment Decision-Making. In this section, we discuss key elements of this document. It is important to note that while Pension Fund trustees are not required to implement each aspect of the guide, they are required to report on each aspect on a 'comply or explain' basis. Six principles are covered in the guide: (i) Effective decision making (ii) Clear objectives (iii) Risk and liabilities (iv) Performance assessment (v) Responsible ownership (v) Transparency and reporting.

2.3.1.1 Effective Decision Making

Regarding effective decision making, trustees are expected to appoint people with the requisite skills, knowledge and recourses to enable them take decisions as well as ensure that these decisions are implemented effectively. The trustees themselves must have the capacity to evaluate any advice they receive and raise relevant questions or challenge the advice they receive. The best practice in effective decision making include the creation of an investment sub-committee and drafting of an investment business plan. Ideally, trustees must be given a remuneration package to make them committed. Care must be taken in contracting and managing external advisers on issues such as strategic asset allocation, investment management and actuarial issues.

2.3.1.2 Clear Objectives

Clear investment objectives should be set for the pension fund. This must take into consideration the nature of the scheme's liabilities, sponsor covenant and the risk tolerance of both trustees and sponsors. There must also be effective communication between the investment advisors and managers. The best practice in this regard is the setting of clear benchmarks and investment objectives. There must be a clear time horizon over which performance is measured. A range of assets must be agreed upon as well as the asset management style (active or passive) that is to be adopted by the fund. The effect of transaction and management costs on fund performance should also be considered. As a best practice, trustees must be willing to accept underperformance at certain periods when market conditions are not favourable. Trustees also have a legal responsibility to put in place internal control mechanisms.

2.3.1.3 Performance Assessment

Performance assessment should be undertaken to determine how effective the investment strategy of the pension fund was. Aside measuring performance of the investment portfolio, there must be an assessment of the effectiveness of trustees and managers. As a best practice, there must be a formal policy and process must state how the evaluations should be carried out. Past performance should be used in selecting advisors, trustees and managers. Most importantly, benchmarks and tracking error limits need to be set. The investment principles and governance compliance statement must be clear and detailed.

2.3.1.4 Responsible Ownership

Funds must have a statement in their policy regarding responsible ownership. This must also contain a statement regarding the scheme's strategy for intervention in the companies they hold a stake in. The goal of this policy is to ensure that the scheme does not override, negate or dilute the policies of the boards of companies in which they have invested. Any monitoring activities undertaken by the pension fund must be open.

2.3.1.5 Transparency and Reporting

There must be clear communication from the scheme to members regarding the management of investments and how the performance for the period compares with the stated objectives. Trustees must communicate with members at regular periods using an appropriate medium. Best practices in transparency ensure improvements in corporate governance within schemes. The fund must make available relevant statements such as the funding strategy statement, statement of investment principles governance compliance statement.

2.3.2 INVESTMENT OBJECTIVES OF SELECTED DC MASTER TRUST PENSION FUNDS IN THE UNITED KINGDOM

As indicated earlier, the overall goal of this thesis is to examine the composition of DC portfolios that are constructed to help the funds meet their objective of capital preservation and liquidity for members. Since there is no minimum return requirement imposed by the UK Pension Regulator, we review the Statement of Investment Principles (SIPS), annual statements and other documents of the various DC

Master trusts in the UK at the end of 2015 to determine the objectives and measures these funds have put in place to reassure contributors and potential contributors that they can entrust their future to them.

A master trust is a trust based defined contribution pension scheme which is made up of non-related employers. Master trusts are governed by a board of trustees and offer the same terms to multiple employees and employers. Mastertrusts make up the majority of DC pension schemes. By the end of 2015, twelve (12) master trust funds had been independently reviewed against the Master trust assurance framework and were on The Pension Regulator's list of DC pension funds with Master trust assurance. PPI (2015) estimates that of the 5.2 million workers who were automatically enrolled by March 31st, 2015, more than half of this number (53%) were registered into Master-trust schemes. This number makes up more than 88% of employees enrolled into trust-based DC pension schemes. Concerning their choice of investment options, Silsock et al. (2015) found that over 99% of master-trust members were in the default fund. This compares with 85% in workplace DC pension schemes.

Table 2(II) Master Trust Assurance List 2015

Master Trust Pension Fund	Membership (As at Dec. 2015)
Smart Pensions	60,000
BCF Pension Trust	2,161
Legal & General WorkSave Master Trust Pension Scheme	97,350
National Employment Savings Trust (NEST)	3,200,000
National Pension Trust	18,000
NOW: Pensions	890,000
SEI Master Trust	217,705
Standard Life DC Master Trust	107,576
The BlueSky Pension Scheme (TBPS)	30,000
The Pensions Trust	240,000
The People's Pension	1,315,000
Welplan	N/A

Source: The Pension Regulator (2015)

The goal of this section is to understand what informs the investment activities of DC pension funds with a particular focus on master trust DC pension funds. We focus on the funds' strategy for preserving the purchasing power of contributions and while ensuring adequate liquidity within their portfolios. We include only those funds whom we identify as having explicit objectives, especially regarding returns (performance targets) and liquidity (realisation of assets).

We found that 5 out of the 12 master trust funds had explicit objectives regarding preserving the capital value of DC contributions or promise a minimum rate of return. The 5 pension plans together make up more than 90% of DC master trust membership which stands to reason that more than 90% of DC contributors in the UK have are invested in plans that offer some form of guarantee.

Majority of the funds examined have set explicitly set performance targets which are often linked to stated inflation or interest rates. It is expected that as the market matures and competition increases, more funds would be more explicit about their targets or strategy for helping members achieve their goal of having adequate income replacement in retirement. Another issue of interest, which we highlight, is if and how these funds gain exposure to real estate assets – the main asset of interest in this thesis. The information for the various funds are drawn from the Statements of Investment Principles and Annual Statements of the selected Master Trust pension funds.

2.3.2.1 National Employment Savings Trust (NEST)

The National Employment Savings Trust (NEST) is a scheme set up by the UK Government to provide a suitable, low-cost pension scheme to help employers meet their obligations under the Pension Act 2008.

NEST invests in funds set up by leading investment managers. The criteria for selecting managers is that they must have a clear objective and most often, the funds invests in a single asset class. The assets invested in must be of adequate security and liquidity.

The overarching objective of the NEST default fund in which the vast majority of members are invested is to provide returns in excess of CPI inflation after all charges, over the long term. The fund trustees believe that risk-based asset allocation is the best driver of long-term performance. Taking account of asset prices, economic conditions and long-term developments enhances long-term performance and informs the strategic decisions that NEST makes.

For the default fund, NEST provides a series of target date funds with asset classes selected to meet the level of risk appropriate for the different stages that the scheme members go through in the course of their career. Three phases – foundation, growth and consolidation – have been designed to help members meet their investment objectives. All three phases are designed with CPI inflation as a benchmark. The Statement of Investment Principles of NEST makes it clear that the idea is to not completely hedge against inflation but to manage inflation. Consequently, instead of setting the target return equal to inflation, the various phases have different objectives linked to CPI inflation. The foundation phase, which is designed to last for the first five years, has an objective of keeping pace with the UK CPI inflation, after charges. The growth phase aims to deliver a return of 3% over and above the UK CPI inflation rate. The consolidation phase has a stated objective of outperforming inflation whiles at the same time minimise return volatility as members approach retirement.

Members who do not wish to be invested in the default fund are given six alternative fund choices – Higher Risk Fund, Lower Growth Fund, Ethical Fund, Sharia Fund and a Pre-retirement Fund. For these funds also, the investment committee ensures that the fund is well diversifies and that the risk taken is appropriate for the retirement age of the DC fund member.

2.3.2.2 NOW Pensions

NOW Pensions was founded by ATP Denmark, one of the largest pension funds in Europe. Although NOW Pensions indicates at the beginning of its Statement of Investment Policies that it would operate as a DC fund which offers no performance guarantees, the fund's stated objective is to deliver a satisfactory return in real terms on contributions invested. Specifically, the fund's overall goal is to maximise retirement pay-out in real terms and also protect members from significant reduction in the value of the individual's pension account. The fund also undertakes to develop an investment strategy appropriate to the planned retirement date of the member. Members will be protected from significant reductions in the value of their pension account.

The fund's risk management approach is expected to ensure that a fund member would have sufficient retirement income that meets their expectations and also ensures that that volatility in expected pension outcome is minimised. The goal of the fund's risk management approach is not to eliminate risk but to ensure that at every point, there is the right balance between the need for risk control and the need to produce assets that help meet the performance targets that have been agreed on.

In terms of investment choices, the fund trustees believe that it is better to provide a unified investment solution that is tailored to the retirement date of members as opposed to giving them a wide array of funds to choose from. Three different funds are provided at each point in the glidepath: Diversified Growth Fund, Retirement Countdown Fund (Series I), Retirement Countdown Fund (Series II).

The performance objective for each of the three funds is set relative to short-term UK interest rates as represented by the Sterling Overnight Interest Rate (SONIA). The diversified growth fund's stated objective is to produce a return of 3% over and above the SONIA rate. Both retirement countdown funds are designed to track the SONIA rate as closely as possible in order to provide security and liquidity for members as they near retirement.

2.3.2.3 The Pension Trust (TPT)

The Pension Trust is one of the providers of occupational pension in the UK, founded by the National Council for Voluntary Organisations in 1946 as the Social Workers Pension Fund. The fund currently has over 9 billion of assets under management.

The stated investment strategy of the Pension Trust (TPT) is the tracking of each fund's liabilities by investing in a combination of main asset (namely stocks, bonds and property) and alternative assets (private equity, hedge fund, insurance policies and annuities). The goal of the default fund manager is to dampen the effects of short-term market movements by tactically adjusting the allocation to the various assets.

All TPT's schemes offer target date funds as default options. The scheme's trustees believe that a dynamic investment approach would enable them to better address the expected retirement date of each participant. In addition to the default fund, the trust also offers a number of self-select funds for members who do not wish to be invested in the default fund. These self-select funds currently include an ethical fund, flexible retirement fund and a growth plan Series 4 fund.

The fund defines investment risk as the annual variation in returns between each fund and the returns of benchmark portfolios that the various funds are meant to track. The default target date fund uses the UK CPI as its overall performance benchmark.

Regarding liquidity, all the range of funds which The Pension Trust invests in are core unified products which are traded on a daily basis and are thus easily realisable. By using a combination of index tracking and active managers, TPT hopes to produce returns in excess of the respective market indices it benchmarks.

2.3.2.4 The People's Pension

The People's Pension (TPP) is a trust-based pension scheme set up by Building and Civil Engineering (B&CE) in 2011 to help employers who require a scheme in order to fulfil their duties under the Pension Act 2008. Membership of the scheme stood at 1,315,000 at the end of 2015.

The broad objective of The People's Pension is to provide adequately for members retirement through investing the contributions of members appropriately. In the long run, the trustees expect that the returns obtained on the default fund would exceed CPI inflation and general salary (wage) growth rate. The default fund takes into consideration members expected retirement date, attitude to risk and their expected method of assessing their retirement savings.

Investment decisions are made on two levels. The strategic management of assets is undertaken by the trustee but scheme investment managers handle the day-to-day management of the scheme's investment. The fund invests in pooled investment funds as opposed to direct investment in assets. The assets selected must provide sufficient liquidity in order to ensure that these assets are realised when members make requests at retirement or earlier.

The different investments are expected to provide protection against specific risk factors. Equity investments are expected to provide returns in excess of CPI inflation over the long run. Funds that contain bonds are expected to provide returns in line with annuity rates and thus provide security for members close to retirement. Cash funds are expected to provide protection against losses in the capital value of accumulated pension especially for members who intend to draw part of their benefits in the form of tax-free cash.

2.3.2.5 Legal and General

Legal and General has about 56 different funds under its governed fund range, which are those funds that are monitored to a high degree by the investment review unit. Performance is monitored quarterly or more frequently. Members' personal accounts are invested in funds that have an acceptable level of liquidity. Funds, such as property funds, that are less liquid are labelled appropriately to warn participants of likely delays in realisation.

Nest states in its annual report (2016) that the fund "recognises that the performance and liquidity of investment markets, interest rate movements and inflation impact the value of investments we hold in shareholders' funds and those to meet the obligations from insurance business, with the movement in certain investments directly impacting profitability" (p. 44).

These funds are managed under two different arrangements – sole governance and shared governance. Sole governance gives the trustees full control of o of pension contributions. A default investment option is provided under the sole governance arrangement. The performance objective of the default fund is to target a real positive return net of fees. The risk of the default fund is also kept at a level lower than the risk of a pure equity portfolio.

Participant companies that opt for shared governance can choose from several funds and could even add a new blend or fund with recommendation of the investment committee. These new funds could then be made available to other participants through Legal and General's WorkSave investment platform or could be set aside for that participant.

Nest also offers annuity contracts to retirees with benefits tied to either CPI inflation or RPI inflation. The annuities often come with a provision that the annuity rate would not reduce if the CPI or RPI rate against which they are hedged becomes negative.

2.3.2.6 Standard Life Pensions

Regarding expected returns on investments, the trustees of the fund state that a distinction would always be made between nominal returns and real returns. The fund would always ensure that inflation and costs are factored into all investment decisions and in comparing different investment options. The overall objective of the Trust is to achieve good outcomes for members net of fees. Volatility in returns is managed by diversifying across a broad range of asset classes.

The fund also has an explicit objective regarding liquidity – which is to look into how to always mitigate the risk that the assets may have to be sold under less favourable market circumstances. One of the options indicated in the SIPS is to suspend redemptions in certain situations.

The fund has a range of default funds that are split into two suites: Active Plus and Passive Plus. Both suites are invested in a range of asset classes such as stocks, bonds and absolute return funds.

The goal of the Active Suit is to give members the opportunity to select funds which match the amount of risk they are prepared to take. The range has five different risk ranges which indicate how much risk the contributor is prepared to accept. For example, the investment goal of the Active Plus Fund III for example is to provide positive investment returns regardless of whether markets are going up or down. They hope to do this by investing in shares, bonds, non-residential property. The fund also aims to diversify globally including investing in emerging markets. The active Plus II is designed to manage the level of risk in a portfolio rather than the level of return. The Passive Plus Funds invest mostly in tracker funds whose returns follow a broad index.

2.4 ALLOCATION WITHIN UK PENSION PORTFOLIOS

This section discusses the current historical allocations within DB and DC pension portfolios and compares the allocation within these schemes. We draw from different surveys and data from the UK office of National Statistics, Towers Watson and the WM Company.

With the increasing dominance of DC pension funds, the portfolio composition of these funds have the focus of several surveys. Schroders, an investment management company carries out a semi-annual survey that analyses the allocation within the default funds of DC pension schemes of the UK's top 350 companies. A stated objective of the survey is to examine the move toward diversification in the portfolios of these funds. The Schroders (2016) survey revealed that the allocation to equities has droped from 79 percent in 2011 to 67 percent in 2016. The allocation to alternative assets has also increased from 7 percent to 13 percent over the same period.

2.4.1 GLOBAL PENSION ALLOCATION

Towers Watson carries out an annual survey of pension funds in 19 countries with a total asset of US$35.32 trillion, accounting for 80% of the combined GDP of these countries. The allocations within the portfolio of these funds are shown in Table 2(III) below. Globally, we see a fall in the allocations to equities within pension portfolios. Bond allocations also appear to be falling. The fall in allocation to stocks and bonds have seen the allocations to alternative assets increase from a low of 7% in 1995 to 24% by the end of 2015.

Table 2(III) Global Pension Asset Allocations (1995 – 2015)

Assets	Years			
	1995	2002	2008	2015
Equities	52	50	48	44
Bonds	36	38	32	29
Cash	5	3	1	3
Others	7	9	19	24

Source: Towers Watson (2016)

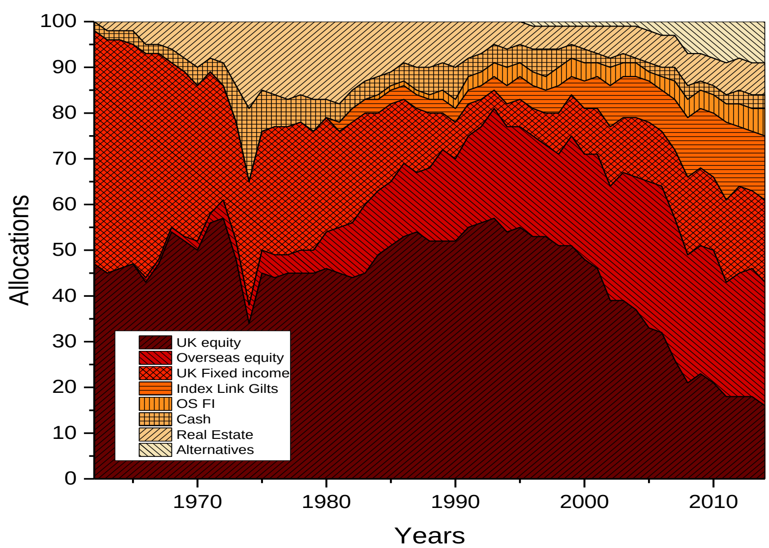
2.4.2 UK PENSION ALLOCATION

The discussion in this section is based on a survey conducted by UBS (2015) using data from the UK Office for National Statistics (ONS) and the WM Company. The allocation cover both DB and DC allocations, although before 2012 the vast majority of pension funds were DB pension schemes. The allocation to various asset classes from 1962 – 2014 can be seen in Figure 2(1). Equities make up the largest part of UK pension portfolios over the whole period. The allocation peaked to equities peaked at 80% in 1993 whiles the lowest allocation of less than 40% was in 1974. Allocations in UK equities has however been falling in favour of overseas equities. Allocation to overseas equities surpassed the allocation to UK equities by the end of 2007. By 2014, overseas allocations were 11% more than the allocation to UK equities.

Apart from equities, a significant allocation within UK Pension portfolios went to fixed income. The allocation to fixed income was driven by developments in the conventional government bonds and index linked bonds. For example, in the 1970s, the market capitalization for both the UK government bond market and the equity markets stood at GB£20bn. By the end of 2013 however, UK bond market only had a market capitalization of GB£1 trillion as against GB£2 trillion for the equity market. UK bond allocations within pension portfolios fell from a high of 51% in 1962 to 4% in 1993. Bonds however made a resurgence in the 1990s. UBS (2015) attributes the renewed interest in bonds to the performance of bonds over the period. Another reason for the increased bond allocations was the demand for assets that offered pension funds a close match of assets and liabilities to fulfil the minimum funding requirements legislation. Pension allocations to bonds at the end of 2014 was 38%.

Aside stocks and bonds, real estate received significant allocations within portfolios especially during periods of high inflation. The allocation to real estate peaked at 19% in 1974. However, real estate allocations between 2000 and 2014 has averaged about 7%. Alternative assets such as hedge funds and private equity has also increased steadily. From a low of 1% in 1996, alternative assets now account for 7 to 9% of pension portfolios. On the whole, UBS (2015) survey shows an increase in allocations within UK pension funds both across asset classes and internationally.

Figure 2(1) UK Pension Allocations (1962 – 2014)



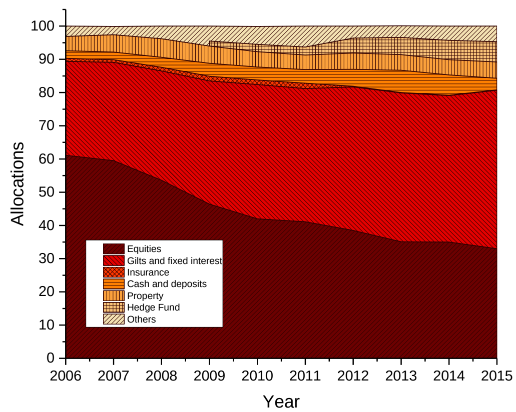
Source: UBS (2015)

2.4.3 UK DC ALLOCATIONS

There has been a renewed interest in the allocation within pension fund portfolios following the shift to DC pension structures. Schroders, a UK investment company, conducts a bi-annual survey of the allocations within DC pension portfolios. The allocations within the portfolio of the top 350 pension funds in the UK between March 2013 and March 2016 are shown in Figure 2(3). About 80% of DC pension portfolios were allocated to equities and a further 10% to bonds. Alternatives and cash made up the remaining allocations. Schroders (2016) defined alternative assets to include property, commodities and hedge funds.

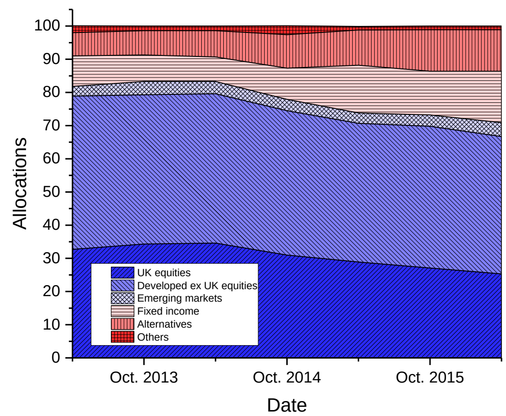
The Pensions Regulator in conjunction with the Pension Protection Fund also undertakes an analysis of the portfolio composition of defined benefit pension funds in the United Kingdom. The allocations in Figure 2(2) shows that within defined benefit portfolios, the allocation to equities has been falling in favour of gilts and other fixed income securities as well as alternative assets. In 2006, the allocation to stocks in DB portfolios was over 60%. This allocation has fallen to 33% by the end of 2015. Bond allocations which stood at 28.8% in 2006 stood at 33% by the end of 2015. Property allocations within DB portfolios has been consistent at around 5% over the entire sample period. Other alternative assets such as hedge funds and insurance policies have increased in allocation from just over 6% in 2006 to 14.4 at the end of 2015.

Figure 2(2) UK DB Pension Allocations (2006-2015)



Source: Pension Protection Fund (2015)

Figure 2(3) UK DC Pension Allocations (2013 – 2016)



Source: Schroders (2016)

A comparison of the two allocations point to a clear lack of diversification within DC pension portfolios, with over stocks making up 70% to 80% of their portfolios. As pointed out in Schroders (2015), this trend appears to be reversing, with bonds and alternative assets increasingly gaining allocations within DC portfolios.

2.5 CONCLUSION

In this chapter, we built on the context provided in Chapter 1 by focusing on the UK pension market. We first provide an overview of the occupational pension sector in the UK before outlining the major changes that have occurred over the past few decades.

The discussion in the chapter shows that DC pension funds have become more prevalent following the introduction of auto-enrolment. Most of the members who have been enrolled onto workplace pension funds are currently enrolled with multi-employer master trust pension schemes such as NEST, NOW Pensions and so on. Over 99 percent have elected not to make take on an active role in deciding how their pensions are invested, hence they have been enrolled onto the default scheme. Consequently, we have decided to use the master trust pension funds as our case study and carry out our analysis from the perspective of a scheme manager investing on behalf of default scheme members. Hence, we analyse different investment objectives as these scheme managers would do at different points in the course of the employee's life cycle.

An analysis of the Statement of Investment Principles (SIPs) of the various master-trust pension funds reveals that most of them have investment objectives pegged to a measure of UK inflation or a risk-free interest rate. NEST for example has its objectives for default scheme members linked to CPI inflation whiles NOW Pension uses the SONIA interest rate as its performance benchmark.

Based on a number of surveys conducted on the allocation within DC and DB fund asset allocations over the years, we confirmed the concerns expressed by many analysts that there is a lack of diversification within DC pension fund portfolios especially when compared with their counterpart DB pension funds. Equities alone made up over 80% of the portfolios of DC funds' portfolios. Schroders (2016) however observed that there appears to be a gradual reduction in the amount allocated to equities in favour of investments in assets such as real estate and other alternative assets.

Another conclusion that we reached in this chapter is that the new legislations that have been introduced in the face of auto-enrolment such as the Freedom and Choice legislation is likely to create further uncertainty in the cash-flow pattern of DC pension funds. This legislation changes when and how members can access their accumulated investments. This is likely to increase the emphasis on liquidity and hence affect the investment decisions of these DC pension funds. Typically, it is easier for DB pension funds to predict what their cash flow pattern would be using factors such as the mortality rates, retirement age etc. Hence, they are in a position to undertake longer term investments. As we mentioned in the Introduction Chapter, the current low-rate environment requires that DC funds look to alternative investments in order to deliver good returns for retirees. Clearly, this is made more difficult when thee funds have to maintain enough liquidity to meet unpredictable outgoings.

In the next chapter, we will review literature on the role of real estate within the investment portfolios of institutional investors such as pension funds. We analyse the role of real estate both as a stand-alone asset and as part of an investment portfolio. The chapter that follows (Chapter 5) would bring together all the issues around liquidity and how this needs to be managed within the investment portfolios of institutional investors such as pension funds. The discussion on liquidity ends with an analysis of a fund product that has become very common among UK DC investors as a vehicle to gain access to the real estate market while maintaining an acceptable level of liquidity.

CHAPTER THREE – THE ROLE OF REAL ESTATE WITHIN INVESTMENT PORTFOLIOS – A REVIEW OF THE LITERATURE

3.0 INTRODUCTION

In this chapter, we review literature on the role of real estate assets within investment portfolios, particularly within the portfolio of pension funds. The goal is not to provide an exhaustive discussion of all the studies that have discussed the role that real estate plays within investment portfolios but to present a broad overview of the various optimisation and econometric approaches that have been utilised in the various empirical studies and also highlight the range of findings obtained from these studies.

In the first part of this chapter, we focus on the theory and practice of portfolio construction. We begin by offering a general introduction to asset allocation – what asset allocation is, the process of asset allocation and its importance for pension funds. Next, we review different asset allocation models that have been developed and implemented in theoretical and empirical studies. We examine the extent to which these models have been used within the real estate literature and the results of these studies and the challenges associated with implementing these models, especially within the context of real estate.

In the second part of this chapter, we focus on the inflation-hedging characteristics of real estate. Real estate has long been viewed as a good hedge against inflation for a number of reasons especially as rental income can be adjusted to reflect increases in general price levels. Beginning with Fama and Schwert (1977), a large number of studies have analysed the ability of real estate to hedge against inflation. We review a large number of empirical studies, particularly, focusing on the method of analysis, assets analysed, time frame and the findings of these studies. On the whole, these studies show that real estate is a good hedge against inflation, although, as observed by Hoesli & Oikarinen (2012), these results have been the results depend on factors such as the method of analysis, geographical setting etc.

3.1 ASSET ALLOCATION – AN INTRODUCTION

In its simplest terms, asset allocation is the practice of dividing resources among different investment options such as stocks, bonds, mutual funds, investment partnerships, real estate, cash equivalents and private equity. The theory is that the investor can lessen risk because each asset class has a different correlation to the others; when stocks rise, for example, bonds often fall. At a time when the stock market begins to fall, real estate may begin generating above average returns.

The important thing in strategic asset allocation is to find a solution that satisfies a set of constraints, the structure of the pension fund and given legislation (Goldman Sachs, 2012). For pension funds, the asset allocation decision aims to balance the long-term goals, short-term obligations and risk tolerance. Creating a diversified portfolio plays a crucial role in balancing the long-term investment goals with the pension fund's short-term obligations. Asset allocation takes the principle of diversification a step further by providing a customized approach for investors to strategically diversify their portfolio among different asset classes. This enables investors to stick to their long-term investment objectives and thus avoid relying on market timing to generate returns. (Goldman Sachs, 2012).

For investors, selecting the types of assets for a portfolio and allocating funds among different asset classes are major decisions. A 70/30 stock/bond portfolio has a different expected return, risk, and cash flow pattern than a 30/70 stock/bond portfolio. Which allocation is more appropriate for a particular investor will depend on how well its characteristics match up with the investment objectives and circumstances described in the investor's investment policy statement (IPS).

It is important to remember that asset allocation is not purely a mathematical process but involves several other considerations. Scott (1991) found that investors attitude to inflation plays a big role in the strategic asset allocation decision of UK investors. In other countries however, investment regulations play a more important role in determining the allocations within pension fund portfolios. Another factor that influences pension fund allocation is the government's need for capital. For example, in Scott (1991) found that in the 1970s, when the UK Government had a substantial borrowing programme, UK pension funds invested more in bonds. This is because governments offer attractive returns when they require additional funds. In the 1980s, the UK Government raised funds mostly by selling off its shares in privatized companies. This period coincided with lower bond allocations within pension portfolios. This is also the time that pension funds invested very heavily in equities.

3.1.1 STRATEGIC ASSET ALLOCATION

Strategic asset allocation is an integrative element of the planning step in portfolio management. In strategic asset allocation, an investor's return objectives, risk tolerance, and investment constraints are integrated with long-run capital market expectations to establish exposures to IPS-permissible asset classes. The aim is to satisfy the investor's investment objectives and constraints. Thus, strategic asset allocation can be viewed as a process with certain well-defined steps. Performing those steps produces a set of portfolio weights for asset classes; we call this set of weights the strategic asset allocation (or the policy portfolio). Thus, strategic asset allocation may refer to either a process or its end result (Maginn et al, 2007).

Strategic asset allocation is both a process and a result. The strategic asset allocation focuses on how to invest assets to maximize the probability of achieving one's long-term goals at an appropriate level of risk. It is the process of determining the target long-term allocations to the available asset classes. The process results in a set of long-term target allocations to applicable investable asset classes (proxied by market indices). The resulting long-term target asset allocations are often formalized into a strategic policy benchmark (policy benchmark for short) or model asset allocation. Using today's popular alpha-beta vernacular, strategic asset allocation is the beta decision, and as such, investment vehicles like mutual funds and hedge funds are not part of the discussion (Idzorek, 2006).

Strategic asset allocation is the translation of an organisation's investment policy. It dictates how a fund's assets should be divided across major asset classes. Broad investment policy is the domain of the board of trustees. It is best to use broad asset classes with widely different fundamentals; sub-asset classes should be left to the implementation stage (Ambachtsheer & Ezra, 1998).

In their seminal and extremely influential work, Brinson et al. (1986) estimated that, over time, 90% of the variance in returns of a typical portfolio is explained by the variance of the portfolio's asset allocation. Ibbotson and Kaplan (2000), among others, confirms this important finding supporting the notion that strategic asset allocation (SAA) is the most important decision in the investment process.

The primary risk exposure of a fund is attributable to its strategic asset allocation. While the investment staff can adjust a fund's risk exposure through tactical asset allocation, the predominant contribution to the variation in a fund's returns comes from the strategic asset allocation (Brinson et al., 1986).

3.1.2 TACTICAL ASSET ALLOCATION

A second major type of asset allocation is tactical asset allocation (TAA). It involves making short-term adjustments to asset-class weights based on short-term expected relative performance among asset classes. Tactical asset allocation involves making short-term adjustments to asset-class weights based on short-term predictions of relative performance among asset classes. TAA can subsume a range of approaches, from occasional and ad hoc adjustments to frequent and model-based adjustments. In practice, TAA often refers to investment disciplines involving short-term (such as quarterly or monthly) adjustments to the proportions invested the various asset classes. Strategic asset allocations are reviewed periodically or when an investor's needs and circumstances change significantly. Among institutional investors, regular annual reviews are now commonplace. Ad hoc reviews and changes to strategic asset allocation in response to the news items of the moment may lead to less thoughtful decisions (Maginn et al, 2007).

Tactical asset allocation is intended to take advantage of opportunities in the financial market when certain markets appear to be out of line. It is designed to facilitate a fund's long-term goals by seeking added value. In other words, it attempts to beat the market. The total fund is adjusted to reflect changes in economic fundamentals. In this respect, tactical asset allocation compares the relative value of each assert class, and underweights or over-weights the major asset classes when values and returns appear to be out of line with economic fundamentals.

A key distinction between tactical and strategic asset allocation is the time frame. Tactical asset allocation occurs more often than strategic asset allocation. It may be performed monthly, quarterly or annually. In fact, any adjustment to a fund's portfolio that is not part of the strategic asset allocation process is a tactical attempt to add value.

Tactical asset allocation is performed by the investment staff for a fund – not the board of trustees. The investment staff apply their knowledge of market conditions to underweight certain asset classes to take advantage of financial markets that are out of alignment. They also look for actively managed alternatives to funds that passively track benchmark risk. Actively managed accounts are alpha generators – that is, they attempt to generate excess return (or alpha) over a broad financial index. Alpha generators can be used to change the return distribution of the strategic allocation. Tactical asset allocation decides how much to allocate to active accounts versus passive benchmarks.

3.2 THE INVESTMENT MANAGEMENT PROCESS FOR PENSION FUNDS

The process of investment management for pension funds consists of three steps – (i) Drafting an investment policy statement (ii) Asset allocation decision (iii) Selecting investment managers in specified mandates (Ang et al., 2014). The contributions of the various steps to the performance of pension funds has however been a subject of much debate. A majority of studies have concluded that that strategic asset allocation accounts for much of the time series variations in the portfolio returns of pension funds (Brinson et al., 1986, 1991; Ibbotson and Kaplan, 2000; Blake et al., 1999; Brown et al., 2010). Brinson et al. (1986) for example concluded that as much as 91.5% of pension fund investment performance is driven by the strategic allocation. Scott (1991) found that although most investors agree that strategic asset allocation is the most important decision facing any pension fund, it is still the least understood. Ibbotson and Kaplan (2000) and Kritzman and Page (2002; 2003) however found security selection to be more important than the other two aspects of pension fund investment management. Andonov et al. (2012) placed equal importance on the various processes.

Scott (1991) concluded that the best way of ensuring an agreement between the various parties of a strategic asset allocation decision is to agree on a benchmark against which performance of the fund can be judged and, in so doing, to determine whether the investment objectives have been fulfilled. Strategic asset allocation is very necessary especially where an external manager is appointed. Once the benchmark is agreed upon, simulation techniques could be used to determine the array of possible outcomes of an investment strategy.

A review of the statements of investment principles of UK defined contribution (DC) mastertrust pensin funds carried out in Chapter 2 showed many of them aim to deliver returns in excess of an inflation or interest rate measure. The actual measure used however varies from fund to fund. Tyagi et al. (2014) found that about 37% of pension funds in the database of CEM Benchmarking Inc. had some form of contractual inflation protection of benefits. The database of CEM Benchmarking Inc. contains information on 978 pension funds drawn from the USA, Canada and Europe with a total of US$10.4 billion under management.

Pension funds that do not rebalance toward their long term asset allocation are described as exhibiting a myopic investment behavior as they base their allocations on recent asset performance (Tyagi et al., 2014). For example, Pannachi and Rastad (2011) find US pension fund's portfolio increased their risk taking following periods of poor investment performance. Hence, although many pension funds rebalance their asset allocations regularly to specific target weights, there is evidence that some funds may intentionally drift from their target allocations. Ang et al. (2014) believes that this may be due to a passive buy and hold strategy, a desire to maintain allocation near cap weights or as a proactive return seeking behavior. Even when they are aware of the limited predictive power of past returns, some pension funds chase returns by buying recent winners, whether asset classes or managers. Others may simply not have the patience to ride out periods of underperformance.

Return chasing could be profitable as financial markets have a tendency to exhibit momentum over multi-month horizons especially if transaction costs are not too high (Jagadeesh and Titman, 1993; Moskowitz et al., 2012; Asness et al., 2013). Over multi-year periods however, financial markets have been found to exhibit a mean-reversal pattern. This makes return chasing unsuitable for long-horizon investors such as pension funds. A number of studies have found that multi-year return chasing has an adverse impact on investors' wealth. For example, investors in the aggregate earn lower dollar weighted returns than time weighted returns, pointing to the effects of ill-timed investments and disinvestments (Dichev, 2007; Friesen and Sapp, 2007). Goyal and Wahal (2008) find that institutional investors who make several hire and fire decisions regarding investment managers tend to lose value over time.

3.3 ASSET ALLOCATION MODELS – A REVIEW OF THE LITERATURE

The amount of an investor's total portfolio placed into each class is often determined by an asset allocation model. Model is used here to mean an approach, technique or method. These models are often designed to reflect the personal goals and risk tolerance of the investor. Furthermore, individual asset classes can be sub-divided into sectors. For example, if the asset allocation model calls for 40% of the total portfolio to be invested in stocks, the portfolio manager may recommend different allocations within the field of stocks, such as recommending a certain percentage in large-cap, mid-cap, banking, manufacturing, etc.

In discussing the role that real estate plays within pension portfolios, we have grouped the asset allocation models used in evaluating the portfolio role of real estate under three headings: heuristic asset allocation, modern portfolio theory (MPT) model, and post-modern portfolios. Heuristic asset allocation approaches do not require any formal modelling. The investor uses very simple approaches, often rule of thumb, to come to a decision on how to split their resources among the alternatives available to them. Perhaps the most widely used model within the asset management industry is Markowitz's mean-variance optimisation framework developed from his Modern Portfolio Theory. Following its introduction, Markowitz's model has been modified in several directions to better capture the risk-return features of various assets and also to make them appropriate for different investor groups.

The following sections provide a discussion of the various approaches and models that have been utilised by pension funds and other institutional investors to make asset allocation decisions. In addition to reviewing literature on the various asset allocation approaches that have been used, the role of real estate within these portfolios is examined. Key terminologies relating to asset allocation are covered initially. This is followed by a discussion of the asset allocation models. We focus on those models which have been applied or, potentially, could be applied to direct real estate portfolios. Studies that have applied these models to direct real estate portfolios are highlighted.

3.3.1 TALMUDIST (NAÏVE) ASSET ALLOCATION

The use of the Talmudist (Naïve) diversification rule has a long history. Many believe this approach traces its origin to the Babylonian Talmud – a collection of rabbinic notes dating back to the fourth century. Writing in about the fourth century, a rabbi named Isaac bar Aha, is said to have given the following asset allocation advice: "A man should always place his money, a third into land, a third into merchandise, and keep a third at hand" (Talmud, 1948).

A natural extension of this rule is the 1/N or the equally weighted investment strategy, i.e. the strategy to split one's wealth uniformly between the available investment possibilities. This has recently received plenty of attention in the literature. Employing the 1/n rule for investment purposes has the disadvantage of not utilizing information on the various parameters, but by the same token, it has the advantage of not being biased in relying on historical parameters that may be much different from future relevant parameters. Equally weighted portfolios have re-emerged as a solution to the problem of estimation error related to MPT portfolios which are discussed later. A possible solution is to impose lower and upper bounds on the weights of each asset. The simplest constraint is to apply equal weights on each of the components of a portfolio (Stevenson, 2005).

Value weighted portfolios can be considered as a more advanced form of heuristic asset allocation. Two of the most popular versions of value-weighting are cap-weighted indices and fundamental indices. The idea of cap-weighted indices dates back to Sharpe (1964) and Lintner (1975) with the introduction of the Capital Market Pricing Model (CAPM). Since then, indices such as the S&P 500 and ASX 200 have become important as passive investment options and benchmarks (Mar et. al., 2009; Tabner, 2009). Cap-weighted indices have been criticised for overweighting expensive stocks and underweighting undervalued stocks (Arnott et al., 2005; Treynor, 2005). Fundamental indices have been put forward as a better option to cap-weighted indices which weight stocks on the basis of performance metrics related to their fundamental values. Coupled with a growing demand and supply for fundamental indices, a growing body of studies continue to provide support for the use of fundamental series (Houwer and Plantinga, 2009; Branch and Li, 2010; Walkshäusl and Lobe, 2010). Critics of fundamental indexing however poing out that the fact that fundamental indexing is effectively an active investment strategy, and that the outperformance of fundamental indices may not be persistent in the long-term (Amenc et al., 2009; Perold, 2007). Both cap-weighted and fundamental indices suffer from the issue of a lack of diversification as they tend to be over-weighted in particular industries especially during extreme market conditions such as the tech-bubble.

A more recent variant of equally weighted portfolios are equal risk portfolios, otherwise referred to as risk-parity portfolios. Maillard et al. (2008) describe equal risk portfolios as a compromise between equally weighted portfolios and minimum variance portfolios. The idea is to attribute equal risk to the different components of an investment portfolio. Instead of using the total risk of a particular asset, the contribution of the asset to the total risk of the portfolio (marginal risk contribution) of the portfolio are considered. Studies conducted by Fernholtz et al. (1998) and Booth & Fama (1992) provide proof that the use of equal-risk portfolios can lead to improved out-of-sample returns.

DeMiguel et al. (2009) have shown that the benchmark 1/N rule outperforms most of the other more involved portfolio strategies in terms of Sharpe ratio, certainty equivalence and turnover, and is not consistently outperformed by any of the other models considered in their study. The authors explain the results by stating that the errors in estimation of the parameters of the optimization models may outweigh the gains of the more advanced methodology. However, in order to ensure that the equal weights are maintained, periodic rebalancing is required as the price of the assets change. Chan et al. (1999) and Jagannathan and Ma (2003) also conclude that it is hard to find an investment policy that consistently outperforms the uniform investment strategy.

Apart from the success of the 1/N rule in empirical studies, there is evidence that uniform investment strategies are actually used in a multitude of situations where agents have to decide on a mix of different alternatives. Bernartzi and Thaler (2001) provide evidence to suggest that investors prefer to use simple approaches – especially as concerns remain about the dependability of estimated returns. Benartzi and Thaler (2001) conduct experiments, where subjects are asked to allocate money to different funds available in hypothetical defined contribution pension plans. The authors find that a significant share of investors used the 1/N rule. In Huberman and Jiang (2006), a paper motivated by the work of Benartzi and Thaler (2001), data on the choice of consumers in actual 401(k) plans is analysed. The authors find that there is a significant share of investors (roughly two thirds) that follow the uniform investment rule.

Within real estate, Lee and Stevenson (2005) highlight the practical difficulty of an equally weight portfolio strategy due to the marked differences in lot sizes between different property sectors. Baum & Struempell (2006) attribute the rise of the popularity of indirect real estate to the lumpy nature of direct real estate. Investors who require regular rebalancing find that it is easier to rebalance their portfolio using indirect rather than direct real estate vehicles. Studies such as Brown (1988), Morrell (1993) and Schuck and Brown (1997) examine the effect of value-weighting on the risk of real estate portfolios. They conclude that several properties are required to reduce risk to the systematic level. Morrell (1993) points out the difficulty of being able to obtain or maintain an equally weighted property portfolio and simultaneously diversify across key market segments. Gold (1995) suggests that instead of using specific allocations, ranges could be used as the efficient frontier is not singular but "fuzzy". This means that different allocations which may appear statistically dissimilar may actually be able to fulfil the same risk-return objective. This suggestion certainly has implications for investment in lumpy assets such as direct real estate and could make it easier to rebalance real estate portfolios.

Aside from the support that equally weighted portfolios have received in empirical studies, there is evidence that many investment analysts actually use it in practice. A survey by Zweig (1998) found that several investment experts follow the 1/N rule, not least of whom is Harry Markowitz, the father of Modern Portfolio Theory. Markowitz is quoted as saying: "My intention was to minimize my future regret. So I split my contribution fifty-fifty between bonds and equities."

3.3.2 MODERN PORTFOLIO THEORY

The most widely used quantitative strategic asset allocation framework is Harry Markowitz's mean-variance optimization, an idea that resulted in a Nobel Prize for Markowitz (Markowitz 1952, 1959). Mean-variance optimization is one of the cornerstones of modern portfolio theory and over the last half century has become the dominant asset allocation model. The procedure maximizes expected return for a given level of risk, or equivalently, minimizes risk for a given level of return (Idzorek, 2006). The diversification theory advocated by Markowitz (1952) asserts that the optimal diversification strategy is a function of the means, variances, and pair-wise correlations of risky assets. Markowitz prescribes that the average returns and covariance matrix should be estimated. The optimisation process then consists adjusting the weights to minimise portfolios ex-ante risk for a stated average return. (Clarke et al., 2006).

Despite its wide-ranging success, the single-period framework suffers from several deficiencies. The common problems that limit the applicability of the classic mean-variance portfolio are as follows:

Assumption of Normal Distribution: Another drawback of the mean-variance approach is that it is approximation-free only when stock returns obey a Gaussian distribution, an assumption known not to hold in real data. This is especially true because the mean-variance (M-V) diversification strategy is very sensitive to possible sampling errors. As noted by Best and Grauer (1991): "a surprisingly small increase in the mean of just one asset drives half of the securities from the portfolio." For example, it has been shown that the assumption of a normal distribution of returns did not offer a good description of the returns of direct real estate (e.g. King and Young, 1994; Young and Graff, 1995; Young et al., 2006; Young, 2008). Also, the covariance and correlation structure of direct real estate returns have been found to be unstable over time.

Sensitivity of Inputs to Input Assumptions: An additional limitation of the mean-variance framework that has received attention in the literature is the sensitivity of the mean-variance model's recommendations to input assumptions. Especially difficult is estimating the expected returns of assets. Michaud (1989) concludes optimisers tend to be "error maximizers" as they often over-allocate to assets with high expected returns and low standard deviation whiles allocating very little to those with low return and high risk. This is typically referred to as "corner solutions", a situation that leads to poor out-of-sample performance.

It has also been observed by many researchers that the ex post analysis often resulted in portfolio weights that are different from those produced out-of-sample. Cheng and Liang (2000) for example found that mean-variance portfolios constructed using different property types were statistically more efficient than equally weighted portfolios only when the test period coincided with the construction period. Bayes-Stein shrinkage estimators have been successfully used to produce increased stability in the estimated portfolios and have led to enhanced portfolio performance (Efron and Morris, 1977; Stevenson, 2001; 2002; 2005 and 2009).

Failure to Capture Liabilities: First, it is difficult to apply to long-term investors such as pension plans, insurance companies, and individuals. For investors with liabilities and goals at particular dates in the future, investment decisions should be evaluated with regard to temporal issues besides static risk-reward trade-offs. In a significant example, a critical risk for a pension plan is making a large contribution just when the sponsoring company is vulnerable to large unexpected costs, such as during the middle of a serious recession. Individuals face similar temporal issues—say, extracting funds from retirement accounts beginning at age sixty-five. The standard definitions of risks; variance of returns, downside risks, semi variance; do not convey information regarding the probability of missing the investor's goals or obligations. The investor must translate portfolio risks into investor risks.

Lack of rebalancing: A final problem with the traditional MV model involves portfolio performance. It is well understood, for example, that the efficient frontier should be truncated at the log-optimal portfolio for long-term investors. Since Markowitz, researchers have studied the properties of points above the log-optimal solution. Likewise, performance may lag since the myopic MV model does not take advantage of additional returns by rebalancing the portfolio to target asset proportions (Luenberger, 1998; Mulvey et al., 2001). A multi-period model will perform better than single-period MV models for long-term investors.

One of the earliest studies to apply Markowitz's model to real estate was that of Friedman (1971) who found that direct real estate dominated mixed asset portfolios. This result was reinforced by Findley et al. (1979) who reported low correlations between direct real estate and the returns of other financial assets and hence its attractiveness. Findley (1979) observed that although the assumption of a quadratic utility function was simplistic, it was adequate for the analysis of the portfolio role of direct real estate. Following these two studies, several dozen studies examined the portfolio role of real estate and recommended what they believed was an 'optimal' allocation to the asset within a mixed-asset portfolio.

Viezer (2010) provides a comprehensive review of the various studies that utilise modern portfolio theory to analyse real estate's role within investment portfolios. They observed that many of these studies use Markowtiz's framework but differed in certain respects. The earlier groups of studies concentrated on how much should be allocated to direct real estate within an optimal portfolio. Studies such as Fogler (1984), Gold (1986). Irwin and Landa (1987) and Firstenberg et al. (1988) suggested an allocation between 10% and 15%. Allocations below 10% were suggested by a handful of studies such as Hartzell (1986) and Kallberg et al. (1996).

Other researchers turned their attention to diversification within real estate portfolios. Different dimensions were examined such as geographical diversification and property type diversification (e.g. Miles and McCue, 1982; Hartzell et al., 1987; Grimssom et al., 1987, Jud et al., 2002). Economic diversification is when local economic indicators are used to determine where to invest. Factors such as crime rate and cost of living have been explored (Hudson-Wilson, 1990; Ziering and Hess, 1995; Hudson-Wilson and Wurtzebach, 1994). Viezer (2000) concluded that property type or geographical diversification was more practical than economic diversification as the cluster membership tends to change from period to period. International diversification across real estate markets was examined by several studies. Wilson and Zurbruegg (2003) concluded that results from such studies supported the belief that diversifying internationally improved real estate portfolio performance. The results however varied according to whether direct or listed real estate data was used in a particular study.

One of the earliest criticisms of the application of modern portfolio theory to real estate is the fact that direct real estate returns are often obtain obtained through an appraisal process as opposed to actual transactions. This is believed to lead to lower volatility estimates, something researchers refer to as appraisal smoothing and hence the high allocations to direct real estate observed in many studies. The most popular approach for correcting for the effect of appraisal smoothing was developed by Geltner (1993) and Cho et al. (2003). Other researchers have used simpler approaches such as using listed real estate returns rather than direct real estate returns (Ennis and Burik, 1991). Some other studies have used transaction data which they believed were more accurate in capturing direct real estate returns than appraisal based indices (Miles et al., 1990).

An obvious problem with direct real estate is that it is difficult to re-balance frequently because of the illiquidity problem (Farrelly and Moss, 2014)

Although many studies have suggested that listed real estate could be used to bring real estate allocations up to a certain target, studies such as Seiler et al. (2001) did not find direct real estate and REITs to be substitutes within a mean-variance portfolio.

3.3.3 POST-MPT PORTFOLIOS

Following the concerns that have been raised about of MPT to direct real estate, researchers have tried different approaches to make the model more suitable or appropriate to real estate assets. Viezer (2010) observed that the efforts have centred on refining the data inputs, employ improved estimation tools and asset allocation models. In this section, two groups of approaches are discussed: those that aim to improve the measure of returns and risk as well as those that employ an asset-liability model (ALM) optimisation framework. The following section reviews different models that have been developed to make up for the shortcomings of the classic mean-variance model.

3.3.3.1 Parameter Uncertainty

A simple approach that has been used to deal with the issue of parameter uncertainty is to impose constraints on the weights of the various assets and a restriction of short-sales. This leads to a greater diversification and hence improved out-of-sample performance (Michaud, 1989; Jorion, 1992; Byrne and Lee, 1995; Stevenson, 2000). Jagannathan and Ma (2003) propose the use of high frequency data as an alternative solution. More complex approaches that have been developed are: Bayesian models, resampling and minimum variance portfolios. These approaches are reviewed in the remainder of this section.

i. Bayesian Models

Although prediction distribution in decision-making was introduced by Zellner and Chetty (1965), its application within finance began in the 1970s. The first step in Bayesian portfolio analysis is formation of prior beliefs, often represented by probability density functions.

These prior reflect information about the macro-economy, asset pricing theories and insights relevant to the dynamics of asset returns. The second step is to formulate the law of motion governing the evolution of returns. The predictive distribution of future asset returns can then be recovered analytically or numerically using the results of the first two steps. The optimal portfolio can then be obtained by maximising the expected utility with respect to the predictive distribution obtained. There are three advantages in employing the Bayesian approach to asset allocation. First, it incorporates information about several quantities of interest. Secondly, it accounts for model uncertainty and estimation risk. Lastly, it provides fast, intuitive and easily implementable numerical algorithms with which otherwise complex economic quantities can be simulated. Five Bayesian models have been developed and used extensively, namely, Shrinkage Estimators, Black-Litterman model, Multi-Prior Model, Copula Opinion Pooling and Belief-Rule Based (BRB) System of Optimisation.

A standard approach for minimising the impact of estimation error is to use shrinkage estimators. These are obtained by shrinking the sample mean, covariance or weights towards a certain target. Jorion (1986) proposes a shrinkage estimator based on mean returns based on the Bayes-Stein approach. Frost and Savarino (1986) utilised a Bayesian approach for an investor whose prior belief about the means and covariance matrix are jointly defined by a Normal-Wishart conjugate prior. Ledoit and Wolf (2003, 2004a, 2004b) propose a variety of shrinkage estimators based on different prior beliefs about the covariance matrix. Authors (Kan and Zhou, 2007; De-Miguel et al., 2009; and Tu and Zhou, 2011) have constructed shrinkage portfolios obtained by directly shrinking the portfolio weights.

The Black-Litterman model was developed by Black and Litterman (1990) and expanded by Black and Litterman (1991, 1992). The model sets the idealized market equilibrium as a point of reference, allows the investor to specify a chosen number of market views in the form of absolute or relative expected returns and a level of confidence for each view. The views are combined with the market equilibrium returns to give more (less) weight on assets where investors have positive (negative) opinions on. Results of several empirical studies show that the resulting portfolios are more stable and better diversified than those obtained using conventional mean-variance optimisation approaches (Gofman and Manela, 2012; Wolff et al., 2012). The Black and Litterman model has also found favour with investment practitioners (Bevan and Winkelmann, 1988). Goldman Sachs regularly publishes recommendations for investor allocations based on Black Litterman models as well as reports describing firms' experience using the model. Investment management firms such as BlackRock, Zephyr Analystics and Neuberger Berman are known to use Bayesian models for their asset allocation. Garlapi et al. (2006) develop a model for an investor with multiple priors with an aversion to ambiguity. They find that compared with portfolios constructed using the Black-Literman Model and MVP portfolios.

One of the problems with the Black and Litterman model is that it assumes that the priors have a normal distribution which have become more and more questionable. The Copula method, developed by Embrechts et al. (1999), blends the prior market distribution with the analyst's views under very general assumptions for the distribution of the views. Essentially, the choice of distribution is handed over to the analyst, who can either fit a certain distribution and simulate using bootstrapping or simply make use of historical observations. Patton (2004) for example uses copulas to build an investment portfolio. After trying a number of models and copulas, he finds that the best model for an investor's utility uses the skewed-t marginal distribution. Similarly, Ricceti (2010) tried models with different copulas (Normal, Student-t, Calsyton, Gumbel, Frank, Mix Copulas and Canonical Vine). They concluded that the best copula model is one that uses the student-t distribution. Tao and Chi (2015) developed a dynamic copula model to detect the change of copula family and copula parameters. They conclude that the dynamic Copula performed better in risk management than the static model.

Within real estate literature, Stevenson (2000) applied Bayes-Stein shrinkage to real estate data and finds that the approach leads to increased stability in the estimated allocations as well as improved performance out-of-sample. A follow up study (Stevenson and Lee, 2005) however did not find the improved performance in ex-ante performance from the use of Bayes-Stein shrinkage or the Minimum variance portfolio for the real estate market. This failure was attributed to the cyclical nature of real estate assets and the fact that the contrarian and mean-reversion effects witnessed in stock and bond markets are not captured within the real estate market.

ii. Resampling

Just like Bayesian models, the Resampled Efficiency was introduced to deal with the issue of estimation errors. The current embodiments of resampled mean-variance optimisation are due to a number of authors (Jobson and Korkie, 1982; Jorion, 1992; DiBartolomeo, 1993 and Michaud, 1998). Resampled Efficiency can be thought of as an averaging process that puts all the alternative frontiers together in a new efficient frontier. Each point on the resampled efficient frontier is obtained by averaging a number of statistically equivalent efficient portfolios.

Generally speaking, Resampled Efficiency is always preferable to a Mean Variance approach because investors are never 100% certain of their estimates. Again, generally speaking, Resampled Efficiency optimized portfolios are less risky as they are optimal, relative to the many ways in which assets and markets may perform, in the investment period. In the case of long-only constraints, Resampled Efficiency leads to more-diversified portfolios, which, as presented by Michaud (1998), are well known to beat simple Markowitz portfolios in out-of-sample tests in a way that is statistically significant. Michaud's portfolios tend to be more diversified and more stable over time than asset allocations produced by traditional optimizers.

Several empirical studies have shown that the performance of the Resampled Efficiency optimised portfolios is better than those of the classic mean-variance portfolio. (Michaud, 1998; Markowitz and Usmen, 2003; Galloppo, 2010 and Becker et al., 2010).

A few studies have applied the resampled mean-variance optimisation approach in the construction of real estate portfolios. Gold (1995) used the procedure of Michaud (1998) to construct property portfolios by using bootstrapping to recreate 1,000 alternative averages and standard deviations. This process led to the creation of more stable portfolios which in turn reduced the need for costly rebalancing of portfolios. Similarly, Liang et al. (1996) use the bootstrapping procedure of Efron (1979) to determine the optimal range of allocation to real estate and conclude that the confidence interval was too large (i.e. a range of 13% to 75%). Zibrowski et al. (1997) added Treasury Bills to the investment portfolio and find a result similar to what Liang et al. (1996). However, when the sample period was extended to five years, Zibrowski et al. (1999) found the optimal allocation to real estate to be very stable although the sample period over which the study was done spanned different economic conditions.

iii. Minimum Variance Model

As pointed out earlier, one of the problems with the mean-variance optimisation procedure is that it tends to be very sensitive to changes in the expected returns with estimation errors leading to sub-optimal results (Jorion, 1985; Best and Grauer, 1992). Apart from expected returns, the expected covariance matrix needs to be estimated. A constant covariance matrix is often assumed. The assumption of a constant covariance matrix has been questioned by many researchers with many pointing to the effect of outliers and non-stationary parameters. (Bengston and Holst, 2002; Ledoit and Wolf, 2004).

Perhaps the most used approach in dealing with estimation errors is the construction of minimum variance portfolios. These portfolios are obtained using the variances and covariances and not average returns as the input, effectively side-stepping the use of estimated returns which happen to be the main culprit in the problem of estimation errors. Stevenson (2009) describes minimum variance models as an extreme case of shrinkage. Jorion (1985) however warns that they are most appropriate when the assets included in the analysis are within the same risk class.

The Minimum variance portfolio model is perhaps the most applied version of Modern Portfolio Theory (MPT) within the investment management community. Surveys by Johnson (2008) and Keefe (2008) conclude that several investment management companies base their investment strategies largely on the minimum variance optimisation approach. Within the real estate literature, Stevenson (1999; 2009) finds that minimum variance portfolios lead to improved performance, especially on an out-of-sample basis when applied to international real estate stocks. When applied to direct real estate, Stevenson and Lee (2005) do not find the same improved performance when the minimum variance approach was applied to direct real estate.

3.3.3.2 Return Distribution

Because of the key role it played in the theory of portfolio selection as set forth by Markowitz more than 55 years ago, the portfolio variance (or, equivalently, standard deviation) is the most well-known dispersion measure. Markowitz (1952) showed that if risk is measured by the variance of returns and expected return by the mean of returns, then uncertain investments can be ordered by their ranking in MV space. A host of theoretical and empirical work suggests variance may not be a suitable proxy for risk. As a consequence, other risk measures such have been explored (Artzner et al., 1999; Bertsimas et al., 2004; Grootveld and Hallerbach 1999; Harlow 1991; Jorion 1997; Rockafellar and Uryasev, 2002.)

Since the mid-1990s, considerable thought and innovation in the financial industry have been directed toward creating a better understanding of risk and its measurement, and toward improving the management of risk in financial portfolios. There has been an even greater sense of urgency to establish better risk management practices after the collapse of the financial markets in the fall of 2008. The following section presents different models that have been developed to incorporate or make use of the advances in the measurement of risk.

i. Semi-Variance Model

Semi-variance is defined as the average of the squared deviations from the mean of all values that are below the mean. Thus, it is a special case of the lower partial moment risk measure. The semi-variance has been found to be a more robust measure of risk from a theoretical perspective, but the variance instead of semi-variance as risk measure was chosen by Markowitz (1959) for technical reasons and computational limitations. Markowitz (1959) mentions that investors' risk perception might be asymmetric. However, it was not until the 1970s that the semi-variance measure of risk, known as lower partial moment of order n (LPMn), was generalized by Bawa (1975) and Fishburn (1977). In particular, they show that LPM optimization is appropriate to produce portfolios that will dominate all other portfolios according to the concept of third order stochastic dominance, which implies an optimal decision rule for any investor who is risk-averse and exhibits decreasing absolute risk aversion.

ii. Mean-Absolute Deviation Models

Instead of using the standard deviation, which is the average of the squared deviations of the possible realizations of portfolio returns from the expected portfolio return, the absolute deviation measures the average absolute value of the deviations of the possible realizations of portfolio returns from the expected portfolio return.

The MAD measure has a number of attractive features such as bypass the covariance matrix computation and easier solving algorithm (portfolio optimisation). So it requires a shorter computation time and improves the computation of optimal portfolios. Moreover, MAD is more stable over time than variance and is less sensitive to outliers and it does not require any assumption on the shape of a distribution. Interestingly, it retains all the positive features of the MV model. MAD is also apt to be used in situations when the number of assets (N) is greater than the number of time periods (T) (Konno & Yamazaki, 1991; Byrne and Lee, 1997, 2004; Brown and Matysiak, 2000; Konno, 2003).

The identification of the Absolute Deviation as a measure of risk prompted the development of portfolio optimisations that use the MAD as a measure of risk (Konno, 1989). Such models have a number of advantages. First, Konno and Yamazaki (1991) show that the MAD approach is equivalent to the MV model if the returns are multivariate normally distributed. Secondly, the MAD model produces optimal portfolios without the need to calculate the covariance matrix and so can be used in situations when N, the number of assets, is greater than T, the number of time periods over which the analysis is performed. Konno and Shirakawa (1994) have shown that the MAD model can handle large problems in real time. A limitation of this approach is that the computational savings from the use of MAD objective functions may in some cases be outweighed by the loss of information from the (unused) covariance matrix (Simaan, 1997).

Byrne and Lee (1997) found that the MAD risk measure gives less weight to outliers and hence may be considered a more stable substitute for the standard deviation. For a portfolio of different regional property types, both the MAD and MPT models selected the same assets with only slight difference in the weights.

iii. Maximum Drawdown (MaxDD)

The MaxDD is formally defined as the loss suffered when an asset is bought at a local maximum, and sold at the next local minimum (Hamelink and Hoesli, 2004). MaxDD has several important advantages over alternative measures of risk. For instance, semi-variance considers standard deviation only over negative outcomes, typically those that constitute the "risk" of a portfolio. While the semi-variance measure may seem appealing, it does not take into account the serial correlation of returns. A drop in 25% drop in equity return is perceived differently by most investors when it is the third consecutive year that it occurs than when it happens for the first time. Therefore, the cumulative outcome might be more informative.

Although it might appear counter- intuitive, the fact that time is not taken into account in the MaxDD criterion is probably very representative of the risk perception by most investors. How relevant is, for instance, the fact that World stocks fell by 51% in the past three years, rather than in two or four years? Time duration does not matter as much as the the magnitude of the fall in prices. Value-at-risk (VAR) is another example of an appealing alternative measure of risk, as it considers both a probability and an absolute level of loss. But contrary to what is the case with the MaxDD, VAR considers a pre-defined time frame over which the loss may occur, and therefore lacks to fully incorporate the time-dependence of financial series.

The MaxDD criterion might appear simple for several reasons. First, the MaxDD for a given series applies to one particular period in the past. Also, it is straightforward to extend Markowitz's Mean-Variance – or Mean-Standard Deviation (M-SD) framework to a Mean-Maximum Drawdown (hereafter M-MaxDD) framework. A portfolio is said to be efficient in M-MaxDD space when no other portfolio yields the same level of return with a lower level of MaxDD, or when no other portfolio yields a higher level of return, for the same level of MaxDD.

A portfolio which is optimal in M-SD space is, by definition, dominating portfolios obtained through optimization under any alternative measure of risk. In other words, a portfolio on the efficient frontier in M-SD space with a given level of return has, by definition, a higher MaxDD than an efficient portfolio in M-MaxDD space with the same level of return. Comparisons have therefore to be done on a trade-off basis, the gain in terms of MaxDD relative to the loss in terms of SD.

Hamelink and Hoesli (2003) investigate the role of real estate in a mixed-asset portfolio when the maximum drawdown (MaxDD), rather than the standard deviation, is used as the measure of risk. They argue that the MaxDD concept is one of the most natural measures of risk, and that such a framework can help reconcile the optimal allocations to real estate and the effective allocations by institutional investors. The empirical analysis is conducted from the perspective of Swiss pension funds who are faced with legal constraints on the weights that can be allocated to the various asset categories and pertains to the period 1979-2002. The authors show that most portfolios optimized in Return/MaxDD space, rather than in Return/Standard Deviation space, yield a much lower MaxDD, with only a slightly higher standard deviation (for the same level of return). The reduction in MaxDD is highest for portfolios situated half- way on the efficient frontier, typically close to those held by pension funds. Also, the reported weights for real estate are much more in line with the actual weights to real estate by institutional investors.

In the study of Lee (2006) MaxDD emerges as the most appropriate risk measure for investors who require a time-dependent risk measure and it is the only risk measure that takes into the account the serial correlations found in the return series utilised. The shortcoming for MaxDD, is that it is influenced considerably by data interval. Hamelink and Hosli (2004) highlight that the higher the frequency, the larger the MaxDD. This is consistent with the findings of Acar and James (1997), which the MaXDD from intra-day data is higher than monthly MaxDD.

iv. Value-at-Risk Models

Value-at-risk (VaR) models are one of the most significant developments in the measurement and management of risk. The value-at-risk of a portfolio is the maximum amount of loss that the portfolio will suffer within a specified time horizon at a certain level of probability (confidence interval).

Although the idea of VaR is easy to understand, there is no standard approach for estimating VaR. Unlike other measures of risk such as the variance and semi-variance, there are several VaR models and implementation techniques that tend to produce varied estimates of risk for the same or very similar portfolios (Bohdalova, 2007). A common approach is to calculate the VaR using historical covariances between different risk factors to assess the effect of a shock on a portfolio whose positions can be mapped to those risk factors (Guldimann, 1995). Blake et al. (2003) offer an approach which provides insights into the factors that determine the long-term VaR, in particular, the impact of mean and volatility assumptions on estimates of long-term VaR.

VaR models also have certain features that make them undesirable from a mathematical standpoint. Value at risk has been deemed to not be a coherent measure of risk as it violates the sub-additivity property required of a good risk measure. VaR models are coherent only when based on the standard deviation of normal distributions. Constructing a portfolio made up of several assets could result in a VaR that is greater than the sum of the individual asset VaRs. This means that one VaR models invariably discourage diversification. (Artzner et al., 1997, 1999).

VaR is an incomplete measure of risk as it does not give any information regarding the amount of losses that would be suffered by a portfolio when the VaR limit is breached. In other words, VaR tends to ignore the losses incurred beyond the VaR limit.

Furthermore, VaR is difficult to optimize when it is calculated from scenarios. Mauser and Rosen (1999), McKay and Keefer (1996) showed that VaR can be ill-behaved as a function of portfolio positions and can exhibit multiple local extrema, which can be a major handicap in trying to determine an optimal mix of positions or even the VaR of a particular mix.

An improved version of the standard VaR is the Conditional Value-at-Risk (CVaR) which is defined as the mean of the tail distribution exceeding VaR. As a measure of risk, CVaR exhibits some better properties than VaR. Rockafellar and Uryasev (2000, 2002) showed that minimizing CVaR can be achieved by minimizing a more tractable auxiliary function without predetermining the corresponding VaR first, and at the same time, VaR can be calculated as a by-product. The CVaR minimization formulation given by Rockafellar and Uryasev (2000, 2002) usually results in convex programs, and even linear programs. Thus, their work opened the door to applying CVaR to financial optimization and risk management in practice. Pflug (2000) and Acerbi and Tasche (2002) proved that CVaR is a coherent risk measure. Rockafellar and Uryasev (2002) further explained the coherence of CVaR, and showed that CVaR is stable in the sense of continuity with respect to the confidence level β. Pflug (2000) and Ogryczak and Ruszczyriski (2002) showed that CVaR is in harmony with the stochastic dominance principles which are closely related to the utility theory. Increasingly, CVaR is becoming more popular in financial management (Andersson et al. 2001, Bogentoft, Romeijn and Uryasev 2001, Topaloglou et al., 2002).

Boassen et al. (2011) however pointed out that CVaR requires an assumption regarding the return distribution. It also requires a large number of return observations that fall below the return target. This makes it very difficult to apply CVaR to real world data. For example, with a sample of 100 observations, a 99% CVaR would be based on only one observation. The other option would be to use simulation techniques to generate lots of scenarios.

3.3.3.3 Liability Driven Investing

A new stream of literature emerged in the 1990s which consider changes in pension liabilities along with the returns and variances of the various assets. The main premise of these studies is that pension fund investment managers are interested in maximising the surplus (difference between asset returns and liability returns) on a risk adjusted basis. Booth (2002) explains that risk is context specific and so any attempt to analyse the investment decision of pension funds that does not take liabilities into consideration is not complete. For pension funds, the context within which they operate is one that requires them to meet future liabilities and so risk from their perspective is the inability to meet those liabilities.

Elton & Gruber (1988) and Sharpe and Tint (1990), among others, propose an asset liability model which takes into consideration not just the returns and variance of assets but also liability returns. The model of Sharpe and Tint (1990) has an objective function which is similar to that of the asset-only optimisation framework of Markowitz (1952) but also incorporates changes in pension liabilities and the covariance of the liability returns and their covariance with the returns of the various assets within the portfolio. The model also allows for different levels of emphasis to be placed to liabilities, the level of risk aversion and the funding level of the pension fund. In addition to allowing the investor gauge the sensitivity of the results to these factors, the model makes it easier for the fund to construct portfolios that suit its nature and objectives. The model treats liabilities as an asset that the pension fund has sold short. Selling short one of two positively correlated assets is equivalent to putting together two assets that are negatively correlated. More complicated simulation models have been used in further studies by Cariño et al. (1994), Consigli and Dempster (1998), and Kouwenberg (2000). These models can handle alternative objective functions, constraints and distributions.

Sharpe (2002) states that assets and liabilities should be measured in terms of market values but liabilities are often determined actuarially. The practice of actuarial valuation smoothing results in a diminished impact of market-related liability risks on optimization solutions of ALM models. Ponds and Quix (2003) confirm that this framework ignores risks and "leads to a self-constructed picture of the financial solidity of a pension fund without any link to financial markets". Asset allocation studies within this smoothing framework are likely to give results quite similar to those of an asset-only approach in which liabilities are ignored and the risk minimizing asset class is cash. On the other hand, with a market rate used for discounting liabilities, the liability value will fluctuate with market forces. Arnott and Bernstein (1988), using a pension surplus framework, make a case for equities and long-dated bonds as the risk minimizing asset classes and point out the high risk inherent in cash under the Financial Accounting Standards Board ruling no. 87. Similar reasoning can be found in Peskin (1997), who uses simulation techniques and an objective function that minimizes expected future pension contributions.

Most of the real estate research on the portfolio role of direct real estate prior to 2000 employed mean-variance optimisation and often found very high suggested allocation for direct real estate. These allocations clearly differed from the allocations observed in practice – leading researchers to question why this is the case. Different approaches (discussed in earlier sections) have been employed to correct for some of the well-known issues with the classic mean-variance model. Starting with Chun et al. (2000), a series of studies began to consider the context of pension funds and adopted the asset liability approach suggested by Wilkie (1985) and Sharpe and Tint (1990).

Chun et al. (2000) developed and applied an asset liability model for a pension fund who invests in real estate along with other assets. The allocation to real estate was found to be between 6 and 13 percent. Listed real estate returns were used as a proxy for real estate returns. Craft (2001) employed a similar model but included both private and listed real estate in their portfolio. The suggested allocation to real estate was about 16% and that to listed real estate was about 10%. Craft (2005) considers the funding ratio and find that fully funded pensions would allocate about 13% to direct real estate and 15% to listed real estate. Underfunded pensions on the other hand allocate less to direct real estate but the same amount of listed real estate. Differences were also observed for different industry sectors' allocation to direct real estate but not to listed real estate.

Booth (2002) finds that, although direct real estate features in immature pension plan portfolios, it only features in them if index-linked government bonds and equities are excluded from the portfolio. Brounen et al. (2010) consider different definitions of liabilities. They model pension liabilities as subject to inflation and interest rates and find that when liabilities are taken account of, direct real estate plays a limited role in the portfolio. The composition of portfolios differed according to the definition of liability used.

3.4 INFLATION HEDGING ABILITY OF REAL ESTATE

As the literature on the portfolio role of real estate developed, a parallel stream of literature which focus on the ability of real estate to hedge against inflation was also developing. This area became a favourite area as researchers carried out studies that analysed real estate returns and compared these to the returns of other assets and macroeconomic variables such as inflation. The earliest studies include Robicheck et al. (1972) and Fama & Schwert (1977). This interest in this area is partly due to the fact that perhaps the most cited justifications for including real estate in the portfolio of investors is its perceived ability to help preserve purchasing power of an investment portfolio over time and thus help achieve real returns which are in line with investment objectives. Hoesli et al. (2012) observed that these studies differ across time periods, market conditions, national boundaries, the components of returns examined and the conditioning variables included. This section focuses on the varied approaches that have been used to analyse the inflation hedging ability of assets, in particular, real estate. Two broad approaches have been used in this type of analysis over the years: regression analysis and vector autoregressive models.

3.4.1 REGRESSION ANALYSIS

Fisher (1930) provided a framework for evaluating the ability of assets to hedge against changing price levels. He made a proposition that the expected nominal rate returns on any asset contain market assessments of the expected rate of inflation. Fisher believed that the real and monetary sectors of an economy are independent of each other to a large extent and that the expected rate of return and the rate of inflation are unrelated as well. Thus, the expected real rate of return is determined by real factors like productivity of capital, the time preferences of investors and investors risk appetite. A market is efficient if it accurately prices inflation expectation to obtain the real rate of inflation.

Fama & Schwert (1977) extended the model of Fisher (1930) by demonstrating that the actual rate of inflation during any period will include both an actual and expected component and thus estimates of expected inflation are necessary before the Fama & Schwert (1977)can be estimated. The difference between the expected inflation and the actual inflation then gives the unexpected inflation. Several approaches have been used over the years to obtain a series for expected inflation. Fama & Schwert (1977) used lagged short-term interest rates as their proxy for expected inflation whiles Fama and Gibbons (1982) made use of correction in short term rates. Series generated from surveys have also been used in some studies e.g. Gultekin (1983) used the Livingston price expectations survey whiles Saunders (1978) used the Carlson and Parking (1975) series of observed price expectations. Several studies have used ARIMA models of the form ARIMA (p,d,q)(SP,SD,SQ)S where p, d, q are orders for autoregressive, differencing and moving average terms respectively whilst SP, SD, SQ are the orders corresponding to seasonal terms and S is the seasonality e.g. Stevenson (2001a) used a number of proxies which included ARIMA (1,0,3) as per Gatzlaff (1994), ARIMA (1,1,3) as per Barkham et al. (1996). GARCH models have also been used in some studies. The proxy with a high correlation with actual inflation is considered the best. It must also have a constant α and a coefficient β which do not significantly differ from 0 and 1, respectively, in a regression of actual inflation and the proxy.

Fama & Schwert (1977) applied their model to a number of assets including real estate, stocks and bonds. They found that residential real estate (represented by the rate of inflation of the Home Price Purchase component of the Consumer Price Index) provided a complete hedge against both the expected and unexpected changes in the US CPI. Limmark and Ward (1988) applied the model of Fama & Schwert (1977) to the UK context and find that the combined property as well as the three sub-sectors analysed viz. office, shops industrial, were a hedge against unexpected inflation. Only the industrial property sub-sector proved to be a hedge against unexpected inflation. Hoesli (1994) used the Swiss real estate mutual fund data given that appraisal based real estate data tend to be adjusted for inflation, which could lead to biased results. They find that whiles real estate provides a positive hedge against inflation, common stocks proved a perverse hedge. Improving the data further, Hamelink and Hoesli (1996) made use of transaction based real estate constructed using a hedonic approach. Although real estate returns were found to be positively correlated with the expected component of inflation, it was negatively correlated with the unexpected component of inflation. Newell (1996) used the Westpac Inflationary Expectations for Australia as a proxy for the unexpected component of inflation. All the office sectors for selected geographical areas were found to be a hedge against actual and expected inflation. Only retail and industrial property were a hedge against unexpected inflation. Interestingly, bonds were not a hedge against expected or unexpected inflation but stocks were a hedge against both.

3.4.2 VECTOR AUTOREGRESSION (VAR) MODELS

Vector Autoregression (VAR) models have also been used extensively to capture the dynamics between asset returns and selected macroeconomic variables, often inflation. VAR models enable researchers to conduct several tests aimed at revealing the relationship between two or more variables. Two conventional techniques that have been employed in understanding the long-run relationship between variables are: (i) the Two-Step Engle-Granger cointegration procedure and (ii) the Johanson Cointegration Test. Causality tests, impulse response and variance decomposition are other tests that can be conducted to further understand the relationship between these variables.

The Engle & Granger (1987) procedure involves first testing the residuals of the model for stationarity. If the residuals are found to be stationary, the series are cointegrated and so have a common long-term equilibrium. A number of issues have been raised with the Engle-Granger procedure. One issue relates to the designation of a left-hand side variable and right hand side variable(s). Practically, one regression can show that the variables are cointegrated. Reversing the order of the variables might indicate no cointegration. This issue is even more complex when three or more variables are included in the model. This is obviously not a desirable feature as we would expect that the test for cointegration should not be affected by how the variables are arranged in the model. A second problem with the Engle & Granger, (1987) procedure is the two steps it entails. The researcher runs a first regression to generate the residuals $(\hat{e}_t)$ which are then used to estimate a second regression of the form $\Delta\hat{e}_t = a_1\hat{e}_{t-1} + \cdots$. Given that a_1 is obtained from an earlier regression, any errors that is introduced in the first regression is carried into the second regression.

The Johansen (1988) procedure is based on maximum likelihood estimation of all the cointegration variables and offers a better alternative for to the Engle-Granger approach. For one, the approach does not rely on the use of the two-step estimation procedure and also test for the presence of multiple cointegrating vectors. Also, it allows the researcher to test the restricted versions of the cointegrating vectors(s) and the speed of adjustment parameters. Granger and Hallman (1991) and Granger (1991) proposed a testing procedure which is appropriate for testing the non-linear relationship between variables. Using this procedure, an algorithm called the alternating conditional expectations (ACE) is used to transform a non-linear relationship into a linear. Cointegration tests are then applied to the linearised relationship. The ACE algorithm was proposed by Brieman and Friedman (1985) as an approach for detecting nonlinearities in multiple regressions. The Autoregressive distributed lagged (ARDL) model of Pesaran et al. (2001) has also been used for cointegration analysis. While the approach has been widely used to test the Fisher effect in several markets, its use within the real estate literature has been limited (Tehrani et al., 2012). This approach uses the bounds testing approach to examine the long run relationship between variables.

Impulse Response Functions and Causality Tests can be used within a VAR framework to further uncover the relationship between the variables in a VAR system. Impulse response functions can be used to describe the reaction of endogenous macroeconomic variables to exogenous impulses or shocks, at the time of a shock and over subsequent points in time. The Granger Causality test is a statistical hypothesis test which is used to determine whether one time series is useful in forecasting another. A time series X is said to Granger-cause Y if it can be shown, usually through a series of t-tests and F-tests on lagged values of X (and with lagged values of Y also included), that those X values provide statistically significant information about future values of Y.

Starting in the 1990s, many real estate researchers employed VAR models exclusively or along with other models, often the Fama & Schwert (1977) framework, in the analysis of the inflation hedging ability of real estate assets. Appendix 3(A) shows a summary of the various studies that have been conducted, the country/time span, analytical approach adopted, assets included in the analysis as well as the key findings. It is easy to see from the Appendix 3(A) that as observed by Hoesli et al. (2012), the conclusions of the various studies depends on several factors: the country, time period analysed, return series and most importantly the variable being hedged against, i.e. CPI Inflation, RPI inflation, PPI Inflation, Interest rate etc. Again, the studies listed in Appendix 3(A) is not meant to be exhaustive; rather, the aim is to provide an overview of the wide range of studies that have examined this subject and the range of approaches that have been used.

3.5 CONCLUSION

In this chapter, we have reviewed literature on the role of real estate as a stand-alone investment and as part of an investment portfolio. As a stand-alone asset, we have focused on the ability of real estate to hedge against inflation. Beginning with the seminal work of Fama & Schwert (1977), we have reviewed several studies that have analysed the inflation-hedging characteristics of real estate. We found that approaches have dominated the literature on inflation hedging – the classic OLS analysis of Fama & Schwert (1977), cointegration analysis and causality tests. Owing to the limitations of these models especially when applied to assets such as real estate, a number of newer approaches have been developed. This includes the newly developed ARDL model of Pesaran et al. (2001). We confirm the observation of Hoesli et al. (2012) that the results of the various studies depends on factors such as the country, time-frame analysed, the real estate return series analysed and the inflation measure used – i.e. whether actual, expected or unexpected inflation.

Studies that have analysed the role of real estate within investment portfolios have mostly been conducted within the Markowitz (1952) framework. In this chapter, we have reviewed several asset allocation models, beginning with the mean-variance optimisation model of Markowitz (1952). The issues surrounding the use of the Markowitz framework within the asset management industry are discussed. In particular, we highlight the limitations of the mean-variance model especially when applied to assets such as real estate. Most of the early studies on the portfolio role of real estate suggested allocations far in excess of what was observed in practice. We have categorised the various asset allocation models into three groups: Heuristic, modern and post-modern portfolio theory models. The post-modern portfolio theory models were designed to overcome some of the limitations identified with the Markowitz (1952) framework. Parameter uncertainty and return distribution of the various assets have been identified in this review as some of the challenges of the Markowitz framework. We identified several models that have been identified to deal with these challenges. The results of studies that have applied these improved models have been found to produce more robust results and suggested allocations to real estate that were closer to the observed allocations within the portfolios of institutional investors such as pension funds.

In subsequent chapters, we apply several of the models identified in this chapter to the determination of the inflation-hedging characteristics of real estate and an understanding of the portfolio role of real estate. In Chapters 6 and 8 we apply different asset allocation models to the determination of an optimal mix of liquid assets that can be added to real estate portfolios and the optimal mix of real estate and other assets within a mixed-asset portfolio respectively. In particular, we apply the mean-tracking error optimisation model which is an extension of the classic mean-variance model in Chapter 6. The extension is made to accommodate the needs of investors who seek to benchmark the returns of another portfolio. In Chapter 8, we use a combination of models that use tracking error and the semi-variance of tracking error as measures of risk to determine the portfolio role of real estate. We also explore the risk-adjusted version of these models in the determination of real estate within mixed-asset portfolios designed to provide a hedge against inflation and interest rate changes.

In Chapter 7, we apply the ARDL model of Pesaran et al. (2001) in the analysis of the long-run cointegrating relationship between real estate and different inflation/interest rates often employed by DC pension funds for the purposes performance measurement and benchmarking. The Toda-Yamamoto approach to testing for granger-causality is also applied to understand the short-run relationship between inflation/interest rates and real estate returns.

APPENDICES

Appendix 3(A) Hedging Ability of Real Estate Assets – Literature Review

Study	Country/ Timespan	Empirical Methodology	Assets Analysed	Actual Inflation	Expected Inflation	Results and/or Conclusions
Fama & Schwert (1977)	USA (1953 and 1971)	Fama & Schwert (1977)	- Stock - Bond - Real Estate	US CPI	- T-Bills rates	- Residential real estate provided a complete hedge against both the expected and unexpected changes in the CPI. - US government bonds were a partial hedge against inflation whiles stocks provided a perverse hedge against both the expected and unexpected inflation. - The coefficient for real estate relative to expected inflation in Fama and Schwert (1977) was 1.19 and relative to unexpected inflation was 0.56, both significant at the 1% significant level.
Limmack and Ward (1988)	UK (1976 – 1986)	Fama & Schwert (1977)	- Real Estate (Various sectors)	UK RPI	- ARIMA estimates - Yield on T-Bills	- Combined property as well as the three sub-sectors analysed viz. office, shops industrial, were a hedge against expected inflation. - Only the industrial property sub-sector proved to be a hedge against unexpected inflation.
Park et al. (1990)			- US REITs	- US CPI	- Livingstone Survey - T-bill returns	- Found US REITs to be negatively related to both expected and unexpected inflation.
Wurtzebach et al. (1991)	(1977 – 1989)		- Office real estate - Industrial properties		-	- Office properties were a hedge against inflation in during low inflationary periods - Industrial properties were an effective hedge against inflation during high inflationary periods.
Hoesli (1994)	Switzerland (1970 – 1991)	Fama & Schwert (1977)	- Real Estate - Real Estate Mutual Funds - Stock	Swiss CPI	- Short term rates - ARIMA models	- Real estate provides a better hedging ability than common stocks. - Real estate was found to provide a positive hedge much of the time - Common stocks proved a perverse hedge.
Barkham et al. (1996	UK (1982 to 1994)	- Granger causality - Johansen cointegration	- UK Property (Ellis monthly property index)	UK RPI	- Yield on T-Bill - ARIMA estimates	- Causality tests indicate that changes in expected and actual inflation influence returns to direct property. - A long-term hedge relationship was also found for property and inflation. - Results of the error correction model estimated however pointed to the fact that property may not be a good hedge against inflation in the short term.
Hamelink and Hoesli (1996)	Switzerland (1978 – 1992)	Fama & Schwert (1977)	- Real Estate (Transaction based returns)	Swiss CPI	- Linear Function - ARCH Model	- Real estate does not provide a better hedge against inflation than stocks or bonds. - Real estate and real estate mutual funds were found to be positively correlated with the expected component inflation but negatively related to the unexpected component.

Matysiak et al. (1996)	UK (1964 – 1993)	Cointegration analysis	- Equities, gilts, listed real estate, commercial property, unsmoothed commercial property	UK RPI	- Structural time series model estimates	- Matysiak et al. (1996) found that the coefficient between property returns and both expected and unexpected inflation were positive, suggesting that property was a hedge against both. - Commercial property was not a short-term hedge. However, in the long-run, there is a positive correspondence between property returns and both expected and unexpected inflation. - Similarly, property shares were found to be a hedge even at the aggregate level, meaning they could be used as a substitute for commercial property.
Miles (1996)	UK (1970 – 1995)	Relative performance measurement, literature review	-	UK RPI	- N/A	- Money invested in 1970 would have doubled in value in real terms by 1995 whereas stocks would have made a little under 6% in real terms per annum. - The results did not support the view that real estate investments are less attractive during low inflationary periods.
Newell (1996)	Australia (1984 – 1995)	Fama & Schwert (1977)	- Office real estate - Retail real estate - Industrial real estate - Bonds - Common stock	Australian CPI	- Westpac Inflationary Expectation	- All property sectors were found to be a hedge against actual inflation, as were common stocks. - Property trusts and bonds however, did not provide a hedge against actual inflation. Similar results were obtained for expected inflation. - Office real estate were found to be a hedge against unexpected inflation, as were common stocks. - Retail and industrial property were to a lesser extent hedges against unexpected inflation. - Bonds did not show any hedging ability against the unexpected component of inflation.
Schofield (1996)	UK (1982 – 1994)	- Regression analysis - Cash-flow scenario analysis.	- Real estate - Index-linked bonds	- UK RPI		- Schofield (1996) show that when regression-based approaches are used, index-linked bonds are a poor hedge against inflation. - Based on the cash-flow based scenario approach, index-linked bonds were found to be a perfect hedge against inflation, provided the impact of lagged indexation is ignored. - Properties were not found to be a perfect hedge against inflation. The authors attribute this to the five-year rent review cycle which makes it difficult, if not impossible, to adjust rents in response to inflation rate changes. - Employing leverage makes real estate investments less prone to inflation.
Hoesli et al. (1997)	UK (1963 – 1993)	- Fama & Schwert (1977) - OLS approach	- Stocks - Bonds - IPD real estate (total and income returns; capital gains)	- UK RPI	- T-bill returns - Fama and Gibbons (1984) - ARIMA (0,1,1) - Harvey (1989)	- Compared to stocks, real estate was a poorer hedge against inflation when total returns, income returns and changes in capital values were analysed. - However, the hedging ability of real estate was better than bonds - The relationship between inflation and real estate also depends on whether annual or quarterly data was used. - Bonds become a better inflation hedge than real estate when unsmoothed return series for real estate are used.
Barber et al. (1997)	UK (1987 – 1994)	- Structural Vector Autoregression Models	- Different Sectors of the IPF Index	- GDP Deflator	N/A	- Results show that property offers a hedge against unexpected inflation rather than the expected trends in inflation.

			(Industrial, Office, Retail and Office). - Components of the property returns: Capital Growth & Rental Values			- Capital values were found to provide a better hedge against inflation than rental values over the period examined (1988 – 1989). - The best sector level hedging was provided by the industrial property sector whiles the office sector was the worst.
Ganesan and Chiang (1998)		-	-	-		-
Stevenson and Murray (1999)	Ireland (1985 – 1996 and 1969 – 1996)	- Fama & Schwert (1977) - Cointegration tests	- Irish real estate returns - Stock - Bonds	Irish CPI	- Lagged short-term interest rates - ARIMA estimates	- Real Estate does not function as an effective inflation hedge but it does produce significant positive real returns. - Stocks and bonds did not function as an inflation hedge, neither do they produce positive real returns.
Quan and Titman (1999)	17 countries (1984 – 1996)	- Regression analysis	- Commercial real estate	CPI GDP		- Commercial real estate was found to be a good long-term hedge against inflation but not on a year-to-year basis.
Stevenson (2000)	UK (1983 – 1995)	- Fama & Schwert (1977) - ma and Schwert (1977) - Engle and Granger Cointegration	- UK Real Estate	UK CPI UK PPI	- Correction in short term rates (Gibbons, 1982). - ARIMA estimates	- North West, Scotland and Yorkshire provided a consistent hedge. There was no evidence of a long-run relationship in any of the other regions. - A larger number of regions registered significant beta coefficients when the UK PPI was used instead of the UK RPI. - Whiles housing may not provide adequate hedge against either the Producer Price Index or the Retail Price Index, the real returns in all cases are positive. - The Engle and Granger Methodology cointegration test uncovered evidence of cointegrating relationship between both the RPI and PPI in all but one of the regional markets analysed. - Results of the Granger Causality test revealed that housing market returns lead inflation.
Stevenson (2001a)	10 international markets (1983 – 1995): Australia, Brussels, France, Toronto, Milan, Japan, Amsterdam, Singapore, UK, USA.	- Fama & Schwert (1977) - Engle and Granger Cointegration - Johansen (1988) Cointegration	- Raw and Hedged REIT Data	CPI	- Lagged T-Bill rates - Fama and Gibbons correction of T-Bill rates - Simple first order autoregressive model - ARIMA estimates	- Results from the OLS estimation show that aside Japan and Australia, none of the assets provide an effective hedge against actual inflation over the short term. - It was found that in many of the cases, REITs did not have any significant economic relationship with the expected or unexpected components of inflation. - There was no evidence of cointegration in all the countries except for the orthogonalized Japanese series

Brooks and Tsolacos (2001)	UK (1968 – 1998)	- Durbin Watson (D-W) statistic - Engle & Granger (1987) - Johansen (1988, 1991) - Johansen and Juselius (1990)	- Property stocks listed on the London Stock Exchange	- 3-Month T-bill rates - 20-year government bond rates		- Found cointegration relationship between UK real estate returns and interest rate spreads, but fail to establish same for the short or long term rates themselves.
Anari and Kolari (2002)	USA (1968 – 2000)	- ARDL - Recursive regressions	- House prices	CPI inflation		- House prices offer a hedge against inflation - Recursive regressions confirm stability of long-run relationship between house prices and inflation.
Chu and Sing (2004)	4 cities in China: Beijing, Chengdu, Shanghai and Shenzen. (1987 – 2002)	- OLS - Cointegration analysis (Engle and Granger) - Granger causality test	- Real estate returns from the Chinese Real Estate Index (CREI)	- CPI inflation	- ARIMA (1.0,3)	- Chu and Sing (2004) found no long-term relationship between inflation and real estate returns. - Causality tests show unidirectional causality from inflation to real estate returns in Chu and Sing (2004) - GDP growth and real stock market returns were not found to be a driver of real estate returns.
Chen and Foo (2006)	UK Tokyo Hong-Kong Taipei Singapore (1971 and 2003)	- Model of Berber et al. (1997) analysis of time series features: Trend, Seasonality, cycle etc.	- Residential real estate series (Various sources)	- RPI for UK - CPI for all other markets		- Singapore residential property was found to offer a hedge against both transient and permanent price shocks. Taipei residential real estate offered a partial hedge against the long-term inflation trend whereas Hong Kong had the worst hedging ability against all three types of inflation.
Huang and Hudson-Wilson (2007)	USA (1978 – 2006)	- Fama & Schwert (1977) -	- NCREIF US Private equity (Sectors: Apartment, office, retail, warehouse; Components of return: Income, capital, total)	US CPI	- Treasury bill interest rates	- Results show that office real estate has the best inflation hedging ability followed by apartments and lastly warehouse. The difference between the performance of apartment and warehouse was quite pronounced. The authors attributed the poor performance of warehouse real estate to the disappearance of lease structures that linked rents to sales as well as allowing for full expense pass-through.
Simpson et al. (2007)	USA (1981 – 2002)	- Fama & Schwert (1977) -	- Equity REIT database of the US Centre for Research on Stock Prices.	- Survey of US inflation expectation (Money Market Services)	- Inflation survey divided into expected and actual component by means of a complex ARIMA structure that included both autoregressive (AR)	- When expected and unexpected changes in the inflation were separated into positive and negative changes, they observed that REIT returns rise in response to changes in either direction. They attributed this result to how market participants process information that it consider to be relevant to inflation.

					and Moving Average (MA) terms	
Le-Moigne and Viveiros (2008)	Canada (1973 – 2007)	- Correlation and time series analysis	- ICREIM/IPD real estate index and Russell-Canadian Property Index	- Canadian CPI	- Lagged Canadian CPI inflation	- When the sample period was split into two: 1973 – 1984 and 1985 – 2007, they observed that real estate only provided a hedge in periods of high inflation and not when inflation rates were low. - On their own however, British Columbia and Quebec's real estate provided a hedge against expected inflation. - The failure of real estate to hedge against inflation, in the latter periods examined by the study, was attributed to an introduction of inflation targeting by the Central bank of Canada.
Erol and Tirtiroglu (2008)	Turkey (1999 to 2004)	- Fama & Schwert (1977) - Fisherian Direct Causality model	- Real Estate - Stock	- Turkish CPI	- T-Bill Rate - Fama and Gibbon (1982) correction in short-term rates.	- When the sample period was divided into periods of moderate and high inflationary sub-periods, there was still evidence that stocks and REITs provided better hedges against inflation for both periods but REITs consistently outperformed stocks.
Hoesli et al. (2008)	UK USA (1977 – 2003)	- Error correction models	- Direct real estate - General stocks - Small cap stocks -	- US CPI - UK RPI (excluding mortgage payments, seasonally adjusted)	- Treasury bill rates - ARIMA estimates	- Only private real estate was found to have a non-significant relationship with anticipated inflation - Unanticipated inflation had a significant positive relationship with private real estate but no relationship with public real estate securities - For the US market, over the long run, securitised real estate provides a complete hedge against inflation whereas direct property is only a partial hedge against expected inflation. - Results from the short-run models suggest that in general, there was no significant inflation hedge provided by any of the assets although real estate assets provided a better hedge than stocks. - With regard to the United Kingdom, all the asset classes partially hedged inflation over the long run. - The coefficients for direct real estate was less than one whiles all the others were greater. - Private real estate recorded a significant positive coefficient. - Over the short run however, only direct real estate provided some hedge against both the expected and unexpected components of inflation.
Attie and Roache (2009)	USA (Various start dates for different assets to Nov. 2008)	- multivariate vector-error correction model (VECM)	- Real estate - Bonds - Equities - Cash - Commodities	- US CPI	N/A	- Over the short run, they find that bonds and equities did not provide a good inflation hedge. - Commodities however provide a good hedge against inflation, particularly over periods of rising inflation. - Over a 12 – 18 month period, they find commodities to be the best performing asset and bonds to be the worst performing. - Beyond this period, bonds outperformed inflation while commodity prices begin to fall in nominal terms. - Equity, they note, was unable to recover short-term losses made and thus performed poorly over all the sample periods examined.
Amenc et al. (2009)	USA (1973 – 2007)	- Vector error correction models (VECM) which allow for	- Real estate (FTSE/NAREIT real estate index) - Stocks	- US CPI	- Return on a constant maturity zero-coupon TIPS	- Results of the study were, among other things, that commodities and real estate are able to offer inflation-hedging over the long term. - The authors compared their liability-hedging investment solution to other approaches typically used by long-term investors and note

		incorporating price and return dependencies	- Bonds - Commodities -			that it offers a more cost-effective option to the use of TIPS and inflation swaps.
Demary (2009)	Australia Denmark Finland France Germany Japan Netherlands Spain UK USA (1970 – 2005)	- cross correlations at different leads and lags - Various VAR approaches: impulse response, forecast error, variance decomposition and causality	- Real Estate -	- GDP - Short-term interest rates	N/A	- The study found that real estate prices fall in response to unexpected increases in the price level. - Declining prices however does not imply that real estate is not a hedge against inflation. - Housing demand shocks are a key driver of money market rates. - 12 to 20 percent of output fluctuations and around 10 to 20 percent of price fluctuations can be traced back to the housing demand shock.
Demary and Voigtlander (2009)	Canada USA France Germany Ireland Netherlands Sweden UK (1998 – 2007)	- Panel data augmented version of the Fama & Schwert (1977) model	- Real Estate data from EPRA -	- CPI	- ARIMA estimates	- Neither stocks nor REITs protect investors against inflation in the countries examined. - Direct real estate however does protect the investor against inflation. - Office and residential real estate were found to provide the best hedge against inflation. - A possible explanation for this is that landlords in residential properties have a higher market power to make occupants accept increases to their rent as inflation increases.
Zhou (2010)	USA (national and ten selected states) (1978 – 2007)	- Engle and Granger (1987) Cointegration - Johansen (1988, 1991) Cointegration - Alternating conditional expectations (ACE) algorithm of Breiman and Friedman (1985).	- US House Prices	- Income - Mortgage rates - Construction costs	- N/A	- Results of the linear cointegration shows that of the series examined, only the City of Cleveland shows evidence of cointegration of house prices and the fundamentals. - Results of the Ramsey (1969) reset test was used to detect errors in the specification of the linear OLS regression and it was found that only the linear specification of Cleveland was correctly specified. - It was found that the transformed house prices are linearly cointegrated with the series for the transformed house price fundamentals for the national series as well as those of six cities: Chicago, Dallas, Philadelphia, Richmond, Seattle and St. Louis.
Zhou and Clements (2010)	China (2000 – 2008)	- Autoregressive Distributed Lag (ARDL) Model - Granger causality test	- Residential real estate prices - Non-residential real estate prices - Aggregate real estate prices - Stocks	- CPI inflation	- ARMA estimates	- No long-run cointegration relationship found between real estate returns and inflation (actual, expected and unexpected). - No short-run causal relationship between real estate prices and inflation. - Residential real estate found to granger-cause actual inflation. - Bi-directional relationship between residential real estate and expected inflation.

						- Non-residential real estate found to granger-cause both actual and expected inflation.
Inglesi-Lotz and Gupta (2011)	South Africa (1970 – 2011)	- ARDL	Allied Bank South Africa Real estate segments: - Luxury - Large middle-segment - medium middle-segment - Small middle-segment - Entire middle-segment	- CPI (excluding housing costs)	-	- All the various real estate segments were found to be cointegrated with the chosen inflation measure over the long-run. - The long-run coefficients which represents the attempt by house owners to maintain their purchasing power was found to range between 0.902 for the luxury segment and 1.111 for the affordable housing segment.
Blake et al. (2011)	UK (1948 – 2007)	- Correlation analysis	- UK Real Estate	- CPI - GDP growth - Wage Growth	-	- A hedge is obtained if an asset is moving at the same time as inflation, or reacting to it, and not merely keeping pace with inflation over time. - In the long run, they found that UK property did not act as an inflation hedge although it does deliver positive returns. - The results however varied according to the type of inflation being analysed and the underlying economic conditions. - When GDP growth was used as the inflation measure, the study recorded coefficients for real total returns were not significantly different from zero. - Capital growth was seen to respond very strongly to CPI inflation but income return did not show any long-term relationship. - Income from UK property did not keep up with CPI inflation, particularly in periods of high inflation.
Tenigbade (2011)	Nigeria (1999 – 2010)(Cities: Ikoyi, Victoria Island, Ikeja)	- Fama & Schwert (1977)	- Real Estate	- CPI	- T-Bill Rate	- An examination of the correlation structure of real estate and inflation showed that real estate was positively correlated with inflation. - Results of the Fama & Schwert (1977) model indicated that the prime commercial property around Ikoyi and Victoria Island acted as a perverse hedge whereas those in Ikeja and its surrounding area offered a complete hedge against inflation.
Case et al. (2012)	USA (1978 – 2011)	- Success Ratio analysis	- REITs - Commodities - TIPS - Stocks - Gold	-	-	- They find that real estate accessed through publicly traded equity REITs provided attractive inflation hedging characteristics. - Short-duration leases, or properties with rents linked to revenues provided the strongest inflation protection. In particular, self-storage, residential properties and shopping centres recorded success ratios higher than the industry average. - The authors also worked within the Markowitz mean-variance framework to determine the optimal allocation that provides the best inflation protection. They find that a blended portfolio with 49% invested in TIPS, 17.5% invested in REITs, 15% in

						commodities, 14% in stocks and 6% in gold achieves a 75% success ratio.
Obereiner and Kurzrock (2012)	Germany (1992 – 2009)	- Fama & Schwert (1977) model - Engle & Granger (1987) cointegration - Johansen (1988) cointegration - Granger Causality tests	- Open ended funds (OEF) - Secial real estate funds (SF)	- CPI	- ARIMA estimates	- Results from the Fama & Schwert (1977) model suggested that in the short run, none of the real estate investment vehicles analysed provide a hedge against either the expected or the unexpected components of inflation. - Cointegration test results show that over the long term, open-ended funds and special real estate funds do provide a hedge against inflation. - Causality tests lend support to the findings of the cointegration tests by suggesting that real estate fund performance is influenced strongly by the German CPI rates over the long run.
Park and Bang (2012)	Korea (2002 – 2010)	- Dynamic ordinary least square (DOLS) regression of Saikkonen (1992) and Stock and Watson (1993). - Vector error correction model (VECM) - Engle-Granger cointegration - Johansen (1988) cointegration	- Real estate (Korean CBRE income return; capital gains) - Equity	- CPI	- ARIMA estimates	- Real estate was found to be a hedge against actual and expected inflation over both the short-run and long run. - Equities were found to have a negative relationship with inflation over the short-run. However, over the long-run, equity returns were found to be cointegrated with inflation. - The error-correction coefficient for inflation and commercial real estate in Park and Bang (2012) was -0.016 and for equities it was -0.292. - An analysis of the rental income shows that it has a positive co-movement with both expected and unexpected inflation. However, compared to the analysis using total returns, the degree of correlation was weaker.
Tehrani et al. (2012)	Third World Countries (1980 – 2011)	- Pesaran et al. (2001) ARDL Bounds Testing approach	- Real Estate - Stock - Time Deposits	- Country Policy and Institutional Assessment (CPIA) Rate	-	- The study found that small and medium size properties are better at hedging against inflation than large, luxury apartments. - Real estate assets were also found to possess better hedging ability than common stocks and time deposits.
Anim-Odame (2014)	Ghana (1992 – 2007)	- Hedonic models	- Residential real estate	- GDP - Interest rate	-	- Results show a positive relationship between GDP growth and the total returns of the Ghanaian residential housing market. - Conversely, the study recorded a negative relationship with interest rates. - These results are stronger when the dollar total returns are translated into Ghana cedi using.

CHAPTER FOUR – DATA AND METHODOLOGY

4.0 INTRODUCTION

This part brings together a discussion of all the issues concerning the data used in our empirical analysis. We first present the sources of each data series used, who construct it, the composition of the index etc. Potential problems with each data source, namely, representativeness, appraisal smoothing etc. are discussed, including a description of how we deal with each of these issues. We then go on to discuss the key benefits of investing in the various assets and also present a discussion of their historical performance over our sample period. In the second part of this chapter, we present a background to the statistical, econometric and optimisation models and techniques that underlie the analysis in the various empirical chapters. The aim is to provide an expanded discussion of the various models and analytical techniques that we implement in the various empirical chapters of this thesis. A summary of these models would be given in the various chapters in which they are applied.

4.1 DATA

4.1.1 ASSET RETURNS

The assets included in this study are grouped under four headings to reflect the allocations observed by studies that have analysed the allocation within pension portfolios (Scott, 1991; UBS, 2015; Schroders, 2016). We group the assets under the following headings: stocks, bonds, real estate and alternative assets. Under alternative assets we have assets such as commodity, hedge funds and private equity. This category also includes developed market equities and emerging market equities, which may normally not be classified as alternative assets. In addition to the main asset classes, we include sub-sectors where data is available.

The various empirical studies in this thesis are conducted from the perspective of a UK pension fund investor who aims to gain exposure to both traditional (core) and alternative asset classes. Very few studies have examined the inflation and interest rate hedging ability of real estate within a portfolio context. Those that have done so (e.g. Koniarski and Sebastian, 2015) have limited the portfolio to real estate and the traditional asset classes of stocks and bonds. Also, very few studies have used sector-level data in their analysis, a situation Spierdjick and Umar (2013) found could lead to inaccurate conclusions being drawn as the behaviour of an asset on a sector level may be different from the behaviour at an aggregate level.

In order to determine the hedging ability of these assets, the relationship between the returns of the assets and selected macroeconomic variables are analysed. We include a number of inflation and interest rate measures to determine the robustness of our results and also to see if the resulting asset portfolios are driven by the inflation or interest rate benchmark chosen by a particular pension fund. We use the UK CPI Inflation rate as the main measure of inflation and the 3-month T-bill rate as the main interest rate measure. The UK RPI Inflation rate is used as an alternative measure of inflation whiles the 3-month LIBOR rate is used as an alternative interest rate.

The analysis in this thesis cover the periods 1991 and 2015. The starting point allows us to include a wider selection of assets as data for most of the alternative assets are only available from the early 1990s compared to the traditional assets such as stocks, bond and real estate that have data going back much farther. The start time of our analysis also coincides roughly with the period when the move towards DC pension structure started in the UK (Broadbent et al., 2006; Turner and Hughes, 2008; Whelan, 2003).

We use quarterly data as the returns of some of the assets included in this study are only available on a quarterly basis. For our out-of-sample analysis, we use a quarterly rebalancing window which reflects the practice within pension funds (Blake et al., 1999; Ibbotson and Kaplan, 2000; Bams et al., 2016; Driessen et al, 2017).

Also, many of the alternative assets are priced in US$. The analysis in this thesis are conducted from the perspective of a UK DC investor and thus it makes sense to convert all returns into UK pound sterling. However, in Chapter 7, we carry out the analysis using non-UK asset returns in both US$ and GB£ to reveal whether a decision to hedge currency risk or not impacts on the ability of non-UK assets to hedge against UK benchmarks. The analysis in the portfolio paper (Chapter 8) is conducted with non-UK asset returns converted back into GB£ to provide focus on the analysis of whether the different benchmarks result in different portfolio composition for DC pension funds.

Published indices are used as proxies of asset return in all cases. We source most of the data from datastream and Bloomberg. We supplement this with data sourced directly from data providers such as Cambridge Associates and the various pension funds.

The following sections explain the sources of returns for the various investment assets and macroeconomic benchmarks. Issues associated with the various data sources would be discussed as well as our approach for dealing with these issues. The specific data required for the each empirical analysis would be discussed in the respective chapters.

4.1.1.1 Direct Real Estate

Apart from stocks and bonds, real estate is the most significant asset class in which pension funds invest (Andonov et al., 2012). Hudson et. al. (2003) explained that the rationale for including real estate in investment portfolios is its ability to reduce risk and achieve a competitive return. Also, real estate delivers strong cash flows which serve as a hedge against inflation. Ling and Naranjo (1997) found that real estate returns were driven by factors such as GDP growth per capita, the term structure of interest rates and some measures of inflation. Similarly, Geltner (1989) found that real estate returns were very sensitive to national consumption. Brounen and Eicholtz (2003) point to real estate's relatively low correlation with equities and bonds. Andonov et al. (2012) found pension fund real estate investments depend on their willingness to invest in alternative assets in general. It also depends on the size of the funds.

Early studies on the role of real estate within investment portfolios have recommended high allocations to direct real estate than what was observed in practice. Many reasons have been put forward for the low allocation that real estate receives in practice. These reasons include lumpiness and illiquidity (Gallagher, 2005; Payton et al., 2007), high management costs (Byrne and Lee, 2005), lack of transparent pricing (Gallagher and Martin, 2005).

In this thesis, we use actual both the IPD Index and the AREF/IPD unlisted funds indices to obtain exposure to the direct real estate market in the UK. In addition to these two series, we also construct a blended real estate index that is made up of an 80% direct real estate (AREF/IPD unlisted fund index) and 20% listed real estate. This is similar to the approach taken by NEST for their real estate investment. We discussed the significance of blended real estate in Chapter 2. The idea of creating blended real estate series also underpins the empirical analysis in Chapter 6. As an additional robustness check, we re-run the analysis where we use the IPD property index using an unsmoothed IPD Index return series. The approach of Geltner (1991, 1993) is used.

The IPD-UK index is constructed by the Investment is the standard benchmark that property investors use to measure the performance of UK direct real estate. It is constructed from valuation and management records of individual properties in complete portfolios, collected directly from investors. The index tracks the performance of over three thousand property investments with a total capitalisation of GB£45 billion as at April 2017. Andonov et al. (2012) note that the IPD index represents the most prevalent database for commercial real estate investment in the United Kingdom. Similarly, Callender et al. (2007) concluded that the IPD index provides a realistic picture of the options that are available to investors who wish to construct a direct real estate portfolio. More than 60 percent of investors in the IPD UK database are pension funds (Bond and Mitchell, 2010). In addition to the aggregate IPD-UK property benchmark, sector levels will be conducted using the three main sub-sectors: Office, Retail and Industrial real estate. For the purposes of this thesis, listed real estate would be classified under stocks.

Although the use of return indices to measure the performance of different asset classes is well established in the literature, some have questioned the use of index returns within the context of real estate investment. The arguments centre around (i) the suitability of real estate indices in tracking the performance of the underlying real estate market and (ii) The accuracy of appraisal based indices in general in the measurement of returns. The first issue has to do with whether investors can actually hold the many assets included in a property index in order to replicate the performance of the index. This is a valid concern especially given how expensive it would be for an average investor to own the number of assets that an index contains. The second issue has to do with the accuracy of appraisal based series in capturing the returns of the underlying market. Statistical issues such as appraisal smoothing also remain a concern among researchers. In the following section, we debate these issues and show that on the whole, appraisal based indices reflect the returns earned by property investors. Also, real estate indices have over time become more reliable and have been shown to reasonably track property returns.

The IPD direct real estate index tracks the performance of the universe of direct real estate assets available to UK institutional investors and fund managers. Some have argued that investors cannot realistically hold the many assets that make up the UK IPD index and so the returns obtained may not be comparable to the IPD benchmark portfolio. Consequently, several empirical studies have investigated the question of whether the IPD benchmark portfolio returns can be replicated using a limited number of properties. The focus of most of these studies has been on the number of properties that are required to create a well-diversified portfolio.

Early studies on diversification and portfolio size were conducted in equity markets. These studies in general found that a small number of stocks were required to produce a reasonable level of diversification. The seminal work of Evans and Archer (1968) provided the simulation approach for subsequent studies. The study examined how the standard deviation of a randomly selected, equally weighted portfolio decreases as portfolios containing 1 to 40 stocks are constructed. The selection of each portfolio size is repeated 60 times and the standard deviation from each trial are averaged out. The results showed that 8 stocks were enough to produce returns that track the returns on the S&P index. The added benefit of having more than ten stocks in the portfolio was very small. Elton and Gruber (1977) applied analytical techniques using average variance and covariance for stocks drawn from the New York Stock Exchange and the American Stock Exchange. They found that 51% of an equally weighted stock portfolio can be eliminated by adding 10 to 20 stocks to the portfolio. Statman (1987) incorporated variations in management and transaction costs and concluded that 30 to 40 stocks make a well diversified portfolio. The added cost of holding more than 40 stocks outweighed the added diversification benefits.

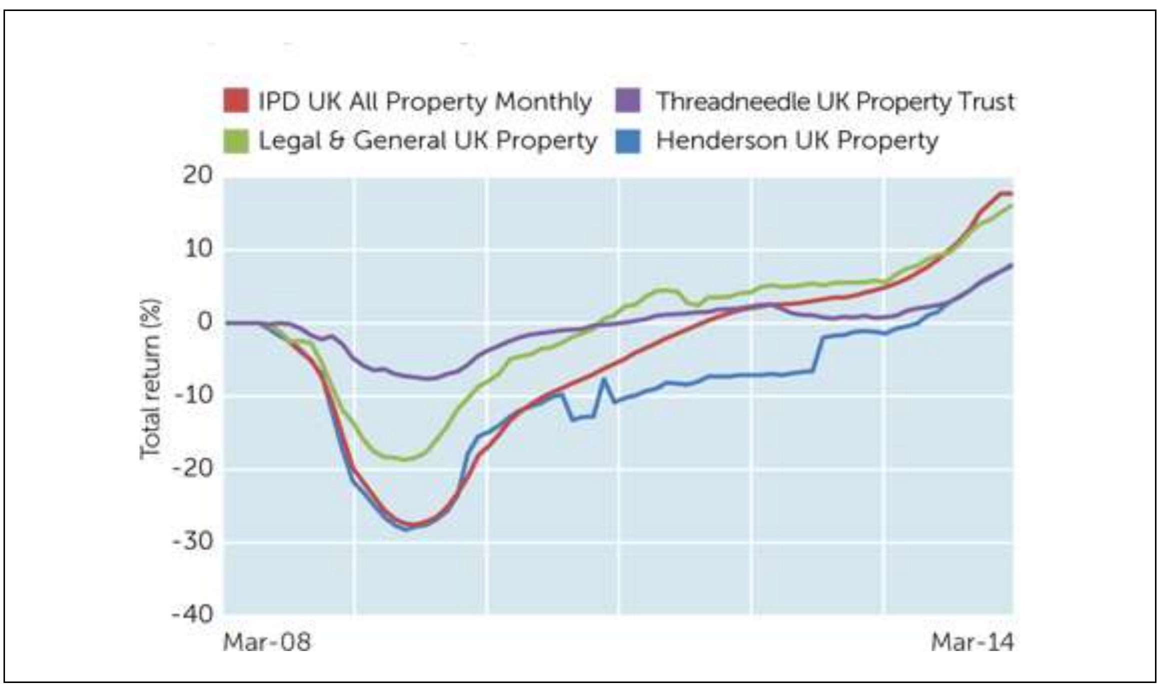
Achieving a reasonable level of diversification is more challenging for direct real estate due to (i) the indivisibility of commercial real estate (ii) High transaction costs associated with real estate investments (iii) Lack of effecting vehicles for short-selling and hedging. Brown and Schuck (1996) believes that a high level of asset-specific risk explains in part the low allocation to direct real estate relative to the allocations suggested by most optimisation models.

Jones Lang Wooten (1986) conducted one of the earliest studies on portfolio size and diversification within the real estate market using the approach of Evans and Archer (1968). They concluded that 20 properties were required to achieve a reasonable level of diversification. Using a similar approach, Barber (1991) estimated that between 40 and 45 properties are required whiles Campbell et al. (2001) concluded 50 randomly selected buildings could help achieve relatively complete portfolio diversification. Byrne and Lee (2000) however found wide dispersions in the results from the various trail sets of portfolios. They concluded that even though a significant amount of risk-reduction can be achieved with 20 properties, 60 to 80 properties would be required to create a portfolio about which an investor can be very confident. Young et al. (2006) found that assuming a normal distribution, only 16 properties would be required to eliminate about a quarter of a single property portfolio's risk. However, when the assumption of normality is relaxed, 88 properties would be required to achieve the same outcome. Fisher and Goetmann (2005) constructed simulated portfolios using data on 4,000 properties bought and sold in the US from 1977 to 2004. They found that increasing portfolio size from 10 to 100 properties could reduce the risk of the portfolio from 3.76% to 1.27%.

Brown (1988) applied an analytical technique to a portfolio of 135 properties and found that only 10% of variations in property returns are explained by market movements. This compares with 30% of market movements in the equity market that is explained by market movements. To achieve a high level of diversification, they concluded that over 200 properties would be required. Byrne and Lee (2003) found that in order to remove all of the unsystematic risk from a property portfolio, a large amount of properties, more than 200, have to be held. As this nearly impossible for most investors, the authors concluded that most properties would still contain some amount of unsystematic risk factors. On the contrary, Brown and Matysiak (2000) found that institutional investors who hold between 20 and 30 properties are able to diversify away much of the property specific risk. The results of) were confirmed by Boulding et al. (2013) who examined how well a real estate index tracks the return movement of portfolios with different numbers of properties. They found that aggregate real estate indices are effective when portfolios of more than twenty properties are considered. They also found that location based indices were better at tracking real estate returns than property-type indices. Callender et al. (2007) found that a large amount of risk reduction can be achieved with a portfolio of 30 to 50 properties. However, to obtain tracking error of less than 1%, over 250 properties are required. Mitchell (2015) analysed the performance records of over a thousand UK commercial properties along with their characteristics and tenancy records. They found that the deviation in sensitivity of individual property returns and the returns of the benchmark IPD All Property portfolio is not large. An implication of this result is that investing in a couple of properties is enough to achieve a reasonable level of diversification and obtain returns similar to the IPD benchmark.

A review of the Statement of Investment Principles and Annual Statements shows that many of the property funds through which pension funds invest in direct real estate are benchmarked to the IPD-UK property total return index or its variants. The graph in Figure 4(1) is adapted from Skjönsberg (2014). The graph compares the monthly total returns of three major real estate funds returns to the total returns of the IPD UK All Property portfolio benchmark. We observe that the returns follow the same pattern, although some funds perform better or worse than the benchmark.

Figure 4(1) IPD All Property Returns and Individual Property Fund Return



Source: Skjönsberg (2014)

There has also been a long standing debate on the suitability of appraisal based indices to track the returns of various assets, especially direct real estate. The main focus has been on valuation smoothing and its effect on the measurement of real estate performance on the index level. Smoothing affects the volatility of an index as well as other statistical properties of the index. Smoothing is attributed to factors such as valuation timing, sticky valuation process and aggregation effects (Geltner, 2003; Brown and Matysiak, 2000). Geltner (1993) believes that the smoothness and lagging associated with appraisal based indices has to do with two sets of factors: (i) how appraisers behave and how individual appraisals are obtained (ii) How the various appraisals are aggregated to form an index. Geltner (1989) believes that smoothing at the individual property level is a result of the fact that appraisers in themselves cannot be certain that their current estimates of market values equals the true market value. Given the market value of the same property for a particular property for a previous year, valuers tend to consider the previous year's estimates at least to some degree. Diaz and Wolverton (1998) found that there is a high tendency for appraisers to anchor on their own previous assessment of value. Similarly, Clayton et al. (2001) found that anchoring on previous values was greater where the property is appraised by the same valuer. To reduce this tendency, it is important to rotate appraisers from one period to the next. Index level smoothing is often a result of what US researchers describe as a stale appraisal problem with respect to NCREIF data. This problem arises from the fact that some properties are valued less frequently than quarterly. In order to retain such properties within an index, the values of intervening quarters are populated with figures from the last appraisal process. This results in a loss of information as movements in the value of properties that are appraised quarterly tend to be dampened by those assets whose values do not move. Even when all assets included in the sample are revalued each quarter, some temporal aggregation could result as not all the properties are valued on the same date.

One of the reasons cited for the high allocation which real estate receives within investment portfolios is that real estate returns are less risky and exhibit low volatility. They also have low correlation with other asset classes and thus present an opportunity for diversification. However, many authors have argued that the low volatility is a function of the valuation process – what they refer to as appraisal smoothing. Byrne and Lee (2005) note specifically that using actual appraisal based real estate index return could lead to corner solutions – a situation where real estate allocations are very high.

Geltner (1989) proposed an approach to unsmooth direct real estate returns on the index level to reveal the 'real' volatility. A number of studies have built on Geltner (1989) but have proposed different approaches to unsmooth appraisal-based property returns (e.g. Geltner, 1993; Quan and Quigley, 1991; De-Wit, 1993; Fisher et al., 1994).

The process of unsmoothing appraisal based real estate returns is not without its critics. Lai and Wang (1998) show that there are scenarios in which appraisal-based returns can exhibit even more volatility than true asset volatility. They question the assumptions often made regarding appraisal-based time series and aver that "it is not reasonable to conclude that something is wrong with appraisal based indices because the variance seems artificially low" (p. 532).

Another issue with using unsmoothed real estate return series is that the various unsmoothing processes or models tend to produce different results (Marcato and Key 2007). Corgel and deRoss (1999) for example found that different assumptions about the appraisal process and the different models proposed to correct the perceived appraisal bias could resulted in very different allocations to direct real estate within optimal multi-asset portfolios. Bond et al. (2012) suggest that smoothing in individual property appraisals is not as great as has been implied from analysis of index-level data. They argue that previous studies utilised models that are too simple for capturing the return generation process for real estate.

Crosby and Diaz (2011) outline three reasons why transaction based indices for real estate have been difficult to construct: (i) limited volume of real estate transactions (ii) lack of transparent market place to observe transactions. (iii) heterogeneous nature of properties. They observed that despite the shortcomings of appraisal based indices, they enable a larger sample to be used with the possibility of greater disaggregation than transaction based indices. The usefulness of appraisal based indices has also been improved over the years by research into their limitation. The increasing availability of transaction based indices has helped in identifying differences between the outcomes and those of appraisal based indices at the more aggregated level. Some researchers have used transaction based indices in place of appraisal based indices. For example, Brounen et al. (2010) used the MIT Centre for Real Estate Transaction based indices instead of the NCREIF Property index to avoid the perceived smoothing and lagging problem of appraisal based indices. Boulding et al. (2013) examined 12,427 repeat sales transactions between 2004 and 2011 and found that aggregate real estate indices do a good job of tracking real estate returns when more than 20 stocks are included in the portfolio. They concluded that aggregate real estate indices can be effective in evaluating direct real estate performance. Devaney (2014) compared the volatilities of different types of indices and found that the UK has similar volatility figures for both appraisal based and transaction based indices.

Many researchers have argued that the unusually high allocation to real estate observed in earlier studies reflect shortcomings of the standard mean-variance framework as opposed to problem with the underlying asset data. In Chapter 3, we provided a detailed discussion of the shortcomings of the mean-variance model and several approaches and models that have been developed to produce better portfolios. More pertinent to this thesis is the use of Asset Liability Models (ALM) within the context of pension funds. ALM models emerged in the early 1990s (Sharpe and Tint, 1990; Leibowitz et al., 1994). Studies that have applied ALM to real estate found allocations that differed greatly from those that worked within a Mean-Variance framework (Chun et al., 2000; Craft, 2001; Craft, 2005; Brounen et al., 2010). Brounen et al. (2010) in particular aver that accounting for inflation within an ALM context was at the heart of discrepancies between reported and predicted allocations to direct real estate. The analysis in the portfolio chapter is carried out within a framework that uses tracking error and semi-variance of tracking error as the measure of risk. Consequently, risk is measured relative to the inflation and interest rate benchmark. This way, the effects of appraisal smoothing on the risk measure is expected to be minimal. Consequently, we do not expect the results of analysis based on actual IPD property index to differ significantly from an analysis using desmoothed index returns. As an additional robustness however, the portfolio analysis chapter would make use of both the actual IPD All Property Index as well as an unsmoothed IPD return series.

4.1.1.2 Publicly Listed Real Estate

It is well known that the REIT market offers investors who want to invest in real estate the opportunity to invest in real estate without running into the problem of illiquidity, management issues as well as high lot sizes and unit costs direct investment in real estate entails (Chiochetti et al., 2002). Although listed real estate investments have been available since the introduction of REITs in the United States in 1960, they only became popular in the United States in the early 1990s owing to a number of factors. These factors include the include the inclusion of REITs in major market indices such as the S&P 500 and the strong performance witnessed by REITs following the burst of the dot-com bubble (Ling and Naranjo, 2003), the low correlation observed between real estate stocks and other stocks (Ross and Zisler, 1991; Kallberg et al., 1996). Real estate investments also increased when the "five or fewer rule" for pension funds in the United States was changed. The rule stipulated that the top five shareholders together cannot own more than 50% of the shares outstanding of REITs. This effectively limited the ability of pension funds to invest in REITs given their large financial resources. The rule was amended in 1993 so that pension funds were no longer seen as single investors but a collection of investors.

REITs have been used as a proxy for listed real estate in a number of non-UK studies. However, in the UK, the first property companies that converted to REITs did so in 2007 and so there is no data for REITs before this time. In this study, we use data for listed real estate companies. The listed real estate benchmark used is the Thomson Reuters Datastream listed real estate stock supersector (Level 3) which is a subset of the financial industry stocks (Level 2).

With the popularity of listed real estate came the question of whether investing in listed real estate could yield the same outcome as investing in direct real estate. Three different strands of literature have emerged regarding the relationship between direct and listed real estate and the role of listed real estate within investment portfolios. One line of research analyses the relationship between listed and direct real estate returns and direct real estate returns whiles another looks at the benefits of adding listed real estate to real estate investment portfolios. A third group of studies examines the role of listed real estate within multi-asset portfolios that may or may not contain direct real estate.

Several studies have compared the returns of listed and direct real estate to reveal whether both series exhibit the same trend and could be considered as substitutes or whether they are both unique and so be used together within a diversified portfolio.

Many of these studies used the style analysis approach of Sharpe (1988, 1992) or vector autoregressive models. While some of the studies analysed the relationship between the direct real estate and listed real estate asset specifically, others considered the relationship between direct real estate and the broader equity market. Myer and Webb (1993) observed that US REIT returns behave more like equities in the short term. They however granger-cause the direct real estate market in the long term. Liang and McIntosh (1998) performed the style analysis of Sharpe (1988, 1992) and concluded that REITs were a unique asset class and so should be added to investment portfolios for enhanced risk-adjusted performance. Ling & Naranjo (1999) examined whether the direct real estate market as well as the REITs market were integrated with the common equity market. While REITs were found to be integrated with the common equity market, direct real estate markets were not. The results were consistent whether the direct real estate series was unsmoothed or not. Similarly, Quan and Titman (1999) found that commonality between direct real estate and domestic equity markets are only evident when data was examined at an aggregate level and over longer time horizons. Pagliari et al. (2005) found that the returns of direct real estate, after adjusting for leverage, smoothing and accounting for other effects, were very similar to REIT returns. This was particularly so between 1993 and 2001. Based on this, they suggested that REITs were a good proxy for direct real estate.

The studies that utilised vector autoregression approaches generally found little evidence of integration between direct and indirect real estate sectors (Wilson et al., 1998). Causality analysis has also been used to investigate this issue by papers such as Myer and Webb (1994), Barkham and Geltner (1995; 1996) and Seiler et al. (1999). Most of these studies revealed that the listed real estate market leads the direct real estate market, implying that information is incorporated into the prices of listed real estate assets more quickly. Barkham and Geltner (1995) found evidence of unlevered and lagged price information transmission from listed real estate market to the direct real estate market in both the UK and USA. Geltner et al. (2007) observed that the returns of listed and direct real estate vary, especially in the short term. Clayton & MacKinnon (2000) believe that variations in direct rand listed real estate returns stem from the fact that information takes longer to transfer from the direct to the listed market. Hoesli & Oikarinen (2012) compare the return of listed and direct real estate using vector error correction models. They find evidence of a long-term relationship in the UK and US markets. However, the relationship between REITs and stock markets is stronger in the short-term. In the long run, REIT returns have similar risk factor exposures to direct real estate.

4.1.1.3 Nominal Bonds

The two main criteria used to categorise bonds are (i) Issuer type and (ii) Term to maturity. There are different types of bonds depending on who the issuer is e.g. government bonds, corporate bonds, municipal bonds etc. Term to maturity refers to the length of time between when the bond is issued and the time the issuer must redeem the bond by paying the principal or face value. Between these two dates, the issuer makes periodic interest (coupon) payments to the bond holder. We include Bonds with different maturities in our studies – All Maturities; 10+ year, 10 year, 5 year, 3 year and 2 year Bonds series. The main sterling corporate indices for the UK do not start until the mid- to late- 1990s. A study by the UK Institute and Faculty of Actuaries (2003) attribute this to the fact that very few companies issued bonds during high inflation periods owing to their reluctance to commit to paying high coupon rates. Also, many bond issues tend to be tightly held (mostly by insurance companies who purchase and hold them to maturity) while some of these bonds were very rarely traded. UBS (2015) observed that as corporate bonds are priced as a spread over government bonds, a rise in interest rates would mean that the return in corporate bonds would go up to the same degree.

Several studies that have analysed the portfolio role of bonds within a multi-asset setting have tended to focus on government bonds (e.g. Chun et al., 2000; Craft, 2001; Bruno & Chincarini, 2011; Koniarski and Sebastian, 2015). In assessing the ability of bonds to hedge against inflation, analysing bonds of different maturities would offer more insight than analysing bonds from different issuers. Mergon (1974) observed that maturity risk is a factor for even the safest bonds there is a higher potential for changes in inflation and interest rates to adversely affect the returns of these bonds. Assuming a constant risk premium as in the expectation hypothesis of Fama (1984), the return pattern of corporate bonds of various maturities is expected to be identical to the returns of government bonds of the respective maturities. After accounting for default and other risk factors, the difference in return for bonds of different terms to maturity is expected to be the same.

The nominal bond series is obtained from the Thomson Reuters DataStream's Benchmark Government Bond Indices which represent returns on government Bonds and is available for several countries based on formulation recommended by the European Federation of Financial Analysts Societies. The maturities included in our study are the maturities that are available for all countries (up to 10 years) although longer maturities are available for countries such as the UK. We use the 10+ year to represent all the maturities greater than 10 years. This way, the results of our study can be replicated in all the other countries for which data is available and compared to the present study.

4.1.1.4 Inflation-Indexed Bonds

Aside analysing the inflation hedging ability of nominal bonds, we also include index-linked bonds. Many studies have taken for granted that these bonds are a complete hedge against inflation given that their income returns are mechanically indexed the given inflation and interest rates. The few that have done so have surprisingly produced mixed results. Most of them found index-linked bonds to not be a good hedge against inflation as they tend not to be highly correlated with contemporaneous inflation. This result has been attributed to the time lag between when the inflation rate is recorded and time the returns are adjusted to reflect the past inflation rate. In the UK, it takes about 3 months or in some cases 9 months for the coupons and principal of inflation-indexed bonds to be adjusted for inflation. Schofield (1996) observed the result of studies that failed to find a strong relationship between inflation-indexed bonds and inflation rates have often used regression analysis, which is designed to mostly detect contemporaneous correlation. In order to find a close correlation between index-linked bonds and inflation, it is necessary to use an approach that makes use of the lag of the variables as well. In our analysis, we use the ARDL model which uses as the exogenous variables the lagged values of the dependent variable and other variables. We hope that this analysis would better capture the dynamic relationship between index-linked bonds and inflation/interest rate changes.

We use the FTSE Actuaries UK Gilts Index series. The series includes all index-linked gilts denominated in pound sterling and quoted on the Stock Exchange. The various index-linked bonds are an 8-month or 3-month indexation lag to the Retail Price Index (RPI) or to the Consumer Price Index (CPI). The index however does not include convertible index-linked gilts and those that are classified as “rump stocks” by the UK Debt Management Office. These are index-linked bonds that are issued in quantities that are too small for an effective market. We include in our index-linked bond series in our analysis – those with maturities less than 5 years and those with maturities more than 5 years.

4.1.1.5 Stocks

Although equity returns depend on corporate earnings and dividend, their returns are also sensitive to interest rates and inflation. The main reason that equity returns are attractive to long-term investors such as pension funds is the fact that they offer superior returns compared to other traditional asset classes (UBS, 2015).

We analyse 17 Stocks sectors which include real estate and infrastructure Stocks. All the Stocks returns are from Thomson Reuters Datastream equity series. The Thomson Reuters Datastream Global Equity Index series provides a reliable benchmark for equity in most countries. Datastream Global Equity Indices draw on the wealth of the Thomson Datastream database to provide a range of equity indices across 53 countries, 32 regions and 170 sectors worldwide. They form a comprehensive, independent standard for equity research and benchmarking. For each market, a representative sample of stocks covering a minimum 75 - 80% of total market capitalisation enables market indices to be calculated. By aggregating market indices for regional groupings, regional and world indices are produced. Within each market, stocks are allocated to industrial sectors using the Industry Classification Benchmark (ICB) jointly created by FTSE and Dow Jones. Sector indices are then calculated. The following sectors are included in our analysis: Oil and Gas; Basic Materials; Industrials – made up of Construction, Industrial Goods and Services; Consumer Goods; Health Care; Consumer Services; Telecom; Technology; Financials – made up of Banks; Insurance; Financial Services and Real Estate.

4.1.1.6 Alternatives

In addition to the traditional assets of UK Stocks, UK Bonds and UK real estate, many institutional investors are turning to alternative asset classes to boost their returns and also to diversify their portfolios as several studies have provided evidence that international equity does provide opportunities for diversification. They are also increasingly stepping out of the UK to other developed and even emerging economies. To reflect this, we include a number of international assets. For these international assets, we make use multi-country funds as most UK institutional investors are likely to invest in these funds than to select funds from specific countries. We include the following alternatives/non-UK assets – Emerging market Stocks, Developed Market ex UK Stocks, commodities, hedge fund and private equity.

i. International Stocks

There has been a strong case for the inclusion of emerging market stocks to further diversify the equity portfolio of pension funds. We make use of the S&P/IFCI index as the benchmark for Emerging Economies. The S&P Emerging BMI captures all companies domiciled in the emerging markets within the S&P Global BMI with a float-adjusted market capitalisation of at least US$ 100 million and a minimum annual trading liquidity of US$ 50 million.

As in Bond et al. (2007), we use a world ex UK return index to gain exposure to the developed market. The Datastream developed equity market ex-UK data serves as our proxy for the developing market Stocks.

ii. *Commodities*

There are a number of commodity indices but the one most used in academic studies is the S&P Goldman Sachs Commodity Index (Bond et al., 2002). The index measures returns of a fully collaterised commodity futures investment rolled forward from the 5th to the 9t business day of each month. It provides investors with a reliable and publicly available benchmark for investment performance in the commodity markets, and is designed to be a "tradable" index. The index is calculated primarily on a world production-weighted basis and includes the principal physical commodities that are the subject of active, liquid futures markets. The index is currently composed of 24 commodities (e.g. energy products, industrial metals, agricultural products, livestock products and precious metals). The wide range of constituent commodities provides the S&P GSCI with a high level of diversification, across subsectors and within each subsector. This diversity mutes the impact of highly idiosyncratic events, which have large implications for the individual commodity markets, but are minimised when aggregated to the level of the S&P GSCI.

Greer (2000) analysed the performance of commodities between 1970 and 2000 and found that the total returns and volatility from unleveraged commodity were comparable to those of stocks. They however found that the returns of commodity and stocks were negatively correlated to each other. This offers an opportunity for diversification. Idzorek (2006) found commodities to be the top performing assets of all the assets they studied.

Gorton and Rouwenhurst (2006) analysed different commodity portfolios drawn from database of Commodity Research Bureau and the London Metal Exchange. The risk premium for these commodity portfolios were similar to that of stocks (about 5% per annum). The standard deviation of commodities was however slightly lower than stocks. Like Greer (2000), they found that commodity returns had a negative correlation with stock and bond returns.

Given the high proportion of energy (average of 72%) contained in the S&P GSCI commodity index, we include two sub-indices - gold and oil. We use the S&P gold and oil indices in order to allow for a direct comparison with the general commodity asset class.

Given that gold is often cited as one of the best inflation hedge, we include it along with the aggregate commodity series to observe if it is indeed better at hedging the broad spectrum of liability benchmarks we include in our study. Riley (2010) believes that given the increasing supply of money, gold represents a good store of value. They found that gold has a potential of offering consistent returns in excess of inflation, especially post the GFC. Ratner and Klein (2015) however found that US stock returns outperformed gold over the sample period they examined.

iii. Hedge Fund

Hedge funds are investment funds that tend not to be highly regulated and so are able to invest in products such as derivatives. They are also able to use techniques such as short selling to enhance their returns and/or reduce risk (Gregoriou and Doffy, 2006).

Investment in hedge funds has a number of benefits, two of which are increased alpha and offering diversification opportunities to investors. Fund and Hsieh (1997) found that hedge funds produce returns that have a low correlation with the returns of standard asset classes and mutual funds. Asness et al. (2001) however find after adjusting for bias in hedge fund indices that the diversification pointed out in studies such as Fund and Hsieh (1997) vanish. A number of studies have examined whether hedge funds provide excess returns on a risk-adjusted basis and whether there is a period of persistent outperformance. These studies include Arggarwal and Jorion (2010) and Eling (2009) found some evidence of persistent outperformance.

The return series for hedge fund which we use for this thesis is obtained from the Hedge Fund Weighted Composite index provided by the Hedge Fund Research Inc. (HFRI). The HFRI Fund Weighted Composite Index is an equally weighted performance index encompassing over 2000 funds which is used by lots of hedge fund managers as a benchmark for their own hedge funds. Funds included in the database and indices report monthly and have at least $50 Million under management or have been actively trading for at least 12 months.

Along with the Credit Suise/Tremont Hedge Fund indices, the HFRI index is the most used hedge fund is the most used index for academic studies as they are regarded as the most transparent and comprehensive (Fung and Hsieh, 2002). The HFRI index tends not to suffer from some of the biases and statistical problems associated with hedge fund indices in general. The statistical problems that hedge fund indices suffer from include non-normality and autocorrelation (Fung et al., 2000; Eling, 2006; Getmansky et al., 2004). To overcome this non-normality problem, Argawal and Naik (2004) propose using different measures of risk and return that account for non-normality.

Hedge fund returns tend to display a non-normal distribution. They display conditions of skewness and leptokurtosis (Eling, 2006; Amin and Kat, 2003). A result of this is that statistical measures such as standard deviation and Sharpe ratios may not work for hedge funds.

Like direct real estate, hedge funds tend to exhibit autocorrelation, leading to an underestimation of their volatility. However, the autocorrelation in hedge fund returns has been attributed to the fact that these funds may old illiquid positions. Getmansky et al. (2004) identified some hedge fund strategies that were more likely to hold illiquid assets. The returns of these funds were found to exhibit more autocorrelation than those funds that do not hold illiquid assets. Similarly, Eling (2009) found that strategies such as convertible arbitrage are more likely to result in high levels of return persistence caused by holding of illiquid assets. Kat and Brooks (2002) tested for autocorrelation in different hedge fund indices. They find autocorrelation at for the different fund types but not at the aggregate level. A number of studies have applied the approach of Geltner (1993), developed to desmooth real estate indices, to hedge funds (Kat and Brooks, 2002; Kat, 2002). Getmansky et al. (2004) suggest two methods that can be employed to estimate smoothing parameter in order to adjust for autocorrelation in hedge fund data – a regression based and a maximum likelihood estimation approach.

The inherent biases associated with hedge fund data include survivorship bias, selection bias and backfill bias. Survivorship bias occurs when funds that are no longer in operation are excluded from an index. As most funds shut down due to poor performance, this results in a positive bias as only funds that survive. Selection bias occurs on two levels. Firstly, only funds that meet a certain criteria, usually of a certain size, are considered for inclusion in an index. Managed funds are excluded from some hedge fund indices. A self-selection bias occurs as only funds have to agree to being added to an index database. Again, a positive bias could occur as only funds that believe they are performing are more likely to put out their performance data. Fung and Hsieh (2002) found that funds that are closed to new investors may opt out of a hedge fund index. Often, closure to new investors connotes superior performance. Back-fill bias results from the fact that new funds added to a hedge fund index often have their performance data added retrospectively to the index. As indicated earlier, funds with superior performance are most likely to be added to the hedge fund database. In order to deal with backfill bias, some researchers suggest eliminating some fund's reported earnings and re-constructing the index (Ackerman et al., 1999; Jagannathan et al., 2010). However, this requires access to the underlying data, which is often not readily available.

The HFRI index does not suffer from survivorship bias as the index retains details of all the constituent funds, whether alive or dead (Agarwal and Naik, 2000; Jaganathan et al., 2010; Liang, 2000). However, like other indices, the HFRI index suffers from biases such as backfill bias and selection bias. It also suffers from non-normality and autocorrelation. As with real estate index, we will, where appropriate desmooth the hedge fund series using the approach of Geltner (1993) and compare the results of the smoothed and desmoothed index to see if there are significant differences in the results.

iv. *Private Equity*

The historical performance of private equity funds has remained uncertain due to the uneven disclosure of private equity returns and concerns regarding the quality of data available for research (Harris et al., 2014). Harris et al. (2014) studied the performance of buyout and venture capital funds. They found that the performance of buyouts consistently exceeded the performance of public markets. Private equity outperformance averaged more than 3% annually. They note that although venture capital performed better than public equities in the 1990s, they performed less than public equities in the 2000s. Kaplan and Schoan (2005) used cash flow data from venture economics to study the return persistence across funds of the General Partner (GP). They found that buyouts earn less than the public market. Venture capital also outperformed better than public markets on a capital weighted basis. They however performed less than the public market on an equally weighted basis. Similar results were found by Gottschalg (2009), Robinson and Sensoy (2011), Higson and Stucke (2012) and Phalippou (2012).

Private equity data was obtained from Cambridge Associates who have data on several private equity and venture capital categories. Other sources of private equity are those from Preqin, Burgiss and Thomson Venture Economics. Harris et al. (2014) found that the performance of data for Cambridge Associates, Preqin and Burgiss were similar. We include three series – US Private Equity, US Venture Capital, Developed ex US Private Equity and Emerging Private Equity. The US Venture capital index is based on funds which represent the majority of the funds raised by US venture capital manages from 1981 whiles the US Private Equity index is based on funds raised by US buyouts, mezzanine, restructuring and private equity funds or partnerships formed from 1986. Return data for the Global ex US. Developed and Emerging Markets Private Equity and Venture Capital Indices is from data obtained from institutional quality funds raised from 700 funds in the developed market and close to 500 in the emerging market.

4.1.2 INFLATION AND INTEREST RATE BENCHMARKS

Three economic concepts, inflation, growth and monetary policy are very important for investors. These represent the three building blocks of investment economics and often interact with each other. For example, when the central bank puts in place a monetary policy aimed at targeting inflation, they may set interest rates that boosts or constraints economic growth. This growth in economy may consequently lead to a rise or fall in inflation.

This study explores the impact of these three building blocks on the performance of various assets and consequently on pension portfolios. We make use of three inflation measures and two short-term interest rates. These rates have been used by many pension fund trustees and pension regulators as a performance benchmark for pension funds.

The idea behind using inflation or growth rates as a minimum return benchmark for pension funds is to ensure that the purchasing power of the contributions are not eroded. Those based performance benchmarks linked to short-term interest rates are meant to ensure that contributors receive a return that at least is equal to the risk-free rate of return (OECD, 2012). The short-term interest rates analysed in this study are the UK Treasury Bill rate (T-bill rate) and the London Interbank Offer Rate (LIBOR).

A review of the Statements of Investment Principles (SIPs) and annual statements UK master trust pension funds revealed that many of these funds measure their performance relative to selected inflation and interest rate benchmarks. Although internationally, growth rates have been used by certain pension funds, none of the UK master trust pension fund trustees have selected a growth rate measure. As the analysis in this thesis are conducted from UK DC investors' perspective, we analyse the relationship between the returns of the various assets and an inflation (UK CPI) and interest rate (the 3-month T-bill rate). This represents the base case. To see if the particular inflation or interest rate impacts on the assets chosen and thus the portfolio structure of DC funds, we use an alternative inflation rate (UK RPI) and an alternative interest rate (the LIBOR rate).

4.1.2.1 Inflation Rates

As inflation is likely to be positive in most economies, investors would want to be receive returns that are in excess of the expected inflation to ensure that they have more purchasing power when they receive their returns. In general, investors consider inflation as unwelcome especially if it is unanticipated and so not captured in the agreed returns. Regulatory agencies and pension trustees often set their minimum acceptable returns equal to inflation in order to protect the accumulated contributions from inflation. Thus, the lump sum at retirement equals at least the sum of the contributions in real terms. An inflation-indexed capital guarantee effectively provides a minimum return of 0% in real terms.

In Chapter Two, we provided evidence of master trust pension funds who have set their investment objective as delivering returns equal to inflation. The challenge then is to find assets that can effectively hedge against inflation over the both the short and long term. Naturally, real assets such as properties are considered a hedge against inflation as rents are one of the contributors to inflation. The price of properties also move up when inflation goes up. Equities are also less likely to suffer from inflation. This is because companies can increase prices during periods of high inflation, leading to an increase in income return to equity holders in the form of higher dividends. As bonds tend to have fixed coupon payments, an increase in inflation would adversely affect investors' purchasing power. On the other hand, an increase in inflation is often accompanied by higher interest rates which could lead to an increase in bond returns.

The inflation measures we use in our analysis are the UK Consumer Price Index (CPI) and the UK Retail Price Index (RPI). The UK Retail Price Index was designed as a compensation index to protect workers from price increases during the First World War. It was officially produced in January 1956 and provided estimates of inflation estimates dating back to 1947. The Consumer Price Index however has a much shorter history, having first been launched in 1996 as the Harmonised Index of Consumer Prices. Its name was changed in 2003 to the Consumer Price Index by the National Statistician. It became the official measure of inflation the same year, replacing the Retail Price Index. Both indices are compiled by the Office of National Statistics, UK.

Both the Consumer Price Index and Retail Price Index are measures of inflation that are supposed to measure the movement in purchasing power of money within the UK. The difference however lies in the fact that the CPI has been designed to be consistent with National Account Principles and thus has a wider coverage than the RPI. There are a number of differences between the CPI and RPI but fundamentally, the CPI is based on spending by all households within the UK whiles the RPI excludes the top 4% of households by income levels and also those who receive much of their income from state pensions and benefits. Another important distinction is that the CPI does not include costs associated with owner occupied housing such as mortgage interest payments, house depreciation, building insurance etc. Also, whiles the CPI captures only spending within the UK (by residents and visitors), it excludes expenditure by UK nationals abroad. Johnson (2012) notes that the main difference between CPI and RPI lies in the way each treats rental and interest costs.

The use to which the CPI and RPI have been put in practice by different stakeholders continues to be the subject of debate with both being used for the two broad purposes for which Price Indices are used – as macroeconomic indicators of inflation and for compensation purposes. The Office of National Statistics has insisted that the use of the CPI, RPI and their derivative indices in the public domain has been, and remains, a political decision made by the government of the day. Earlier studies on the inflation hedging ability of UK real estate such as Limmack and Ward (1988) and Barkham et al. (1996) have used the RPI whiles later studies like Demary and Voigtlander (2009) and Blake et al. (2011) have used the CPI.

The choice of inflation measure in these studies has been largely to ensure that the study captures what is considered the official measure of inflation in a particular country as well as measures used by previous studies on inflation-hedging. In Japan, DC Pension funds must provide at least one capital guaranteed product among their investment alternatives. In the Slovac republic, a zero% rate of return is required every six months, above which the managers of the fund can charge a fee on the investment earnings. If they fail to make the minimum, they are responsible for making up the difference (OECD, 2012). Our choice of inflation rates are the UK Consumer Price Index (CPI) and Retail Price Index (RPI),

4.1.2.1 Interest Rates

One of the main tools of monetary policy for central banks are short-term interest rates. Short-term rates are set by central banks and serve as the rate at which banks lend to individuals and businesses. The rate also serves as an anchor for all other rates of return within the economy as it represents the lowest interest rate that investors must earn in the short term (UBS, 2015).

Aside protecting themselves against a loss in the purchasing power of their investments, most investors wish to earn at least the risk-free rate on their investments. This is also the view of pension regulators who use a certain measure of risk-free rate as their choice of minimum return benchmark. Mukherji (2011) notes that most practitioners and academics tend to readily use returns on short-term or long-term government securities as the choice of risk free rate for most purposes. A few studies that have examined the interest rate sensitivity of real estate assets Hoesli et al. (2008), Demary (2009) and Anim-Odame (2014) have used the T-bill rate for the countries analysed. The ATP system in Denmark requires that 80% of the contributions are guaranteed based on the interest rate that the ATP can obtain in the market when contributions are paid. Thus, the current 1-year interest is assigned to each annual contribution made and is valid until retirement. Also, the seven-year Swiss Government Bonds rate is the minimum return threshold for pension funds which operate the mandatory system – law BVG/LPP (OECD, 2012).

The London Interbank Offer Rate (LIBOR) is a reference rate at which large banks indicate that they are able to obtain wholesale funds from each other on an unsecured basis. The rate is credited to a Greek banker, Minos Zombanakis who in 1969 was able to arrange $80 million in loans from a syndicate of banks. The rate used for this transaction, which has come to be known as the LIBOR rate, represents the at which the most credit worthy institutions are able to obtain funding and thus serves as a lower bound for the borrowing rate for less credit worthy individuals and institutions.

Prior to the 2007, the LIBOR followed the same trend as the Treasury bill rate and other short-term rates. However, following the 2008 financial crisis, it began to display greater volatility. Also, reports of manipulations following investigations by US investors and other regulators also affected the credibility of LIBOR rate as a risk-free benchmark. The Bank for International Settlement (Bank de

Pagos and Basilea, 2013) has questioned the continued use of the LIBOR rate as a reference rate as the banking market has shrunk following the global financial crisis and the dispersion of bank credit has increased sharply, making average rates for unsecured interbank funding not a good proxy for bank funding costs let alone a good proxy for risk free rates. In this thesis, we use the 3-month T-bill rate and 3-Month GB£ LIBOR rate as the interest rates to see if an asset that hedges against one of the measures necessarily hedges against the other.

4.2 TIME SERIES FEATURES OF ASSET RETURNS AND INFLATION/ INTEREST RATES

In this section, we investigate the time series features of the returns of the various assets as well as the inflation/interest rates analysed in this thesis. An understanding of the time series features is important in the selection of appropriate analytical tools later on in this thesis. The analysis carried out here would also provide background information for the results that would be obtained later on in this thesis.

We analyse the return and risk features of the various assets including average returns, volatility and historical index growth of the various assets as well as the inflation/interest rates. We then go on to discuss the issue of serial correlation of return series and how it affects the private market assets included in our analysis. The approach of Geltner (2003) is employed in the unsmoothing of the data series found to exhibit serial correlation. The effects of the unsmoothing process are also discussed. We also explore the distributional properties of the various assets and benchmarks before delving into the issue of stationarity. In all cases, we particularly highlight the time series features of the real estate and the alternative assets that are included in our analysis.

4.2.1 RETURNS AND RISK MEASURES

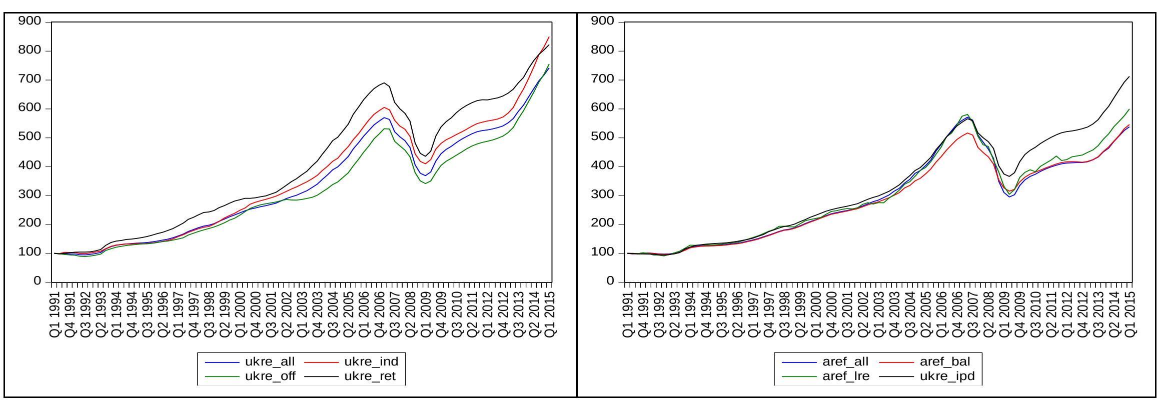
Table 4(1) shows the performance of the various assets. Overall, we observe that stocks and private equity sectors recorded the highest average returns with UK technology sector stocks holding the top spot with an average return of 4.5% per quarter. In fact, all the top 20 best-performing assets were either stocks or private equity. The low earning assets were short-term bonds and commodities. Commensurate with their returns, technology sector stocks and private equity stocks had the highest standard deviations. Although among the assets with the lowest returns, commodities had a high standard deviation.

Apart from stocks and the private equity sectors, real estate delivered good returns. The IPD industrial real estate sector delivered returns of 2.34% per quarter, just below long-term bonds with maturity greater than 10 years. Interestingly, we find that the IPD real estate sectors produced some of the lowest standard deviations, along with bonds. We observe that the returns of the other real estate vehicles were all lower than the IPD real estate returns. This is because the AREF fund and the Blended/Hybrid real estate series contain a certain amount of cash and listed real estate respectively. The returns of the Blended/Hybrid real estate series was however higher than the AREF fund returns because unlike the AREF fund, these hybrid funds use listed real estate as their liquidity buffer. Unfortunately, although these assets produced returns that were still below the returns of the IPD portfolio, its standard deviation was above that of the IPD series. This leads to questions about the benefits of these funds, beyond infusing additional liquidity into the portfolios. In Chapter 6, we examine different approaches to creating blended/hybrid real estate funds which have better risk-return characteristics and also more closely tracks the returns of the underlying real estate market.

As indicated earlier, private equity and venture capital sectors produced the highest returns of the alternative assets whiles commodities produced the lowest returns. We notice that converting alternative assets from US dollars into pound sterling results in a slight dip in the returns. However, this does not affect the ranking of the various alternative assets.

The historical chart of the various IPD real estate sectors are presented in Figure 4(2) along with a comparison of the returns of the various real estate vehicles. We rebase all the indices to the first quarter of 1991 and track the growth of each index over the period 1991 – 2015. Figure 4(2) also confirms the results obtained for the average returns as we see the IPD UK industrial real estate sector having the highest index value by the first quarter of 2015. However, the graph also shows that until recently, the retail real estate sector has dominated all the other real estate sectors. Compared to the other real estate vehicles, we see that the IPD benchmark fund outperforms all the other real estate vehicles.

Figure 4(2) Historical Returns – IPD Property Sectors



We can see from Table 4(2) that longer maturity bonds consistently performed better than shorter maturity bonds, pointing to an upward slopping yield curve for the UK market. For example, an investment of £100 2-year bonds in the first quarter of 1991 would have grown to £381, £631 if invested in 7-year bonds and £844 if invested in bonds with maturity greater than 10 years. The value of the aggregate bond portfolio was close to the value of 7-year bonds, valued at £623 by the first quarter of 2015. Short-term index-linked bonds with maturity less than 5 years produced the worst performance, underperforming 2-year bonds (index value = 352.84). However, the index-linked bond portfolio containing bonds with maturity greater than 5 years produced returns close to 10 year bonds, resulting in an index value of £682.35. The value of these index-linked bonds also exceeds the returns of the aggregate nominal bond portfolio.

Figure 4(3) compares the index evolution of the various inflation and interest rates analysed included in our studies. We see that the two inflation rates follow the same pattern whiles the two interest rate benchmarks also follow a similar pattern. LIBOR interest rates was higher than T-bill rates and the inflation rates whiles RPI inflation dominated CPI inflation. This in a sense explains why investors may prefer to have their returns hedged against interest rate benchmarks and RPI inflation over CPI inflation, as recently seen in the resistance to a change in UK pension indexation benchmark from RPI inflation to CPI inflation.

Figure 4(3) Historical Returns - Inflation and Interest Rates

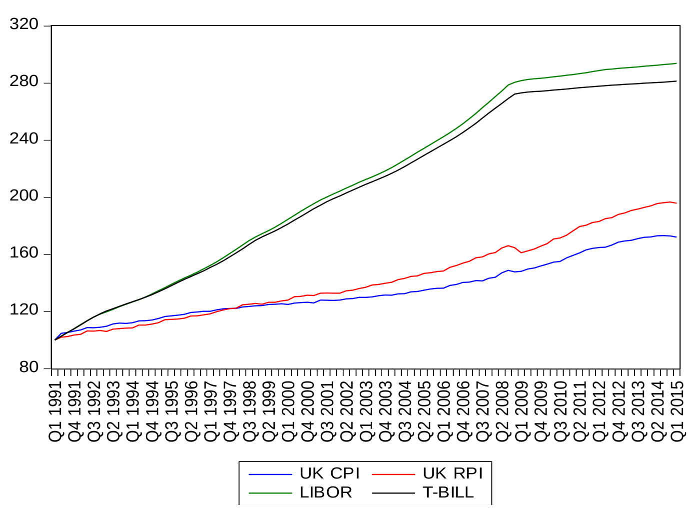


Table 4(I) Descriptive Statistics – All Assets

	Mean	Median	Max.	Min.	Std. Dev.	Index Growth	Skew.	Kurtosis	Jarque-Bera	Prob.
IPD Property										
IPD All Property	2.09	2.44	12.06	-12.96	3.17	712.85	-1.33	9.07	177.68	0.00
IPD Industrial	2.28	2.63	8.53	-12.20	2.96	835.76	-1.67	8.61	172.11	0.00
IPD Office	2.08	2.53	12.99	-12.62	3.40	707.64	-1.08	7.08	86.08	0.00
IPD Retail	2.23	2.52	12.87	-13.80	3.32	809.29	-1.26	9.78	211.39	0.00
Other Real Estate Vehicles										
AREF – All Funds	1.79	2.50	10.50	-18.50	3.78	546.03	-2.31	12.05	417.61	0.00
AREF – All Balanced Funds	1.78	2.30	8.00	-13.40	3.15	538.38	-1.90	9.06	206.53	0.00
Hybrid Real Estate	1.95	2.36	13.04	-13.18	4.16	600.09	-1.07	5.32	40.08	0.00
UK Bonds										
Index linked bonds - 0-5 Years	1.34	1.20	4.63	-2.30	1.28	352.84	-0.06	3.75	2.36	0.31
Index linked bonds - 5+ years	2.07	2.14	9.76	-7.35	3.17	682.35	-0.14	3.51	1.37	0.50
Bonds – All lives	2.03	2.19	9.90	-6.42	3.11	623.89	0.09	2.94	0.15	0.93
Bonds – 10 + years	2.41	1.84	15.96	-9.29	4.51	843.95	0.23	2.98	0.87	0.65
Bonds – 10 year	2.19	2.38	11.52	-8.26	3.70	701.65	0.04	3.21	0.20	0.91
Bonds – 7 year	2.04	2.02	8.61	-5.58	2.93	631.55	-0.06	2.86	0.13	0.94
Bonds – 5 year	1.79	1.70	7.51	-4.57	2.40	511.93	-0.02	3.04	0.01	1.00
Bonds – 3 year	1.63	1.50	5.69	-2.11	1.63	452.18	0.47	2.99	3.54	0.17
Bonds – 2 year	1.44	1.17	5.03	-1.12	1.30	381.07	0.87	3.47	13.26	0.00
UK Stocks										
Aggregate stocks	2.14	3.17	17.25	-20.61	8.13	663.85	-0.69	3.51	8.71	0.01
Banks	3.44	4.01	40.54	-38.79	13.82	966.71	-0.16	3.92	3.81	0.15
Basic Materials	2.95	4.00	27.93	-43.80	13.14	652.39	-0.83	4.29	17.81	0.00
Consumer goods	3.71	4.21	32.95	-32.27	10.69	1907.78	-0.05	4.01	4.16	0.12
Construction	2.80	4.18	22.66	-24.64	10.46	800.44	-0.34	2.59	2.59	0.27
Consumer services	2.55	3.26	21.20	-21.88	8.79	743.29	-0.52	3.45	5.24	0.07
Financial services	3.26	4.76	23.04	-23.75	10.39	1210.38	-0.39	2.92	2.44	0.30
Health care	2.88	3.36	24.49	-14.59	7.21	1125.70	0.07	3.41	0.77	0.68
Industrial	3.29	4.15	29.30	-31.35	10.92	1278.45	-0.49	3.98	7.82	0.02
Industrial goods and services	2.91	3.15	22.51	-26.94	9.56	985.12	-0.53	3.62	6.12	0.05
Insurance	3.07	5.09	29.47	-30.84	11.60	932.05	-0.43	3.27	3.25	0.20
Oil	2.74	4.09	25.58	-26.64	9.11	928.93	-0.47	3.53	4.70	0.10
Technology	4.50	4.82	127.0 4	-54.61	20.93	1230.61	1.77	14.44	579.36	0.00
Telecom	3.12	3.74	46.02	-25.20	12.64	891.55	0.46	4.38	11.11	0.00
Utilities	3.47	3.94	21.36	-13.67	7.15	1946.79	0.00	2.62	0.58	0.75
Listed real estate	2.64	4.86	33.08	-34.18	11.74	563.36	-0.65	3.72	8.95	0.01
Alternatives in US$										
Commodities - all	0.91	1.67	30.84	-46.22	11.72	132.40	-0.70	5.10	25.71	0.00
Commodities - gold	1.35	1.38	15.77	-21.63	6.43	295.59	-0.22	3.62	2.38	0.30
Commodities - oil	2.26	3.47	41.55	-57.70	17.55	214.87	-0.27	3.70	3.15	0.21
Developed ex UK stocks	2.46	3.39	26.00	-21.84	8.78	670.84	-0.38	3.84	5.19	0.07
Developed ex US private equity	3.56	4.03	21.64	-22.50	7.23	2581.47	-0.50	4.70	15.78	0.00
Emerging private equity	1.87	2.17	14.02	-17.50	5.41	519.64	-0.46	4.34	10.63	0.00
Emerging stock market	3.05	3.86	36.09	-27.89	13.24	834.48	-0.06	2.91	0.08	0.96
US private equity	3.68	4.01	17.80	-15.40	5.04	2874.85	-0.58	5.07	22.79	0.00
US venture capital	4.42	3.47	84.06	-19.99	11.78	3805.54	3.40	23.73	1924.08	0.00
Hedge funds	1.72	1.67	13.52	-10.41	3.54	483.12	-0.74	6.12	48.25	0.00
Alternatives in GBP										
Commodities - all	0.78	3.29	24.05	-46.21	12.54	113.07	-1.06	5.02	34.70	0.00
Commodities - gold	1.22	1.28	20.78	-24.20	8.36	252.42	-0.11	3.01	0.19	0.91
Commodities - oil	2.18	3.65	45.23	-57.68	18.37	183.49	-0.35	3.62	3.50	0.17
Developed ex UK stocks	2.29	3.40	21.55	-32.68	9.72	572.86	-0.78	4.08	14.60	0.00
Developed ex US private equity	3.64	3.90	31.80	-37.07	11.06	2204.42	-0.45	4.83	16.74	0.00
Emerging private equity	1.81	2.10	27.82	-33.01	8.40	443.74	-0.51	6.15	44.32	0.00
Emerging stock market	2.94	3.83	34.53	-40.62	14.30	712.59	-0.24	3.01	0.97	0.62
US private equity	3.58	4.33	22.04	-31.30	7.71	2454.95	-0.92	6.49	63.10	0.00
US venture capital	4.26	4.22	80.51	-28.78	12.61	3249.70	2.30	16.03	771.31	0.00
Hedge funds	1.57	1.89	15.02	-27.25	6.14	412.56	-1.04	6.96	80.72	0.00
Inflation/Interest Rates										
UK CPI	0.57	0.47	4.72	-0.73	0.66	172.15	2.62	17.20	925.57	0.00
UK RPI	0.70	0.60	2.15	-2.13	0.68	195.94	-0.47	5.23	23.65	0.00
LIBOR	1.15	1.28	2.99	0.13	0.69	293.80	0.09	2.71	0.47	0.79
T-bills	1.11	1.22	3.18	0.09	0.70	281.37	0.20	3.01	0.63	0.73

4.2.2 NORMALITY OF DATA

The Jarque-Bera and the Shapiro Wilk tests are used to test the hypothesis that the asset return series included in this study are normally distributed. Both tests calculate the probability that the sample was drawn from a normal distribution. The hypothesis are:

H_0: The sample data is normally distributed
H_1: The sample data is not normally distributed

If the probability value is greater than the pre-defined significance level, we cannot reject the null hypothesis that the data is normally distributed i.e. if the probability is greater than the significance level, the data is normally distributed.

The results, presented in Table 4(2) confirm the assertion of Brooks (2002) that financial data are mostly not normally distributed in spite of the fact that most techniques in econometrics assume that they are. He further noted that, the availability of more sophisticated statistical tools means that researchers can still proceed to use these series in their analysis as these available tools can correct for most types of non-normality.

Table 4(II) Distribution of Data

	Skewness	Kurtosis	Jarque-Bera		Shapiro-Wilk	
			Statistic	Prob.	Statistic	Prob.
IPD Property						
IPD All Property	-1.33	9.07	177.68	0.0000	0.86	0.0000
IPD Industrial	-1.67	8.61	172.11	0.0000	0.88	0.0000
IPD Office	-1.08	7.08	86.08	0.0000	0.91	0.0000
IPD Retail	-1.26	9.78	211.39	0.0000	0.85	0.0000
Other Real Estate Vehicles						
AREF – All Funds	-2.31	12.05	417.61	0.0000	0.79	0.0000
AREF – All Balanced Funds	-1.9	9.06	206.53	0.0000	0.85	0.0000
Hybrid Real Estate	-1.07	5.32	40.08	0.0000	0.92	0.0000
UK Bonds						
Index linked bonds - 0-5 Years	-0.06	3.75	2.36	0.3100	0.98	0.0837
Index linked bonds - 5+ years	-0.14	3.51	1.37	0.5000	0.99	0.5794
Bonds – All lives	0.09	2.94	0.15	0.9300	0.99	0.9642
Bonds – 10 + years	0.23	2.98	0.87	0.6500	0.99	0.6699
Bonds – 10 year	0.04	3.21	0.2	0.9100	0.99	0.9520
Bonds – 7 year	-0.06	2.86	0.13	0.9400	0.99	0.9309
Bonds – 5 year	-0.02	3.04	0.01	1.0000	0.99	0.9217
Bonds – 3 year	0.47	2.99	3.54	0.1700	0.97	0.0471
Bonds – 2 year	0.87	3.47	13.26	0.0000	0.94	0.0002
UK Stocks						
Aggregate stocks	-0.69	3.51	8.71	0.0100	0.95	0.0017
Banks	-0.16	3.92	3.81	0.1500	0.98	0.1411
Basic Materials	-0.83	4.29	17.81	0.0000	0.96	0.0033
Consumer goods	-0.05	4.01	4.16	0.1200	0.98	0.2267
Construction	-0.34	2.59	2.59	0.2700	0.98	0.2480
Consumer services	-0.52	3.45	5.24	0.0700	0.97	0.0455
Financial services	-0.39	2.92	2.44	0.3000	0.98	0.1702
Health care	0.07	3.41	0.77	0.6800	0.99	0.5041
Industrial	-0.49	3.98	7.82	0.0200	0.98	0.0655
Industrial goods and services	-0.53	3.62	6.12	0.0500	0.97	0.0493
Insurance	-0.43	3.27	3.25	0.2000	0.98	0.0712
Oil	-0.47	3.53	4.7	0.1000	0.98	0.3359
Technology	1.77	14.44	579.36	0.0000	0.84	0.0000
Telecom	0.46	4.38	11.11	0.0000	0.97	0.0174
Utilities	0	2.62	0.58	0.7500	0.99	0.5984
Listed real estate	-0.65	3.72	8.95	0.0100	0.96	0.0098
Alternatives in US$						
Commodities - all	-0.7	5.1	25.71	0.0000	0.96	0.0072
Commodities - gold	-0.22	3.62	2.38	0.3000	0.98	0.2551
Commodities - oil	-0.27	3.7	3.15	0.2100	0.98	0.2211
Developed ex UK stocks	-0.38	3.84	5.19	0.0700	0.97	0.0132
Developed ex US private equity	-0.5	4.7	15.78	0.0000	0.96	0.0104
Emerging private equity	-0.46	4.34	10.63	0.0000	0.97	0.0273
Emerging stock market	-0.06	2.91	0.08	0.9600	0.99	0.8609
US private equity	-0.58	5.07	22.79	0.0000	0.96	0.0028
US venture capital	3.4	23.73	1924.08	0.0000	0.71	0.0000
Hedge funds	-0.74	6.12	48.25	0.0000	0.92	0.0000
Alternatives in GBP						
Commodities - all	-1.06	5.02	34.7	0.0000	0.93	0.0001
Commodities - gold	-0.11	3.01	0.19	0.9100	0.99	0.8737
Commodities - oil	-0.35	3.62	3.5	0.1700	0.98	0.2167
Developed ex UK stocks	-0.78	4.08	14.6	0.0000	0.96	0.0095
Developed ex US private equity	-0.45	4.83	16.74	0.0000	0.96	0.0064
Emerging private equity	-0.51	6.15	44.32	0.0000	0.95	0.0010
Emerging stock market	-0.24	3.01	0.97	0.6200	0.99	0.8569
US private equity	-0.92	6.49	63.1	0.0000	0.95	0.0006
US venture capital	2.3	16.03	771.31	0.0000	0.82	0.0000
Hedge funds	-1.04	6.96	80.72	0.0000	0.94	0.0002
Inflation/Interest Rates						
UK CPI	2.62	17.2	925.57	0.0000	0.82	0.0000
UK RPI	-0.47	5.23	23.65	0.0000	0.95	0.0016
LIBOR	0.09	2.71	0.47	0.7900	0.92	0.0000
T-bills	0.2	3.01	0.63	0.7300	0.91	0.0000

4.2.3 SERIAL CORRELATION

A critical pillar of many analytical frameworks built on a premise of "normality", is the assumption that asset returns from period to period are independent and identically distributed. However, if one month's return is 'influenced' by the previous month's return, then there may be a need to account for this effect in future asset projections (Sheikh and Qiao, 2010). We find that the examining the autocorrelation structure does not show autocorrelation in assets other than direct real estate. However, an application of the Box Pierce autocorrelation test reveals significant first-order autocorrelation in almost all the private market assets. The results are presented in Appendix 4(B) to 4(F).

We use the simplest reverse-engineering model of Geltner et al (1993) to unsmooth our real estate return series. The model is expressed as:

$$r_t = \frac{r_t^* - \alpha r_{t-1}}{1-\alpha} \qquad \mathbf{4(1)}$$

Where r_t^* is the smoothed return during period t, r_t is the corresponding unsmoothed return during period t and α is the smoothed parameter between 0 and 1.

Table 4(III) Unsmoothed Return Series

	Mean	Median	Max.	Min.	Std. Dev.	Index Growth	Skew	Kurtosis	Jarque-Bera	Prob.
UNSMOOTHED UK REAL ESTATE										
IPD All Property	2.19	2.04	23.94	-25.15	5.33	683.60	-0.85	13.75	478.64	0.00
IPD Industrial	2.34	2.48	16.22	-23.22	5.06	788.05	-1.31	9.99	225.20	0.00
IPD Office	2.22	2.35	26.07	-23.69	5.59	693.67	-0.70	11.65	310.26	0.00
IPD Retail	1.88	2.15	17.00	-24.80	4.99	553.01	-2.05	13.62	523.63	0.00
UNSMOOTHED PRIVATE MARKET ALTERNATIVES										
Hedge Fund	0.73	1.26	29.90	-43.02	11.72	118.98	-0.60	4.66	16.89	0.00
US Private Equity	1.81	3.65	41.65	-54.23	17.63	167.23	-0.17	3.48	1.42	0.49
US Venture Capital	1.38	1.40	15.63	-21.74	6.43	304.79	-0.22	3.66	2.58	0.28
Dev. ex-US Private equity	1.26	1.62	13.34	-10.89	3.43	320.17	-0.63	5.76	37.09	0.00
Emerging Private Equity	2.30	2.40	16.49	-12.67	4.67	799.63	-0.30	4.63	12.12	0.00

Given that the idea of unsmoothing is to correct the bias created by the serial correlation present in the data, we re-run the Box Pierce Analysis to show whether correlation is present in our data has been corrected following the unsmoothing process. We find that an application of the reverse-engineering model of Geltner (1993) helped to eliminate the autocorrelation in most of the asset series.

Unsmoothing the IPD real estate series resulted in an increase in the standard deviation of the various IPD sectors. The average returns also increased marginally for all but one of the IPD real estate sectors. This increase in the average return of unsmoothed series could be due to the fact that the series are now quite volatile and possibly have larger recovery from drawdowns. Unsmoothed series also tend to lead the original series. When using unsmoothed series for portfolio choices however, it is often the volatilities that are of interest, not the average returns. Like real estate, the standard deviation of the private market alternative assets also increased once the return series was unsmoothed. However, the average returns fell marginally.

4.2.4 STATIONARITY

A non-stationary time series is a stochastic process with unit roots or structural breaks (Nkoro and Uko, 2016). A non-stationary process could be trend stationary (deterministic) process (TSP) or difference stationary process. If the trend of a time series is predictable and not variable, it is said to be trend stationary. In the case of a deterministic trend, the divergence from initial value is purely random and tend to disappear quickly and not contribute to affect the long-run development of the time series. Integrated stochastic trend however affects the long run development of the time series. Consequently, it is important to purge the time series of this trend. The approach used to remove the trend would depend on whether the series is difference stationary process or trend stationary process.

A trend stationary process becomes stationary after the removal of the deterministic trend whiles difference stationary processes become stationary after the series is differenced. It has been shown that most time series are difference stationary processes rather than trend stationary processes. Using differenced variables for regressions imply loss of relevant long run properties or information of the equilibrium relationship between the variables under consideration. Hence, there is a need to use an approach which retains the relevant long run information of the variables.

A unit root is a feature of processes that evolve over time that can cause problems in statistical inference involving time series if 1 is a root of the process's characteristic equation. Such a process is non-stationary. The Augmented Dickey-Fuller and Phillips Perron unit root test are used to test the Stationarity of our asset return series. The results of these tests are presented in Table 4(IV).

The results of these tests are mixed. We found that most of the assets were integrated of order 1(i.e. I(1), a few assets such as the IPD office sector, utilities stocks, technology stocks, index –linked bonds and aggregate bonds were stationary (i.e. I(0)). This result implies that we applying standard techniques such as the Johansen cointegration and the Granger Causality tests would result in spurious results. In the theoretical framework section, we discuss this issue further and recommend approaches that are capable of handling both I(0) and I(1) variables within a single equation.

Table 4(IV) Unit Root Test

	Variable	Augmented Dickey Fuller Level	Augmented Dickey Fuller 1st difference	Phillips Perron Level	Phillips Perron 1st difference
Real Estate	IPD Industrial	-2.3957	-3.6783**	-1.6588	-3.8630**
	IPD Office	-3.1846*	-3.5351**	-2.1257	-3.6608**
	IPD Retail	-2.3119	-4.5243***	-1.4706	-3.9405**
	IPD All Property	-2.7740	-4.1782***	-1.8206	-3.8365**
	AREF – All Funds	-1.4111	-3.5294***	-0.9945	-3.6990***
	AREF – All Balanced Funds	-2.4065	-3.4841**	-1.6017	-3.6845**
	Hybrid Real Estate	-2.5803	-4.4557***	-1.7819	-4.4961***
Stocks	Aggregate stocks	-1.6390	-9.9032***	-1.6389	-9.9009***
	Listed real estate	-1.9536	-8.1283***	-2.2106	-8.1294***
	Oil	-2.0091	-11.7094***	-1.7542	-12.0894***
	Basic Materials	-2.5752	-8.9015***	-2.7214	-9.1519***
	Industrial	-2.6344	-10.5828***	-2.6344	-10.5448***
	Construction	-2.3550	-9.6652***	-2.4861	-9.6753***
	Industrial goods and services	-2.5128	-10.5821***	-2.5669	-10.5821***
	Consumer goods	-3.0188	-11.0569***	-3.0008	-11.5138***
	Health care	-2.5536	-9.7936***	-2.5826	-9.7947***
	Consumer services	-2.7106	-9.7781***	-2.7543	-9.7781***
	Telecom	-3.1430	-8.2942***	-2.2420	-8.3133***
	Technology	-1.4787	-8.2444***	-1.8294	-8.4546***
	Utilities	-3.2766*	-8.8663***	-3.0622	-8.9115***
	Banks	-1.9707	-9.8565***	-1.9520	-9.8718***
	Insurance	-2.0604	-10.2640***	-2.1685	-10.2459***
	Financial services	-2.3447	-8.2837***	-2.5922	-8.2837***
Bonds	Index-Linked Bonds (0-5)	-3.1663**	-4.8320***	-3.1673**	-9.1623***
	Index-Linked Bonds (5+)	-0.2422	-8.6080***	-0.2422	-8.5421***
	All lives	-2.8611*	-7.9817***	-3.0126**	-8.5473***
	10+ year bonds	-2.7243	-7.8037***	-2.7243	-9.0393***
	10 year bonds	-3.0024	-7.5918***	-3.1035	-8.4429***
	7 year bonds	-2.9493	-8.5852***	-2.9626	-8.5274***
	5 year bonds	-2.8221	-8.4206***	-2.8420	-8.3694***
	3 year bonds	-2.1550	-8.1937***	-2.1465	-8.1438***
	2 year bonds	-1.5153	-7.3509***	-1.5291	-7.2815***
Alternatives (in GB£)	Emerging stock market	-2.7238	-7.5272***	-2.4041	-7.4888***
	Developed ex US private equity	-3.0736	-7.4435***	-2.1749	-7.4526***
	Commodities – all	-1.6094	-8.3276***	-1.7338	-8.2220***
	Commodities - oil	-1.3336	-7.7587***	-1.2328	-7.6962***
	Commodities - gold	-1.9285	-9.1366***	-1.9528	-9.1444***
	Hedge funds	-2.0203	-7.9093***	-1.4438	-7.8805***
	US private equity	-2.3163	-7.4060***	-2.1037	-7.4266***
	US venture capital	-2.0151	-5.3734***	-1.6592	-5.5011***
	Developed ex US stocks	-2.3758	-7.9250***	-2.7183	-7.9413***
	Emerging private equity	-2.4662	-7.1335***	-2.2068	-7.1093***
Alternatives (in US$)	Emerging stock market	-2.7238	-7.5272***	-2.4041	-7.4888***
	Developed ex US private equity	-3.0736	-7.4435***	-2.7183	-7.4526***
	Commodities – all	-1.9346	-8.1116***	-1.6589	-7.9931***
	Commodities - oil	-1.3336	-7.7587***	-1.2328	-7.6962***
	Commodities - gold	-1.9285	-9.1366***	-1.9528	-9.1444***
	Hedge funds	-2.0203	-7.9093***	-1.4438	-7.8805***
	US private equity	-2.3163	-7.4060***	-2.1037	-7.4266***
	US venture capital	-2.0151	-4.9552***	-1.6592	-5.5011***
	Developed ex US stocks	-2.3758	-7.9250***	-2.1749	-7.9413***
	Emerging private equity	-1.7538	-6.1456***	-1.4843	-6.1469***
Inflation and interest rates	UK CPI	-2.1069	-12.1044***	-2.1758	-12.1625***
	UK RPI	-2.2544	-5.8300***	-2.4178	-10.5144***
	T-BILL	0.6143	-3.3174**	0.3263	-3.0393***
	LIBOR	0.3793	-3.0598	0.3994	-2.9515***

Note: *, **, *** denotes that the null can be rejected at 10%, 5% and 1% levels of significance respectively.

4.3 THEORETICAL FRAMEWORK

As discussed in Chapter 1, this thesis addresses two key issues from the perspective of DC pension funds, the issue of liquidity and capital preservation. The first part of this thesis looks at the illiquidity associated with real estate investments vis-à-vis the growing emphasis on liquidity by institutional investors, particularly, DC pension funds. The discussion here shows that real estate funds can be structured in a way that makes them an appropriate investment vehicle for DC pension funds to access the real estate market. The liquidity part of this thesis is made up of two empirical chapters – Chapters 5 and 6. The first empirical chapter, Chapter 5, is largely exploratory. In this chapter, we discuss the concept of liquidity and how different aspects of liquidity are measured within the mainstream finance literature. Empirical applications of these measures of liquidity within the field of real estate is also presented. The chapter ends with an examination of different ways in which liquidity can be managed within the investment portfolios of pension funds. Chapter 6 focuses on hybrid or blended real estate funds which have become popular among DC pension funds as a way to access the direct real estate market whiles maintaining an acceptable level of liquidity. For an asset to be considered liquid enough for DC pension funds, it needs to be priced and traded on a daily basis. Blended/hybrid real estate products promise daily liquidity and dealing. To do this, these funds allocate a significant amount of their assets to liquid, publicly traded assets, often cash and listed real estate. Since these portfolios contain assets other than direct real estate, their returns, understandably, tend to deviate from the returns of the underlying property market. The goal of Chapter 6 is to determine the optimal range and mix of assets that these funds need to hold in order to deliver property-like returns as much as possible. We employ the tracking error optimisation approach which is an extension of the Classic Markowitz optimisation framework. The extension is made to accommodate the needs of investors who wish to benchmark their performance against that of another portfolio. The benchmark portfolio for the optimisation in Chapter 6 is the IPD All Property portfolio. In order to gauge the ability of the various portfolios to produce out-of-sample performance that mimics the performance of the IPD direct property portfolio, we employ the dynamic conditional correlation within a GARCH framework.

As discussed in the preceding chapters, inflation hedging is important for all investors but is particularly important for institutional investors such as DC pension funds who have return promises that are tied to inflation and interest rate changes. The second part of this thesis is dedicated to the identification of assets which have the ability to hedge against the inflation and interest rates which some UK master trust DC pension funds have adopted in their Statements of Investment Principles. In Chapter 7, we use a number of econometric models to analyse the ability of real estate assets to hedge against inflation and interest rate changes. The Autoregressive Distributed Lag (ARDL) approach to cointegration is used to determine the long-run inflation and interest rate hedging ability of the range of assets which

DC pension funds invest in. This approach is preferred as it has the ability to handle cointegration relationship among variables irrespective of their order of integration. Similarly, the Toda and Yamamoto (1995) approach to testing for Granger causality is adopted to determine the short-run inflation hedging ability of the various assets.

The fourth empirical chapter analyses the optimal allocation within portfolios designed to hedge against inflation and interest rate changes. As in Chapter 6, this chapter also makes use of the tracking error optimisation model along with a semi-variance optimisation model. The risk-adjusted versions of the two models are also implemented i.e. Sharpe ratio for the model based on tracking error and Sortino ratio for the one that uses semi-variance as the measure of risk. In determining the role that real estate plays within the resulting portfolios, we run the analysis without any real estate series initially and then with different real estate vehicles. We also unsmooth the real estate series to determine whether the allocation to real estate is driven by the appraisal smoothing problem associated with real estate and other private market assets. The procedure of Geltner (2003) is used in unsmoothing the real estate series. This procedure and its implementation as well as its effect on real estate and the various private market series are also presented in this chapter.

In the following sections, we provide a background to all the models identified in the summaries provided above. The goal is to have an extended discussion on the methodologies that we implement in the various empirical chapters. A summary of the models implemented would still be given in the respective chapters.

4.3.1 STATIONARITY AND COINTEGRATION TECHNIQUES

Econometric models have often been formulated based on the assumption that the underlying time series are stationary or at least stationary around a deterministic trend. In other words, econometric models have been formulated based on the assumption that the means and variances of the variables are constant and not dependent on time. It has however been shown that most time series tend to diverge away from their mean over time. These series are said to be non-stationary.

In order to overcome the issues relating to non-stationarity of time series and prior restrictions on the lag structure of a model, econometric analysis of time series data has increasingly moved towards cointegration. Cointegration techniques help to detect the presence of steady state equilibrium between variables. If two series do not cointegrate, spurious regression could result and the results become meaningless.

The approaches of Granger (1981); Engle & Granger, (1987), the Johansen and Juselius (1990) and the Autoregressive Distributed Lag (ARDL) models of Pesaran and Shin (1995) and Pesaran et al. (2001)

have become the standards for determining long run relationship between time series that are non-stationary.

These cointegration models can also be re-parameterised to the Error Correction Model (ECM) which gives the short-run dynamics and long-run relationship of the underlying variables. This way, cointegration models are versatile enough to estimate the long relationship between non-stationary variables and reconciling the short-run dynamics with long-run equilibrium (Nkoro and Uko, 2016).

Cointegration approaches make it easier to retrieve the relevant long-run information regarding the relationship between variables that may be lost on differencing. Cointegration techniques integrate short-run dynamics with long-run equilibrium and helps obtain realistic estimates of models and thus aid in meaningful forecast and policy implementation (Nkoro and Uko, 2016).

Cointegration is concerned with the analysis of long run relationships between integrated variables and reparameterising the relationship between the considered variables into an Error Correction Model. The approaches of Granger (1981), Engle & Granger (1987) are however not applicable if the variables are integrated of different orders for example where Series A is I(1) and series B is I(0). The ARDL cointegration technique on the other hand, can be used to determine the long-run relationship between variables integrated of different orders (Pesaran and Shin, 1999; Pesaran et al., 2001). The re-parameterised result of the ARDL model gives the short-run dynamics and long-run relationship of the variables being considered.

The next section presents the theory behind the Autoregressive distributed lag model and how the long-run and short-run models are derived.

4.3.2 ARDL APPROACH TO COINTEGRATION

This section sets out the theory behind Autoregressive distributive lag (ARDL) models as well as a derivation of the approach for analyzing the long-run and short run relationships between variables. The procedure that we have used to practically implement this model in E-Views are also explained.

ARDL models have been in existence for a long time but have recently become popular as an approach for examining Cointegrating relationships due largely to the seminal works of Pesaran and Shin (1998) as well as Pesaran et al. (2001). The authors argue that ARDL models have the advantage of handling cointegration with an inherent robustness to a misspecification of the orders of integration of the relevant variables. There are three cases of interest regarding the order of integration of variables:

1. That all the variables are $I(d)$ for some $0 \leq d$ and are not cointegrated. In this case, least squares techniques can be used to estimate and interpret equation 1 above.

2. All variables are $I(1)$ and are cointegrated. Here, least squares techniques can be used to estimate the long-run relationship by regressing y_t on $x_{j,t}$ for $j=1,\cdots k$ in levels. Alternatively or complementarily, least squares can be used to estimate the speed of adjustment of short-run dynamics to the cointegration relationship by regressing the appropriate error-correction model (ECM).
3. Some variables are $I(0)$ and others are $I(1)$ and some of the $I(1)$ variables are cointegrated.

Conventional cointegration approaches such as those of Engle & Granger (1987), Phillips and Ouliaris (1990) and Johansen (1995) fail when some variables are $I(0)$ and others are $I(1)$ as in Case 3. It is often important to pre-test for the presence of unit root in each of the variables of interest before proceeding to use the conventional cointegration approaches. This sometimes leads to misclassification as most unit root tests are known to suffer from size and power issues (Perron and Ng, 1996). The bounds test for cointegration proposed by Pesaran et al. (2001) is however not subject to the same restrictions and is thus able to handle the nuances of Case 3. ARDL models are the standard for estimation when a researcher chooses to remain skeptical of the orders of integration of the underlying variables.

ARDL models are linear time series models in which both the dependent and independent variables are related both contemporaneously and across their lagged values. Given that y_t is the dependent variable and $x_1,\cdots,x_k$

are k explanatory variables, a general $ARDL(p,q_1,\ldots..q_k)$ model is given by:

$$y_t=a_0+a_1t+\sum_{t=1}^{p}\psi_i y_{t-i}+\sum_{j=1}^{k}\sum_{l_j}^{q_j}\beta_{j,l_j}x_{j,t-l_j},+\epsilon_t$$

where ϵ_t are the usual innovations, a_0 is the constant term, and a_1, ψ_i, β_{j,l_j} are respectively the coefficients associated with a linear trend, lags of the k regressors $x_{j,t}$ for $j=1,\cdots k$.

If let L denote the lag operator and define $\psi(L)$ and $\beta_j(L)$ as the as the lag polynomials:

$$\psi(L)=1-\sum_{t-1}^{p}\psi_i L^i \quad \text{and} \quad \beta_j(L)=\sum_{l_j=0}^{q_j}\beta_{j,l_j}L^{l_j}$$

Equation 1 can then be re-written as:

$$\psi(L)y_t = a_0 + a_1 t + \sum_{j=1}^{k} \beta_j(L)\, x_{j,t} + \epsilon_t \qquad \textbf{4(3)}$$

4.3.2.1 Representations of ARDL models

ARDL models are often specified in general form as in Equation 1. However, there are three different representations. The first representation is used for intertemporal dynamic estimation whiles the second is used for post-estimation derivation of the long-run equilibrium relationships. The third representation is a reduction of equation 1 to the conditional error correction representation in the Pesaran et al. (2001) bound test.

The three representations require decomposition using the Beveridge-Nelson approach. According to this approach, $\psi(L)$ and $\beta_j(L)$can be decomposed as:

$$\psi(L) = \psi(1) + (1\text{-}L)\tilde{\psi}L^i \quad \text{and} \quad \beta_j(L) = \left(\tilde{\beta}_j(1) + (1\text{-}L)\tilde{\beta}_j(L)\right)$$

where

$$\tilde{\psi}(L) = \sum_{i=0}^{p} \tilde{\psi}_i L^i \quad \text{and} \quad \tilde{\psi}_i = -\sum_{r=i+1}^{p} \psi_r$$

$$\tilde{\beta}_j(L) = \sum_{l_j=0}^{q_j-1} \tilde{\beta}_{j,l_j} L^{l_j} \quad \text{and} \quad \tilde{\beta}_{j,l_j} = -\sum_{s=l_j+1}^{q_j} \beta_{j,s}$$

and

$$\psi(1) = 1 - \sum_{i=1}^{p} \psi_i \quad \text{and} \quad \beta_j(1) = \sum_{l_j=0}^{q_j} \beta_{j,l_j}$$

It is important to note that $\psi(L) = 1 - \psi^*(L)$ where $\psi^*(L) = \sum_{i=1}^{p} \psi_i L^i$. Furthermore, observe that:

$$\psi^*(L) = \sum_{i=1}^{p} \psi_i L^i = \left(\sum_{i=1}^{p} L^{i-1}\right) L = \left(\psi^*(1) + (1\text{-}L)\widetilde{\psi}^*(L)\right) L$$

where

$\widetilde{\psi}^*(L) = \sum_{r=i+1}^{p} \psi_i L^{i-1}$, $\tilde{\psi}_i^* L^{i-1}$, $\tilde{\psi}_i^* = -\sum_{r=i+1}^{p} \psi_r$, and $\psi^*(1) = \sum_{i=1}^{p} \psi_i$

For any series z_t one can always write:

$$z_t = z_{t-1} + \Delta z_t$$

i. Intertemporal Dynamics Regression

The first step in the application of ARDL models is an estimation of the intertemporal dynamics. Here, we are interested in the relationship between y_t on both its own lags as well as the contemporaneous and lagged values of the k regressors $x_{j,t}$. Equation 4(2) can be cast into the following representation:

$$y_t = a_0 + a_1 t + \sum_{i=1}^{p} \psi_i y_{t-i} + \sum_{j=1}^{k} \beta_j(1) x_{j,t} + \sum_{j=1}^{k} \tilde{\beta}_j(L) \Delta x_{j,t} + \epsilon_t \qquad 4(4)$$

where we use the first difference notation, $\Delta = (1\text{-}L)$. Given that equation 4(4) does not explicitly solve for y_t, it is often considered as a regression for intertemporal dynamics. Within a more practical setting, equation 4 can be restated as:

$$y_t = a_0 + a_1 t + \sum_{i=1}^{p} b_{0,i} y_{t-1} + \sum_{i=1}^{p} b_j x_{j,t} + \sum_{j=1}^{k} \sum_{l_j=1}^{q_j-1} c_{j,l_j} \Delta x_{j,t-l_j} + \epsilon_t \qquad 4(5)$$

ii. Post-Regression Derivation of Long-Run Dynamics

The second representation of the ARDL model attempts to derive the long-run relationship between y_t and the k regressors. This representation solves for y_t in terms of $x_{j,t}$. Having estimated the regression equation in model 5, we can use equation 6 to derive the long-run parameters post-estimation. The second representation is formulated thus:

$$y_t = \psi^{-1}(1) \left(a_0^* + a_1 t + \sum_{j=1}^{k} \beta_j(1) x_{j,t} + \sum_{j=1}^{k} \beta_j^*(L) \Delta x_{j,t} + \epsilon_t^* \right) \qquad 4(6)$$

iii. Error Correction Representation

The objective here is to test for cointegration by reducing a typical VAR framework to its conditional error correction form. This representation of the ARDL is considered the most interesting and receives a lot of attention in applied work. Equation 4(7) is the Conditional Error Correction form of the ARDL model in equation 4(2):

$$\Delta y_t = a_0 + a_1 t - \psi(1) EC_{t-1} + \left(\widetilde{\psi}^{*}(L)\Delta_{x,t-1}\right) + \sum_{j=1}^{k} \beta_j (L) \Delta x_{j,t} + \epsilon_t \qquad \mathbf{4(7)}$$

The error correction term, denoted as EC_{t-1}, represents the Cointegrating relationship when y_t and $x_{1,t}, \cdots, x_{k,t}$ are cointegrated.

Pesaran et al (2001) propose the bound test for cointegration as a test on parameter significance in the Cointegrating relationship of the conditional error correction model. The test is a standard F – or Wald test for the following null and alternative hypotheses:

$$H_0 \qquad \psi(1) \cap \{B_j(1)\}_{j=1}^{k} = 0 \quad \textit{(Variables are not cointegrated)}$$

$$H_1 \qquad \psi(1) \cap \{B_j(1)\}_{j=1}^{k} \neq 0 \quad \textit{(Variables are cointegrated)}$$

The computed test statistic is compared to two asymptotic critical values that correspond to the polar cases of all variables being purely I(0) or purely I(1). This implies that the critical values lie in the lower and upper tails, respectively, of a non-standard mixture distribution involving integral functions of Brownian motions. When the test statistic is below the lower critical value, one fails to reject the null and concludes that cointegration is not possible. If however the test statistic is above the upper critical value, one rejects the null and concludes that cointegration is indeed possible. In either cases, knowledge of the Cointegrating rank is not necessary. However, when the test statistic falls between the lower and upper critical values, it is important to have knowledge of the Cointegrating rank to proceed any further.

Pesaran et al. (2001) offer five alternative interpretations of the Conditional Error Correction model depending on whether deterministic terms integrate into the error correction term. The ARDL model can be formulated with: (i) No constant and trend; (ii) Restricted constant and no trend; (iii) Unrestricted constant and no trend; (iv) Unrestricted constant and restricted trend and (v) Unrestricted constant and unrestricted trend.

The first step in implementing the ARDL model involves checking the data to see whether there are some clear trends or structural changes which may have to be taken into consideration later in the analysis. We take the nature log (ln) of the various asset return indices to improve the distributional property of the series and then check this data.

Once this is done, we proceed to test for the order of integration to ensure that none of the series under consideration is integrated of order 2 or higher. We run a two tests, the Augmented Dickie Fuller

Test and the Philips Peron Test on the level series and first difference of the series. We confirm that most of the data series are I(1) with a few being I(0).

We specify the ARDL model with unrestricted trend and intercept in the first instance and then re-specify without a trend and intercept term. Both models are estimated with a maximum lag length of 4 as we are dealing with quarterly data. E-Views 9 provides an algorithm that automatically selects the most appropriate lag structure given the model specified by the user. The model selected is one which minimises some information criterion, for example, the Akaike (AIC), Schwarz (BIC), Hannan-Quinn (HQ) criterion. We check the lag structure of the various models to determine that indeed the model lag structure selected is indeed optimal. In addition to inspecting the lag structure, we also run the Ramsey Reset Test to ensure that the resulting model selected by EViews captures the relationship being investigated. We also proceed to verify that the residuals from the model selected are serially uncorrelated using the Breusch-Godrey Serial Correlation LM Test. Residual homoscedasticity is also tested using the Heteroskedasticity Test of Breusch-Pegan Godfrey. Where there is a problem with residual serial correlation, this is corrected by increasing the lag length of both the dependent variable and regressors. Residual heteroskedasticity can be corrected by adjusting the coefficient covariance matrix to Newey West (HAC). It is important to note that whiles serial correlation leads to biased results, heteroskedasticity only leads to inefficient estimation. Therefore, it is more important to remove residual serial correlation.

Once we are satisfied the models are properly specified, we test for the presence of cointegration using the Bounds Test. Since the F-statistic distribution is non-standard, the critical values have to be calculated. Pesaran et al. (2001) and Narayan (2005) both developed two bounds of critical values. A lower bound applies when the variables are stationary and an upper bound is applicable when the variables are integrated of order one (i.e. I(1)). We can reject the null hypothesis of no cointegration if the F-statistic is higher than the upper bound. We accept the null hypothesis if the F-statistic is below the lower bound. If the F-statistic falls between the upper and lower critical bounds, the results are inconclusive.

If the series are cointegrated, we can proceed to test for the speed of adjustment by estimating the Cointegrating and long run form of the ARDL model. We expect the Error-Correction term (CointEq(-1)) to be negative and statistically significant to indicate how any movements into disequilibrium are corrected for within one period.

4.3.3 GRANGER CAUSALITY TEST – TODA AND YAMAMOTO (1995) APPROACH

One way of thinking about the ability of an asset to hedge against a particular benchmark is to examine the contribution that the benchmark makes in the prediction of the asset's return or vice versa. This predictability can be assessed by employing the principles of Granger causality to examine whether the past values of returns of the asset being examined aids in the prediction of the inflation/interest rate changes or vice versa. This is undertaken using either the restricted or unrestricted versions of the models below:

$$x_t = \sum_{i=1}^{l} a_{1i} x_{t-i} + \sum_{i=1}^{l} \beta_{1i} y_{t-i} + \gamma_1 E_{t-1} + \varepsilon_{1t} \qquad \textbf{4(8)}$$

$$y_t = \sum_{i=1}^{l} a_{2i} y_{t-i} + \sum_{i=1}^{l} \beta_{2i} x_{t-i} + \gamma_2 E_{t-1} + \varepsilon_{2t} \qquad \textbf{4(9)}$$

Where x and y represent asset returns and the inflation/interest rate respectively. The restricted version of each equation only includes the lagged values of respective dependent variable. The third term in both equations is an error correction term, which should be included where there is evidence that the variables are cointegrated (Engle & Granger, 1987).

Wald test is used to test whether all of the lagged values of x and y equation are simultaneously equal to zero in order to find out whether x granger causes y.

If $\sum \beta \neq 0$, x Granger causes y;

If both $\sum a \neq 0$ and $\sum \beta \neq 0$, then there exists a bidirectional causality between x and y.

It is important to understand that granger causality does not imply one variable causes changes in the other. When we say that $x_{1t}, x_{2t}, \ldots, x_{nt}$ Granger-cause y_t, we mean that past values of x are correlated with current values of y. Granger-causality can run in one direction, both directions or there is no Granger-causality at all.

Whiles the Granger representation theorem suggests that for there to be cointegration among two variables, there must be a causal relationship running in at least one direction, some studies have however shown that this is not necessarily the case. For example, Ogaki and Reinhart (1998) provide an example to show that a cointegrated time series does not necessarily have an error correction representation. Gujarati (2003) also indicated that relationship between two variables does not necessarily imply causality.

In this study, we employ the Granger non-causality approach of Toda and Yamamoto (1995) to test the relationship between asset returns and the inflation/interest rates. This approach has the advantage that it can be applied without first testing the cointegration properties of the system. Also, if the order of integration does not exceed the fitted lag length of the model, then the Toda and Yamamoto (1995) approach can be applied whether the series are integrated in levels or first differences (i.e. I(0) AND I(1) (Toda and Yamamoto, 1995; Zapata and Rambaldi; 1997; Caporale and Pittis, 1999).

Following Fang et al. (2018), we specify the following equations to establish the relationship between asset returns and the selected inflation/interest rates:

$$\ln(y_t)=\beta_0^1+\sum_{i=1}^{K+d\max}\beta_{1i}^1 \ln y_{t-i}+\sum_{i=1}^{K+d\max}\beta_{2i}^1 \ln x_{t-i}+\varepsilon_t \qquad \mathbf{4(10)}$$

$$\ln(x_t)=\beta_0^2+\sum_{i=1}^{K+d\max}\beta_{1i}^2 \ln x_{t-i}+\sum_{i=1}^{K+d\max}\beta_{2i}^2 \ln y_{t-i}+\varepsilon_t \qquad \mathbf{4(11)}$$

where *d max =maximum order of integration.*

The coefficient matrices of the last $d\ max$ lagged vectors in the model not used in the estimation as these are regarded as zeros. This way, we can test linear or non-linear restrictions on the first k coefficient matrices using the standard asymptotic theory (Toda and Yamamoto, 1995).

In equations 4(10) and 4(11), the hypothesis that asset return is does not Granger-cause inflation/interest rate movements is tested using the following: H_0: $\beta_0^1=0$, i=1,2,……K. The hypothesis that inflation/interest rate movements does not Granger-cause asset return changes is also testing as follows: H_0: $\beta_0^2=0$, i=1,2,……K.

4.3.4 STATIC AND DYNAMIC CONDITIONAL CORRELATIONS

Correlation estimates are critical inputs for most types of financial analysis. For example, in asset allocation, a forecast of the covariance matrix of returns is required, a key input of which is the correlation between the assets. Correlation measures the direction and strength of relationship between different variables. The Pearson correlation coefficient can be calculated mathematically thus:

$$\varrho_{XY}=\frac{\mathrm{cov}(X,Y)}{\sqrt{\sigma_X^2\sigma_Y^2}}=\frac{\sum_{t=1}^{n}(X_t-\overline{X})(Y_t-\overline{Y})}{\sqrt{\sum_{t=1}^{n}(X_t-\overline{X})^2\sum_{t=1}^{n}(Y_t-\overline{Y})^2}} \qquad \mathbf{4(12)}$$

Many financial theories rely on the assumption of constant variances and covariances. However, it has been shown that tail events exist where these parameters may change drastically. It is therefore better to calculate a conditional correlation which estimates correlation based on all information available up to a particular point in time. Chong et al. (2012) found that in most cases, the average correlation is identical to the unconditional correlation estimated across the entire sample. Where this is not the case, the average conditional correlation is lower; pointing to the fact that during periods of increased volatility, an upward bias is introduced into the conditional coefficients. This is consistent with the view of Forbes & Rigobon, (2002).

A number of approaches have been used to estimate the conditional correlation – rolling window, exponential smoother and the Dynamic Conditional Correlation model. The rolling correlation is easy to estimate and is capable of capturing time-variation and clustering of cross asset returns (Anderson and Romaindo, 2008). However, Anderson and Romaindo (2008) observed that since all the windows in a rolling correlation analysis are given the same weight, they tend to adjust very slowly to new information. This problem becomes greater with longer window lengths. Regarding the window, many authors have observed the difficulty in choosing a window length as there is no theoretical or empirical basis for selecting this (Case et al., 2012; Ziering et al., 1999). There could also be huge changes in correlation estimates when there are abnormally small or large return observations, especially as these observations enter or leave the window. Forbes & Rigobon (2002) found that rolling correlation coefficients tend to be prone to bias. They explained that as volatility increases in one asset market, Heteroskedasticity in returns may cause the correlation coefficient to be biased upward.

To make up for the drawbacks of the rolling correlation method, Multivariate Generalised Autoregressive models have been proposed and used in many studies. Engle (2002) suggests using the Dynamic Conditional Correlation (DCC) model. The DCC model calculates the conditional correlations as a function of past volatilities of assets and the covariance between them. Given that all past information is used in the otimisation process, there is no difficulty in selecting a window length as with rolling correlations. Engle (2002) found that the multivariate and univariate volatility forecasts are consistent with each other. The volatility forecasts and the correlations of the original assets remain unchanged when new variables are added to the system, depending on the way the model is revised. Also, when applied to typical financial applications it was found that DCC models revealed important time varying features that might otherwise be difficult to quantify.

The Dynamic Conditional Correlation model estimates a GARCH (1,1) specifications, employing the resulting standardized residuals to estimate the time varying correlation matrix. In order to accomplish this, the residuals are transformed by their estimated standard deviations $\Xi_t = {\varepsilon_t}/{\sqrt{h_t}}$.

The covariance matrix can be expressed as $H_t \equiv D_t R_t D_t$, where D_t is a diagonal matrix of univariate GARCH volatilities. $R_t = Q_t^{*-1} Q_t Q_t^{*-1}$ is the time varying correlation matrix, with Q_t as described by:

$$Q_t = (1 - a - b)\overline{Q} + a\left(\Xi_{t-1}\Xi'_{t-1}\right) + Q_{t-1} \qquad \mathbf{4(13)}$$

$\overline{Q}$ is the unconditional covariance of standardized residuals resulting from the first stage estimation, and Q_t^* is a diagonal matrix composed of the square root of the diagonal elements of Q_t. As with the standard GARCH (1, 1) model the coefficients of the DCC (1, 1) model are estimated by the maximum likelihood procedure using the algorithm of Broyden–Fletcher–Goldfarb–Shanno (BFGS). The log-likelihood function, under the assumption of conditional multivariate normality can be displayed as follows:

$$L(\vartheta) = -\frac{1}{2}\left[TN \ln (2\pi) + \sum_{t=1}^{T} \ln\left|H_t + \Xi_t' H_t^{-1} \Xi_t\right|\right] \qquad \mathbf{4(14)}$$

where Ξ_t is an $N\times1$ vector stochastic process, with $H_t = E_{t-1}\left(\Xi_t \Xi_t'\right)$, being the $N\times N$ conditional variance-covariance matrix.

The Dynamic Conditional Correlation model has the advantage of being a two-step process and so is generally less computationally intense and suitable for big systems (Cappiello et al., 2006).

4.3.5 UNSMOOTHING TECHNIQUES

A critical pillar of many analytical frameworks built on a premise of "normality", is the assumption that asset returns from period to period are independent and identically distributed. However, if one month's return is 'influenced' by the previous month's return, then there may be a need to account for this effect in future asset projections (Sheikh and Qiao, 2010). The s-th order autocorrelation coefficient for a stationary time series r_t is:

$$\varrho_s = \frac{\operatorname{cov}(r_t, r_{t-s})}{\operatorname{var}(r_t)} \qquad \mathbf{4(15)}$$

Autocorrelation can also be tested on the significance of the autocorrelation coefficient obtained from equation 4(15) using the Box Pierce Q-statistics and their probability value. The Q-statistic is a test for the null hypothesis that there is no autocorrelation to order p. It is computed as:

$$Q=T\sum^{p}\varphi(n)^2 \qquad \text{with } Q\sim\chi^2_p \qquad \textbf{4(16)}$$

where T is the sample size and $\varphi(n)$ is the nth-order sample autocorrelation. Q is asymptotically distributed as $\varphi(n)^2$ with degrees of freedom equal to the number of autocorrelations.

Several approaches have been developed to help eliminate the smoothing problem in appraisal based return series. The most popular of these approaches include those of Geltner et al. (1991; 1993), Fisher et al. (1994) and Cho et al. (2003); Booth and Marcato (2004). These models have largely been successful in generating real estate series that have a higher volatility compared to the 'smoothed' returns. They have also been found to reduce the lagging effects when compared to public listed real estate series. A confirmation of real estate's higher than observed volatility is provided by the development of transaction-based series for example the MIT real estate series.

It is important to note however that real estate still records significantly lower volatility than other financial assets. The use of unsmoothed series have also been found to allocations that still exceed what is observed in practice. (Hudson-Wilson et al., 2003; Worzala and Sirmans, 2003; Bond et al., 2007). This has been attributed to an added ex-ante liquidity premium that is not accounted for in conventional practice, to investor's inability to diversify away specific risk fully due to large lot sizes or simply to the distributional characteristics of real estate returns (IPF, 2004; Bond et al., 2007; Baum & Struempell, 2006; Young, 2007).

The model of Geltner et al (1993) has been applied within real estate and hedge fund literature to unsmooth the returns of assets that have been found to be autocorrelated. The approach applies a reverse filter to recover the true return as given in equation 4(17):

$$r_t^u=\frac{(r_t^*-(1-a)r_{t-1}^*)}{a} \qquad \textbf{4(17)}$$

where:
r_t^u = the unobserved true return
r_t^* is the observed appraised value and
a is a parameter between 0 and 1. If no smoothing is present in the returns, then the value of $a=1$

The unsmoothing parameter, α, is based on a judgment concerning the degree of smoothing present in the real estate market. Giliberto (1992) found based on their survey of industry practitioners that real estate investors view the asset's 'true' volatility as being about half the volatility of equities. Stevenson (2000), however points out that the use of different assumptions could result in different results and so proposed a first-order autoregressive (AR1) model, following Fisher et al. (1994), which can correct return series for autocorrelation without having to set parameters arbitrarily. The AR1 model is referred to by Stevenson (2000) as a Full Information Model alternative which should provide an adequate figure. This model assumes that real estate returns follow a first-order autoregressive process. Therefore, α can be estimated as the β coefficient in the following OLS regression:

$$r_t^* = \alpha + \beta r_{t-1}^* \tag{4(18)}$$

The underlying corrected return can be retrieved from the equation below:

$$r_t^u = \frac{r_t^*}{1-\alpha} - \frac{\alpha}{1-\alpha} r_{t-1}^* \tag{4(19)}$$

Fisher et al. (1994) and Geltner (1993) have suggested adjusting for autocorrelation at higher lags to account for seasonality in data, especially as witnessed in the NCREIF index which displays a level of fourth order autocorrelation, since the data is at quarterly frequency, this fourth order-autocorrelation is viewed as evidence of seasonality. A smoothing process for lags 1 and 4 can be formulated as shown in equation 4(20):

$$r_t^u = \frac{r_t^* - \alpha(-1) * r_{t-1}^* - \alpha(-4) * r_{t-4}^*}{1 - \alpha(-1) - \alpha(-4)} \tag{4(20)}$$

where:

$a(-1)$ = first-order autocorrelation
$a(-4)$= fourth-order autocorrelation

Some researchers have applied unsmoothing techniques that use a time-varying alpha. Brown & Matysiak (1997) who offer a smoothing model with a time varying alpha based on rolling window serial correlations. Chaplin (1997) used a regime switching approach to unsmooth real estate series, following Quan and Quigley (1991). A similar approach is used by Lizieri et al. (2012).

4.3.6 ASSET ALLOCATION MODELS

4.3.6.1 Markowitz (1952) Mean-Variance Model

In the typical mean-variance model of asset allocation without short-selling and no riskless borrowing or lending, the portfolio manager's objective is to select a combination of assets that minimise the risk of the portfolio subject to a given level of return and the constraints that the asset weights are non-negative and sum to one. Mathematically, the objective function is given as:

$$\min \frac{1}{2} \sum_{i,j=1}^{n} w_i w_j \sigma_{ij} \qquad \mathbf{4(21)}$$

s.t.

$$\sum_{i=1}^{n} w_i \tilde{r}_i = r_P$$

where:

$\sum_{i,j=1}^{n} w_i w_j \sigma_{ij}$ = variance of the return of a portfolio containing n different assets.

$\sum_{i=1}^{n} w_i \tilde{r}_i$ = expected rate of return of a portfolio containing n different assets.

4.3.6.2 Mean-Tracking Error Models

Although it is informative for an investor to determine which combinations of assets help achieve a certain amount of return with minimum risk, this does not really fit the goal of most investors. Most investors are concerned with the real return that they obtain at the end of the period i.e. the returns after accounting for the loss in purchasing power. Other investors also measure their performance relative to a certain benchmark such as the returns on Treasury securities.

Bruno & Chincarini (2010) specify an objective function which characterises an investor who wishes to maximize his real returns subject to some minimization of the nominal deviation from inflation. In this thesis, we expand the context to include both inflation and interest rate changes. It is important to note that this is equivalent to performing Markowitz (1952) mean-variance analysis on real returns.

The objective function specified by Bruno & Chincarini (2010) is:

$$\min\left[V\left(r_{P,t,t+k} - \pi_{t,t+k}\right)\right] \qquad \text{s.t.} \qquad r_{P,t,t+k} - \pi_{t,t+k} = \tilde{\mu}_P \qquad \mathbf{4(22)}$$

where $r_{P,t,t+k}$ is the return of the investor's portfolio from time t to time t+k, $\pi_{t,t+k}$ is the inflation rate from time t to time t+k, and $\tilde{\mu}_p$ is the real return target of the portfolio.

The objective function that we implement in this thesis is to minimise the tracking error of the portfolio with a given inflation or interest rate benchmark. We select a group of assets for the DC pension investor that helps to achieve this goal. The problem can be re-written as:

$$\min_{w_i}\left[V\left(\sum_{i=1}^{N} w_{i,t,t+k}-\pi_{t,t+k}\right)\right] \quad \text{s.t.} \quad \sum_{i=1}^{N} w_i r_{i,t,t+k}-\pi_{t,t+k}=\tilde{\mu}_p \qquad \mathbf{4(23)}$$

subject to some additional constraints. We can write the above in matrix notation as:

$$\min_{w} w'\sum w-2w'\gamma \qquad \text{s.t.} \qquad w'\mu=\tilde{\mu}_p+\pi_{t,t+k} \qquad \mathbf{4(24)}$$

where γ is an N-dimensional vector of the covariances between individual asset returns and the inflation rate over the investment horizon spanning *t* to *t+k*, $\sum$ is the variance-covariance matrix of the asset classes and inflation, and w represents the weights of the portfolio of asset classes.

$$\gamma=\begin{bmatrix} C\left(r_1,\pi_{t,t+k}\right) \\ \vdots \\ C\left(r_N,\pi_{t,t+k}\right) \end{bmatrix}$$

Constraints can be added to prohibit short selling of asset classes and that the sum of weights sum to 1.

In our study, we run In-sample optimisations are run for the periods 1990– 2015. We use a 5 year estimation horizon for the out-of-sample estimations. The estimations are first done with data from the first quarter of 1991 to the fourth quarter of 1995. This estimate is used to construct the optimal portfolios for the next quarter. The 5-year window is moved forward by one quarter and a new portfolio is re-estimated using data from the second quarter of 1991 to the first quarter of 1996. This process is repeated until the first quarter of 2015.

A modified version of the Tracking Error Optimisation Model is used in the optimisation in Chapter 6 which seeks to create a portfolio that contains direct real estate and liquid publicly traded assets namely as listed real estate, aggregate stocks, cash and bonds of various maturities. We use a generalised form of the tracking error optimisation model which seeks to minimise the tracking error variance for a given expected excess return. The following numerical optimisation model is implemented in this thesis:

$$\min_{w_k} \sum_{k=1}^{T} \left(r_{index,t} - \sum_{k=1}^{N} w_k r_{k,t} \right)^2 \qquad \textbf{4(25)}$$

Subject to:

$\sum_{t=1}^{T} \left(r_{index,t} - \sum_{k=1}^{N} w_k r_{k,t} \right) = 0$

$\sum_{k=1}^{N} w_k = 1$

$L < w_k < U$

Where:

$r_{index,t}$ = the return on the direct real estate benchmark at time t

$r_{k,t}$ = the return on the kth asset at time *t*

w_k = the weight assigned to the *k*th asset

The optimizer selects a combination of assets that provide the lowest tracking error relative to the IPD UK index returns, subject to the constraints of zero expected tracking error, unit sum of weights and a set allocation to direct real estate. The weight set for direct real estate ranged from 0% to 90%, in 10% intervals.

4.3.6.3 Semi-variance Optimisation

Bruno & Chincarini (2011) again suggest an alternative model to more accurately specify an investor's optimisation problem in terms of minimising downside risk, rather than variance. This approach is also more suitable for dealing with asset returns that are not normally distributed:

$$\min_{w_i} \frac{1}{T} \sum_{j=1}^{T} \left[\min \left(\sum_{i=1}^{N} w_{i,t}\, r_{i,t,t+k} - \pi_{t,t+k},\ 0 \right)^2 \right] \qquad \textbf{4(26)}$$

s.t. $\left(\sum_{i=1}^{N} w_{i,t} r_{i,t,t+k} - \pi_{t,t+k} \right) = \tilde{\mu}_p$

4.3.6.4 Sortino and Sharpe Ratio Optimisation

In this study, we use a generalised form of the Sharpe ratio where the risk-free rate is replaced with the selected inflation and interest rate benchmarks:

$$\text{Shape ratio}=\frac{E\left[R_p\text{-}R_b\right]}{\sigma_p} \qquad \mathbf{4(17)}$$

where σ_p is the portfolio standard deviation.

Similarly, a generalised Sortino ratio is used. The target return is replaced with the returns on the selected inflation and interest rate benchmarks:

$$\text{Sortino Ratio}=\frac{E\left[R_p\text{-}R_b\right]}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(R_p\text{-}R_b\right)^2 f(t)}} \qquad \mathbf{4(28)}$$

$f(t)=1$ if return $<$ target return

$f(t)=0$ if return $\geq$ target return

In-sample portfolios are estimated from the first quarter of 1991 to the first quarter of 2015 for which we have data available for all the 32 variables. The out of sample portfolios are estimated from the beginning of 1991 plus five additional years. This estimate is used to construct portfolios for the next quarter. The window is then expanded forward by a quarter and a new portfolio re-estimated. This process is repeated until the first quarter of 2015. The VBA code for the construction of the out-of-sample portfolios are given in the Appendix.

4.4 CONCLUSION

This Chapter is made up of two parts. In the first part, we presented the asset classes and sectors that we analyse in this thesis. In total, we have 65 variables made up of 11 variables representing direct real estate, 16 variables for stocks and 9 bond sectors. We had a total of 25 variables capturing different alternative asset sectors. 4 variables are used for our inflation/interest rate benchmarks. A list of these variables is presented in Appendix 4(A). All of these variables are used in our analysis to demonstrate how the results change given the specific asset class or sector returns that is used. Spierdijk and Umar (2013) demonstrated that the time series features of an asset class (at the aggregate level) could differ considerably from the time series features of the component sectors.

Once we outline the data sources, we proceed to carry out some preliminary analysis. The aim of this analysis is to provide some insight into the return and risk of the various asses and the inflation/interest rates. We also explored some time series features that we believe could have a bearing on the selection of an appropriate analytical framework for subsequent analysis involving the respective assets. We analysed and discussed the distribution properties of our data, the serial correlation and stationarity of the various variables. The results show for example that the various assets had different degrees of integration. Most of the series were not found to be normally distributed. Furthermore, private market assets such as direct real estate and some alternative assets were found to exhibit significant autocorrelation. An application of the reverse engineering model of Geltner (2003) helped to get rid of the autocorrelation, although it also altered the return of the assets affected.

After gaining insight into the time series features of our data, we proceed to discuss the various analytical approaches that are subsequently used in our empirical analysis. We present a detailed background to each of the models and the appropriateness of each model given the objectives we pursue in the respective chapters and the results of the time series analysis conducted in this chapter.

APPENDICES

Appendix 4(A) List of Variables

IPD Real Estate Sectors
1. IPD All Property
2. IPD Industrial
3. IPD Office
4. IPD Retail

Unsmoothed IPD Real Estate Sectors
1. IPD All Property
2. IPD Industrial
3. IPD Office
4. IPD Retail

Other Real Estate Vehicles
1. AREF – All Funds
2. AREF – All Balanced Funds
3. Hybrid Real Estate

Stocks
1. Aggregate stocks
2. Oil
3. Basic Materials
4. Industrial
5. Construction
6. Industrial goods and services
7. Consumer goods
8. Health care
9. Consumer services
10. Telecom
11. Technology
12. Utilities
13. Banks
14. Insurance
15. Financial services
16. Listed real estate

Bonds
1. Index linked bonds - 0-5 Years
2. Index linked bonds - 5+ years
3. Bonds – All lives
4. Bonds – 10 + years
5. Bonds – 10 year
6. Bonds – 7 year
7. Bonds – 5 year
8. Bonds – 3 year
9. Bonds – 2 year

Alternatives (IN US$)
1. Emerging stock market
2. Developed ex UK stocks
3. Commodities – all
4. Commodities – oil
5. Commodities – gold
1. Hedge funds
2. US private equity
3. US venture capital
4. Developed ex US private equity
5. Emerging private equity

Alternatives in GB£
1. Hedge funds
2. US private equity
3. US venture capital
1. Developed ex US private equity
2. Emerging private equity
3. Emerging stock market
4. Developed ex US stocks
5. Commodities - all
6. Commodities - oil
7. Commodities - gold

Unsmoothed Private Market Alternatives
1. Hedge funds
2. US private equity
3. US venture capital
4. Emerging private equity
5. Hedge funds

Appendix 4(B) Correlograms: UK Real Estate (Original)

UKRE All

Date: 04/09/18 Time: 06:21
Sample: 1 97
Included observations: 97

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.752	0.752	56.600	0.000
		2	0.481	-0.19...	80.032	0.000
		3	0.242	-0.10...	86.024	0.000
		4	0.107	0.053	87.209	0.000
		5	-0.02...	-0.14...	87.255	0.000
		6	-0.11...	-0.04...	88.534	0.000
		7	-0.22...	-0.16...	93.693	0.000
		8	-0.30...	-0.09...	103.54	0.000

UKRE Industrial

Date: 04/09/18 Time: 06:23
Sample: 1 97
Included observations: 97

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.744	0.744	55.434	0.000
		2	0.499	-0.12...	80.573	0.000
		3	0.275	-0.11...	88.287	0.000
		4	0.142	0.035	90.365	0.000
		5	0.017	-0.10...	90.396	0.000
		6	-0.08...	-0.08...	91.171	0.000
		7	-0.16...	-0.04...	93.896	0.000
		8	-0.18...	-0.01...	97.706	0.000

UKRE Office

Date: 04/09/18 Time: 06:24
Sample: 1 97
Included observations: 97

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.765	0.765	58.558	0.000
		2	0.531	-0.13...	87.093	0.000
		3	0.311	-0.12...	96.946	0.000
		4	0.143	-0.03...	99.049	0.000
		5	-0.03...	-0.17...	99.164	0.000
		6	-0.15...	-0.03...	101.53	0.000
		7	-0.27...	-0.17...	109.44	0.000
		8	-0.37...	-0.15...	124.73	0.000

UKRE Retail

Date: 04/09/18 Time: 06:25
Sample: 1 97
Included observations: 97

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.724	0.724	52.398	0.000
		2	0.434	-0.18...	71.406	0.000
		3	0.200	-0.07...	75.486	0.000
		4	0.099	0.086	76.488	0.000
		5	0.030	-0.06...	76.582	0.000
		6	-0.02...	-0.05...	76.662	0.000
		7	-0.12...	-0.13...	78.302	0.000
		8	-0.21...	-0.08...	83.126	0.000

Appendix 4(C) Correlograms: UK Real Estate (Unsmoothed)

UKRE All

Date: 04/09/18 Time: 13:07
Sample: 1 97
Included observations: 97

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.131	0.131	1.7191	0.190
		2	-0.00...	-0.02...	1.7270	0.422
		3	-0.13...	-0.13...	3.6592	0.301
		4	0.001	0.038	3.6593	0.454
		5	-0.06...	-0.07...	4.0783	0.538
		6	-0.01...	-0.01...	4.0948	0.664
		7	-0.07...	-0.06...	4.6876	0.698
		8	-0.19...	-0.20...	8.6637	0.371

UKRE Industrial

Date: 04/09/18 Time: 13:09
Sample: 1 97
Included observations: 97

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.017	0.017	0.0299	0.863
		2	0.020	0.020	0.0699	0.966
		3	-0.07...	-0.07...	0.6579	0.883
		4	0.009	0.011	0.6658	0.955
		5	-0.02...	-0.02...	0.7337	0.981
		6	-0.07...	-0.08...	1.3452	0.969
		7	-0.08...	-0.08...	2.1700	0.950
		8	-0.02...	-0.02...	2.2366	0.973

UKRE Office

Date: 04/09/18 Time: 13:10
Sample: 1 97
Included observations: 97

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.076	0.076	0.5826	0.445
		2	0.046	0.040	0.7948	0.672
		3	-0.07...	-0.07...	1.3152	0.726
		4	0.035	0.045	1.4412	0.837
		5	-0.10...	-0.10...	2.5535	0.768
		6	-0.05...	-0.04...	2.8254	0.830
		7	-0.06...	-0.03...	3.2119	0.865
		8	-0.27...	-0.28...	11.105	0.196

UKRE Retail

Date: 04/09/18 Time: 13:10
Sample: 1 97
Included observations: 97

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.115	0.115	1.3316	0.249
		2	-0.03...	-0.04...	1.4291	0.489
		3	-0.15...	-0.14...	3.7757	0.287
		4	-0.03...	-0.00...	3.9182	0.417
		5	-0.00...	-0.01...	3.9266	0.560
		6	0.044	0.024	4.1303	0.659
		7	-0.03...	-0.05...	4.2954	0.745
		8	-0.13...	-0.13...	6.2220	0.622

Appendix 4(D) Correlograms: Private Equity (Original Series in US$)

US Private equity

Date: 04/09/18 Time: 06:28
Sample: 1 97
Included observations: 97

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.376	0.376	14.178	0.000
		2	0.280	0.161	22.121	0.000
		3	0.128	-0.02...	23.805	0.000
		4	0.086	0.008	24.570	0.000
		5	-0.03...	-0.09...	24.725	0.000
		6	0.001	0.032	24.725	0.000
		7	-0.11...	-0.11...	26.163	0.000
		8	0.006	0.093	26.166	0.001

US Venture Capital

Date: 04/09/18 Time: 06:29
Sample: 1 97
Included observations: 97

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.601	0.601	36.183	0.000
		2	0.479	0.184	59.372	0.000
		3	0.325	-0.03...	70.130	0.000
		4	0.044	-0.31...	70.327	0.000
		5	-0.03...	-0.02...	70.476	0.000
		6	-0.07...	0.083	71.123	0.000
		7	-0.08...	0.073	71.974	0.000
		8	-0.10...	-0.11...	73.244	0.000

Developed ex US Private Equity

Date: 04/09/18 Time: 06:30
Sample: 1 97
Included observations: 97

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.225	0.225	5.0632	0.024
		2	0.136	0.090	6.9339	0.031
		3	-0.07...	-0.12...	7.4680	0.058
		4	0.017	0.049	7.4978	0.112
		5	-0.12...	-0.12...	9.2343	0.100
		6	0.184	0.243	12.797	0.046
		7	-0.11...	-0.20...	14.178	0.048
		8	-0.12...	-0.14...	15.964	0.043

Emerging Private Equity

Date: 04/09/18 Time: 06:33
Sample: 1 97
Included observations: 97

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.434	0.434	18.856	0.000
		2	0.213	0.030	23.431	0.000
		3	0.041	-0.07...	23.598	0.000
		4	-0.02...	-0.02...	23.654	0.000
		5	-0.03...	-0.00...	23.813	0.000
		6	-0.05...	-0.02...	24.087	0.001
		7	-0.08...	-0.06...	24.891	0.001
		8	-0.12...	-0.07...	26.598	0.001

Appendix 4(E) Correlograms: Private Equity (Unsmoothed Series in US$)

US Private equity

Date: 04/09/18 Time: 13:15
Sample: 1 97
Included observations: 97

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.010	0.010	0.0103	0.919
		2	-0.02...	-0.02...	0.0840	0.959
		3	-0.09...	-0.09...	1.0058	0.800
		4	-0.05...	-0.05...	1.3538	0.852
		5	-0.03...	-0.04...	1.4966	0.913
		6	-0.06...	-0.08...	1.9637	0.923
		7	-0.02...	-0.03...	2.0298	0.958
		8	-0.08...	-0.10...	2.8877	0.941

US Venture Capital

Date: 04/09/18 Time: 13:15
Sample: 1 97
Included observations: 97

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.023	0.023	0.0507	0.822
		2	-0.05...	-0.05...	0.4012	0.818
		3	0.002	0.004	0.4015	0.940
		4	-0.00...	-0.00...	0.4015	0.982
		5	-0.08...	-0.08...	1.1747	0.947
		6	-0.12...	-0.11...	2.6902	0.847
		7	0.030	0.025	2.7867	0.904
		8	-0.07...	-0.09...	3.3746	0.909

Developed ex US Private Equity

Date: 04/09/18 Time: 13:16
Sample: 1 97
Included observations: 97

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.002	0.002	0.0003	0.986
		2	0.210	0.210	4.4500	0.108
		3	0.071	0.074	4.9681	0.174
		4	0.070	0.028	5.4718	0.242
		5	0.115	0.090	6.8475	0.232
		6	0.124	0.108	8.4704	0.206
		7	0.010	-0.03...	8.4808	0.292
		8	0.216	0.168	13.521	0.095

Emerging Private Equity

Date: 04/09/18 Time: 13:17
Sample: 1 97
Included observations: 97

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.00...	-0.00...	0.0056	0.940
		2	0.011	0.011	0.0181	0.991
		3	0.033	0.034	0.1318	0.988
		4	-0.09...	-0.09...	1.0574	0.901
		5	-0.06...	-0.06...	1.4575	0.918
		6	-0.17...	-0.18...	4.8332	0.565
		7	0.105	0.112	6.0010	0.540
		8	-0.03...	-0.03...	6.1175	0.634

Appendix 4(F) Correlograms: Hedge Fund

Hedge Fund (Original series in US$)

Date: 04/09/18 Time: 06:26
Sample: 1 97
Included observations: 97

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.254	0.254	6.4642	0.011
		2	0.072	0.008	6.9877	0.030
		3	0.022	0.001	7.0351	0.071
		4	-0.10...	-0.11...	8.1723	0.085
		5	-0.12...	-0.07...	9.6866	0.085
		6	-0.17...	-0.13...	13.075	0.042
		7	0.049	0.148	13.331	0.064
		8	-0.00...	-0.05...	13.336	0.101

Hedge Fund (Unsmoothed series in US$)

Date: 04/09/18 Time: 13:14
Sample: 1 97
Included observations: 97

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.002	0.002	0.0005	0.982
		2	-0.00...	-0.00...	0.0085	0.996
		3	0.001	0.001	0.0085	1.000
		4	-0.09...	-0.09...	1.0216	0.907
		5	-0.07...	-0.07...	1.6585	0.894
		6	0.066	0.065	2.1166	0.909
		7	-0.13...	-0.14...	4.0972	0.769
		8	0.011	0.004	4.1114	0.847

Appendix 4(G) E-Views Code for Estimating Dynamic Conditional Correlations

```
load "sample s1"
'set sample range
sample s1 1992Q3 2014Q4
scalar pi=3.14159

'defining the return series in terms of y1 and y2
series y1=dre
series y2=dre_all1

'fitting univariate GARCH(1,1) models to each of the two returns series
equation eq_y1.arch(1,1,m=1000,h) y1 c
equation eq_y2.arch(1,1,m=1000,h) y2 c

'extract the standardized residual series from the GARCH fit
eq_y1.makeresids(s) z1
eq_y2.makeresids(s) z2

'extract garch series from univariate fit
eq_y1.makegarch() garch1
eq_y2.makegarch() garch2

'Caculate sample variance of series z1, z2 and covariance of z1and z2 and correlation between z1 and z2
scalar var_z1=@var(z1)
scalar var_z2=@var(z2)
scalar cov_z1z2=@cov(z1,z2)
scalar corr12=@cor(z1,z2)

'defining the starting values for the var(z1) var(z2) and covariance (z1,z2)
series var_z1t=var_z1
series var_z2t=var_z2
series cov_z1tz2t=cov_z1z2

'declare the coefficient starting values
coef(2) T
T(1)=0.2
T(2)=0.7

' ..........................................................
' LOG LIKELIHOOD for correlation part
' set up the likelihood
' 1) open a new blank likelihood object and name it 'dcc'
' 2) specify the log likelihood model by append
' ..........................................................

logl dcc
dcc.append @logl logl

'specify var_z1t, var_z2t, cov_z1tz2t
dcc.append var_z1t=@nan(1-T(1)-T(2)+T(1)*(z1(-1)^2)+T(2)*var_z1t(-1),1)
dcc.append var_z2t=@nan(1-T(1)-T(2)+T(1)*(z2(-1)^2)+T(2)*var_z2t(-1),1)
dcc.append cov_z1tz2t=@nan((1-T(1)-T(2))*corr12+T(1)*z1(-1)*z2(-1)+T(2)*cov_z1tz2t(-1),1)

dcc.append pen=(var_z1t<0)+(var_z2t<0)

'specify rho12
dcc.append rho12=cov_z1tz2t/@sqrt(@abs(var_z1t*var_z2t))

'defining the determinant of correlation matrix and determinant of Dt
dcc.append detrRt=(1-(rho12^2))
dcc.append detrDt=@sqrt(garch1*garch2)
dcc.append pen=pen+(detrRt<0)
dcc.append detrRt=@abs(detrRt)

'define the log likelihood function
dcc.append logl=(-1/2)*(2*log(2*pi)+log(detrRt)+(z1^2+z2^2-2*rho12*z1*z2)/detrRt)-10*pen

'estimate the model
smpl s1
dcc.ml(showopts, m=500, c=1e-5)

'display output and graphs
show dcc.output
graph corr.line rho12
show corr
```

Appendix 4(H) VBA Code for Blended Real Estate Optimisation

```
Sub Blended2()

' Blended2 Macro

' Keyboard Shortcut: Ctrl+k

'

For i = 1 To 98

Worksheets("LD_" & i).Activate


    ActiveWindow.SmallScroll Down:=-15

    Range("B38").Select

    SolverReset

    SolverOk SetCell:="$E$37", MaxMinVal:=2, ValueOf:=0, ByChange:="$B$28:$L$28", _

        Engine:=1, EngineDesc:="GRG Nonlinear"

    SolverAdd CellRef:="$B$28:$L$28", Relation:=3, FormulaText:="0"

    'Set minimum return to average real estate return

    SolverAdd CellRef:="$B$33", Relation:=3, FormulaText:="$L$25"


    SolverAdd CellRef:="$B$36", Relation:=2, FormulaText:="1"

    'Set real estate return = 0/0.50/0.7/0.8 OR 0.9

    SolverAdd CellRef:="$L$28", Relation:=2, FormulaText:="0.90"


    SolverOk SetCell:="$E$37", MaxMinVal:=2, ValueOf:=0, ByChange:="$B$28:$L$28", _

        Engine:=1, EngineDesc:="GRG Nonlinear"

    SolverOk SetCell:="$E$37", MaxMinVal:=2, ValueOf:=0, ByChange:="$B$28:$L$28", _

        Engine:=1, EngineDesc:="GRG Nonlinear"

    SolverSolve userFinish:=True

        SolverFinish keepFinal:=1

Next

ActiveWorkbook.Save

End Sub
```

Appendix 4(I) VBA Code for Mean-Tracking Error Optimisation Model

```
Sub modified()

' modified Macro

' Keyboard Shortcut: Ctrl+m

For i = 1 To 78

Worksheets("LD_" & i).Activate

ActiveWindow.SmallScroll Down:=-9

    SolverReset

    SolverOk SetCell:="$B$43", MaxMinVal:=2, ValueOf:=0, ByChange:="$B$28:$AG$28", _

        Engine:=1, EngineDesc:="GRG Nonlinear"

'No short sale constraint

    SolverAdd CellRef:="$B$28:$AG$28", Relation:=3, FormulaText:="0"

'Weight of liability benchmark = 0

    SolverAdd CellRef:="$AG$28", Relation:=2, FormulaText:="0"

'Sum of weights = 1

    SolverAdd CellRef:="$B$40", Relation:=2, FormulaText:="1"

        SolverOk SetCell:="$B$43", MaxMinVal:=2, ValueOf:=0, ByChange:="$B$28:$AG$28", _

        Engine:=1, EngineDesc:="GRG Nonlinear"

    SolverSolve userFinish:=True

    SolverFinish keepFinal:=1

    Next

ActiveWorkbook.Save

End Sub
```

Appendix 4(J) VBA Code for Mean-Semi-Variance Optimisation Model

```
Sub modified()

' modified Macro

' Keyboard Shortcut: Ctrl+m

For i = 1 To 78

Worksheets("LD_" & i).Activate

ActiveWindow.SmallScroll Down:=-9

    SolverReset

    SolverOk SetCell:="$B$38", MaxMinVal:=2, ValueOf:=0, ByChange:="$B$28:$AG$28", _

        Engine:=1, EngineDesc:="GRG Nonlinear"

'No short sale constraint

    SolverAdd CellRef:="$B$28:$AG$28", Relation:=3, FormulaText:="0"

'Sum of liability benchmark = 0

    SolverAdd CellRef:="$AG$28", Relation:=2, FormulaText:="0"

'Sum of weights = 1

    SolverAdd CellRef:="$B$40", Relation:=2, FormulaText:="1"


    SolverOk SetCell:="$B$38", MaxMinVal:=2, ValueOf:=0, ByChange:="$B$28:$AG$28", _

        Engine:=1, EngineDesc:="GRG Nonlinear"

    SolverSolve userFinish:=True

    SolverFinish keepFinal:=1


Next

ActiveWorkbook.Save


End Sub
```

Appendix 4(K) VBA Code for Sharpe Ratio Optimisation Model

```
Sub modified()

' modified Macro

' Keyboard Shortcut: Ctrl+m

For i = 1 To 78

Worksheets("LD_" & i).Activate

ActiveWindow.SmallScroll Down:=-9

    SolverReset

    SolverOk SetCell:="$B$48", MaxMinVal:=1, ValueOf:=0, ByChange:="$B$28:$AG$28", _

        Engine:=1, EngineDesc:="GRG Nonlinear"

'No short sale constraint

    SolverAdd CellRef:="$B$28:$AG$28", Relation:=3, FormulaText:="0"

'Sum of liability benchmark = 0

    SolverAdd CellRef:="$AG$28", Relation:=2, FormulaText:="0"

'Sum of weights = 1

    SolverAdd CellRef:="$B$40", Relation:=2, FormulaText:="1"


    SolverOk SetCell:="$B$48", MaxMinVal:=1, ValueOf:=0, ByChange:="$B$28:$AG$28", _

        Engine:=1, EngineDesc:="GRG Nonlinear"

    SolverSolve userFinish:=True

    SolverFinish keepFinal:=1


Next

ActiveWorkbook.Save


End Sub
```

Appendix 4(L) VBA Code for Sortino Ratio Optimisation Model

```
Sub modified()
'
' modified Macro
'
' Keyboard Shortcut: Ctrl+m
'
For i = 1 To 78
Worksheets("LD_" & i).Activate
ActiveWindow.SmallScroll Down:=-9
    SolverReset
    SolverOk SetCell:="$B$46", MaxMinVal:=1, ValueOf:=0, ByChange:="$B$28:$AG$28", _
        Engine:=1, EngineDesc:="GRG Nonlinear"
'No short sale constraint
    SolverAdd CellRef:="$B$28:$AG$28", Relation:=3, FormulaText:="0"
'Sum of liability benchmark = 0
    SolverAdd CellRef:="$AG$28", Relation:=2, FormulaText:="0"
'Sum of weights = 1
    SolverAdd CellRef:="$B$40", Relation:=2, FormulaText:="1"

    SolverOk SetCell:="$B$46", MaxMinVal:=1, ValueOf:=0, ByChange:="$B$28:$AG$28", _
        Engine:=1, EngineDesc:="GRG Nonlinear"
    SolverSolve userFinish:=True
    SolverFinish keepFinal:=1

Next
ActiveWorkbook.Save
```

Appendix 4(M) E-Views Code for Estimating Dynamic Conditional Correlations

```
load "sample s1"
'set sample range
sample s1 1992Q3 2014Q4
scalar pi=3.14159

'defining the return series in terms of y1 and y2
series y1=ipd_all
series y2=uk_cpi

'fitting univariate GARCH(1,1) models to each of the two returns series
equation eq_y1.arch(1,1,m=1000,h) y1 c
equation eq_y2.arch(1,1,m=1000,h) y2 c

'extract the standardized residual series from the GARCH fit
eq_y1.makeresids(s) z1
eq_y2.makeresids(s) z2

'extract garch series from univariate fit
eq_y1.makegarch() garch1
eq_y2.makegarch() garch2

'Caculate sample variance of series z1, z2 and covariance of z1and z2 and correlation between z1 and z2
scalar var_z1=@var(z1)
scalar var_z2=@var(z2)
scalar cov_z1z2=@cov(z1,z2)
scalar corr12=@cor(z1,z2)

'defining the starting values for the var(z1) var(z2) and covariance (z1,z2)
series var_z1t=var_z1
series var_z2t=var_z2
series cov_z1tz2t=cov_z1z2

'declare the coefficient starting values
coef(2) T
T(1)=0.2
T(2)=0.7
' ..........................................................
' LOG LIKELIHOOD for correlation part
' set up the likelihood
' 1) open a new blank likelihood object and name it 'dcc'
' 2) specify the log likelihood model by append
' ..........................................................
logl dcc
dcc.append @logl logl

'specify var_z1t, var_z2t, cov_z1tz2t
dcc.append var_z1t=@nan(1-T(1)-T(2)+T(1)*(z1(-1)^2)+T(2)*var_z1t(-1),1)
dcc.append var_z2t=@nan(1-T(1)-T(2)+T(1)*(z2(-1)^2)+T(2)*var_z2t(-1),1)
dcc.append cov_z1tz2t=@nan((1-T(1)-T(2))*corr12+T(1)*z1(-1)*z2(-1)+T(2)*cov_z1tz2t(-1),1)

dcc.append pen=(var_z1t<0)+(var_z2t<0)

'specify rho12
dcc.append rho12=cov_z1tz2t/@sqrt(@abs(var_z1t*var_z2t))

'defining the determinant of correlation matrix and determinant of Dt
dcc.append detrRt=(1-(rho12^2))
dcc.append detrDt=@sqrt(garch1*garch2)
dcc.append pen=pen+(detrRt<0)
dcc.append detrRt=@abs(detrRt)

'define the log likelihood function
dcc.append logl=(-1/2)*(2*log(2*pi)+log(detrRt)+(z1^2+z2^2-2*rho12*z1*z2)/detrRt)-10*pen

'estimate the model
smpl s1
dcc.ml(showopts, m=500, c=1e-5)

'display output and graphs
show dcc.output
graph corr.line rho12
show corr
```

CHAPTER FIVE – ESTIMATING AND MANAGING LIQUIDITY WITHIN PENSION FUND INVESTMENT PORTFOLIOS

5.0 INTRODUCTION

This chapter is in two parts. The first part a review literature on the different ways in which liquidity is captured and measured within asset markets and the extent to which these approaches have been adopted within the real estate market. In part two, we look at different ways in which liquidity can be managed within the portfolios of institutional investors such as pension funds. We also provide a discussion of how liquidity affects the investment decisions of pension funds, specifically UK DC pension funds. A version of this chapter has been published by the Journal of Real Estate Literature under the title: Liquidity, a review of dimensions, causes and empirical applications in real estate markets.[1]

An asset can be said to be liquid if large quantities can be traded in a short period of time without moving the price too much. Accordingly, several alternative measures of liquidity have been used in the literature, including the price impact of trade, the bid–ask spread, share or dollar volume, and turnover, among others. Liquidity from an institutional investor's point of view is the ability to meet their obligations as and when they fall due, at all or without incurring significant costs. The goal of liquidity management is to ensure that there is no misalignment of an investment portfolio's liquidity profile and the cash flow demands of investors (Kathura and Myers, 2013).

We can think of several obvious ways in which an investor benefits from having a good liquidity management system in place. Some of these are the ability to: (i) exercise market timing skill, (ii) rebalance a portfolio, (iii) meet capital calls, (iv) reallocate part of the portfolio to newly discovered opportunities or exit from unproductive investments, and (v) respond to shifts in risk appetite.

Portfolio Rebalancing: Investors choose portfolios they believe are optimal given their views and attitude about expected return and risk. Once they establish their optimal portfolio, however, price changes among the component assets cause the actual weights of the portfolio to drift away from the optimal targets, and the portfolio becomes sub-optimal. If the portfolio comprises only liquid assets, investors can restore the optimal weights easily, though not without cost. However, to the extent that some portion of the portfolio is allocated to illiquid assets, investors cannot implement the full solution, and

[1] Ametefe, F., Devaney, S., & Marcato, G. (2016). Liquidity: A review of dimensions, causes, measures, and empirical applications in real estate markets. *Journal of Real Estate Literature*, *24*(1), 1-29.

the portfolio remains sub-optimal. For example, the 2008 financial crisis left many investors coping with illiquidity at a time when the liquid portion of their portfolios experienced significant losses in value. As the liquid portion of a portfolio loses value, the illiquid portion represented a larger share of the portfolio than before. However, these illiquid assets could not be sold to meet immediate liquidity needs without incurring significant losses.

Capital Calls: Investors periodically need to liquidate a portion of their portfolios to meet capital calls. Pension funds, for example, may need to raise cash in order to make unanticipated benefit payments to retirees. Many endowment funds and foundations commit to private equity and real estate funds which demand capital sporadically as investment opportunities arise. Private investors occasionally need to replace lost income to meet their consumption demands. These liquidations may drive the portfolio away from its optimal mix, and to the extent that part of the portfolio is allocated to illiquid assets, the investor may not be able to restore full optimality.

Market Timing: Some investors are skilled at anticipating the relative performance of asset classes or risk factors. This improves the expected utility beyond the portfolio's initial expected utility.

New Opportunities: Investors may discover new managers or strategies or just better ways to reconfigure their existing portfolios. Alternatively, investors may wish to exit existing positions they no longer expect to perform as originally contemplated.

Shifting Risk Appetite: Investors may become more or less averse to risk as their circumstances change. The presence of illiquid assets limits the extent to which investors can respond to their shifting risk appetites.

The Pension Regulator (2016) believes that investment governance within DC schemes is one of the most influential factors in the delivery of good outcomes for DC members. Consequently, all trustee members are expected to have a good understanding of issues relating to investment and to always make decisions based on advice from qualified persons. A qualified investment manager is required for the management of any investments. Regarding liquidity, the Code of Practice references the Occupational Pension Schemes Regulation (2005) which requires that trustee boards invest predominantly in assets that are traded on a regulated market. Although DC pension funds can invest in investment options that are not traded on a regulated market, they are expected to identify these assets as such in their Statement of Investment Principles and offer an explanation of why they believe it is appropriate to include these assets in that form. They should also spell out how these illiquid investments align with the objectives set out in their Statement of Investment Principles. Section 108 of the Code of Practice requires that consideration is also given to asset protection and what would happen in the event of a problem. Factors such as indemnity insurance, compensation schemes applicable and the overall conclusion about the security of assets to members and employers. DC providers are also required to be in constant communication with members about when and how they wish to take their DC benefits. In particular, matters such as flexible access to benefits and the particular approaches to investment of members must be taken into account.

It is important liquidity guidelines are incorporated into the investment policy statements of institutional investors under the risk management section or a separate liquidity management section. A clear liquidity guideline is vital especially during periods of market stress. This guideline serves to document the degree of acceptable liquidity during both normal and stress market environments. Liquidity management should be part of a broader risk management practice. Consequently, the liquidity profile of investment portfolios should be analysed along with other indicators of portfolio risk such as the standard deviation, value at risk, maximum drawdown etc. Also, given the impact that regulatory changes have on portfolios, it is also important for asset managers and trustees stay abreast with regulatory changes. This would ensure that they can better analyse the liquidity implications of each change (Kathura and Myers, 2013).

5.1 LIQUIDITY: DIMENSIONS AND CAUSES

The role of liquidity in determining asset prices is the subject of a vast research literature spanning a period of more than thirty years. A recent paper by Brunnemeier and Pedersen (2009) both theoretically and numerically modeled the relationship between the two main aspects of an asset's liquidity: trading as defined by "the ease with which it is traded" and funding, represented by "the ease with which investors or traders can obtain funding."

Goodhart (2008) contends that liquidity has so many facets that it is often counter-productive to use it without further and closer definition. In this spirit, Bond et al. (2004) spent the main part of their literature review addressing this definition in the context of real estate markets reached, among others, two main conclusions:

- liquidity does not only represent the amount of transaction activity but its impact on costs and prices as well;
- no unique definition of liquidity exists and research should consider several dimensions of this risk.

Furthermore, adding one dimension to the ones highlighted in Bond et al. (2004), we can identify five main characteristics of market liquidity:

(i) Tightness: the cost of trading even in small amounts;

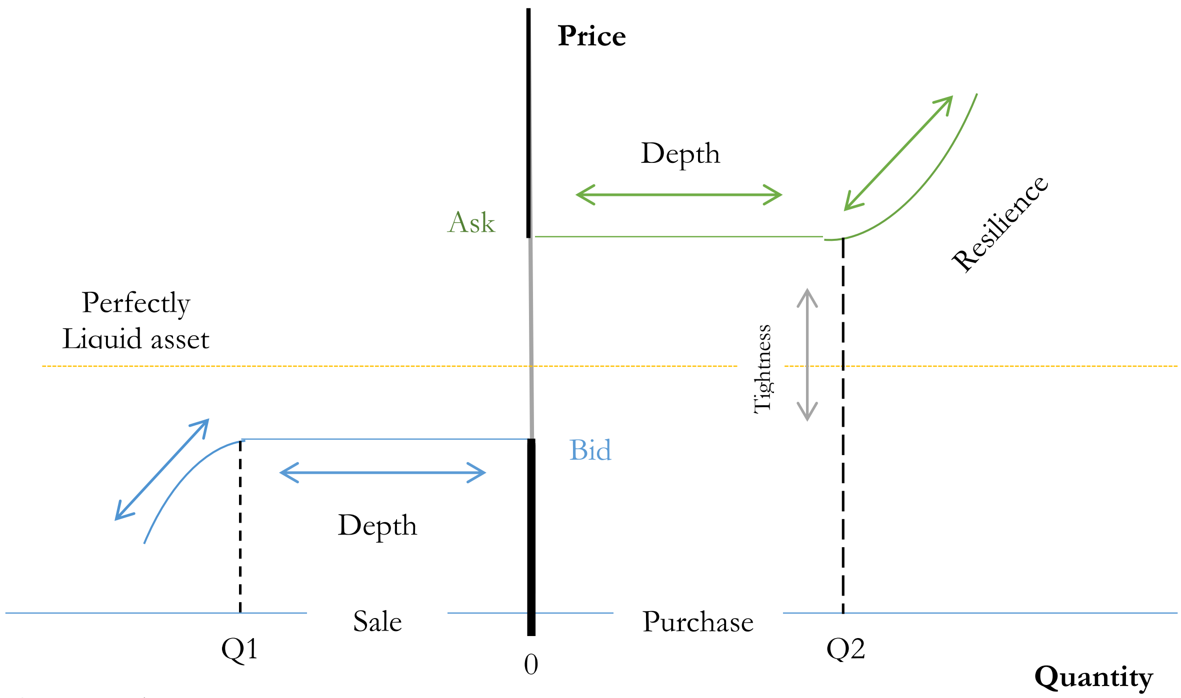
(ii) Depth: the capacity to sell/buy without causing price movements;

(iii) Resilience: the speed at which the marginal price impact increases as trading quantities increase;

(iv) Breadth: the overall size of the volume traded;

(v) Immediacy: the cost (discount/premium) to be applied when selling/buying quickly.

Figure 5(1) Dimensions of market liquidity.



Source: Kyle (1985)

Following from Kyle (1985), the first three dimensions of market liquidity are graphically represented in Figure 5(1) – adapted from Kerry (2008) – where demand and supply curves can be compared with the ones of a perfectly liquid asset. On the demand side (Purchase), even with a minimum amount of transacted volumes, the buyer needs to pay a cost to enter the transaction (normally referred as one half of the bid/ask spread). If the buyer then decides to increase the order flow, initially the marginal impact (i.e. first derivative of the demand function) is zero and the length of this horizontal part of the curve defines the market depth of an asset. However, after a certain threshold, the marginal impact of an additional unit of trading volume increases and the speed of this continuous increase defines the resiliency of such market. The same (but inversely) applies to a seller and the supply function (Supply). Clearly, both demand and supply functions for a liquid asset (represented with a dotted line) are flat as no price impact is identified for any volume of trading activity.

If markets were fully efficient, assets would be perfectly liquid. In other words, assets with similar cash flows should reflect similar valuations. However, some asset/market characteristics may lead to different valuations (and expected returns) for investments with similar cash flows and the main reason for such differences is the presence of market imperfections. A recent working paper by Vayanos and Wang (2012), following other works done by O'Hara (1995) and Hasbrouck (2007) in market microstructure and Amihud et al (2005) in asset pricing – surveyed the liquidity literature both theoretically and empirically. They categorise market imperfections in six main groups we briefly present.

Firstly, participation costs arise because there is no immediate and continuous access to the entire population of counterparty agents in a trade (i.e. sellers cannot interact with all buyers and vice versa). Hence agents have to incur in a cost to enter the market and this makes agents willing to invest only if a compensation for this cost is offered in terms of liquidity premium (Huang and Wang, 2009; Amihud and Mendelson, 1980). Another consequence is the infrequent arrival of agents into the market, with market makers almost obliged to take losses. A clear example of such expenses in real estate markets is represented by the absence (for some market segments) of an active secondary market (e.g. derivative products for small market segments) and the entry of hedge funds and more aggressive players just before and during the most recent economic crisis.

Secondly, transaction costs refer to the expenses associated with the execution of a trade and can make the effective buying and selling price of the same transaction diverge. A consequence is that assets with transaction costs trade at a lower price in equilibrium (i.e. offer a premium) but this effect can be mitigated by the lengthening of the investment horizon (Amihud and Mendelson, 1986; Acharya and Pedersen, 2005; Beber et al, 2012). Examples of transaction costs are represented by taxes and brokerage fees, which are notoriously higher for assets such as real estate (in the UK we can assume that the cost associated to the buyer and seller is approximately equal to respectively 5.25% and 2.25%). Another clear example is offered by a measure of tightness (in the categorisation above) which indicate different levels of liquidity in the difference between bid-ask spreads in equity and property derivatives (i.e. total return swaps) markets.

Thirdly, asymmetric information can exist because agents have access to private information (not observable by others), or information are obtained by different sources or processed differently. This situation will lead to a liquidity premium agents want to access to invest in markets with a high proportion of private information (O'Hara, 2003; Easley and O'Hara, 2004) and it can also cause spill-over effects for asset/market liquidity because of information inefficiencies (Cespa and Foucault, 2014). This market imperfection is especially key for markets with scarce and thin information such as real estate, where we can observe a greater difference of offer prices than in more efficient markets such as the ones of equities or bonds.

Fourth, imperfect competition is linked to the different dimension of market players and hence their asymmetric impact on prices which is either due to their size or information advantage. The main seminal work in this area is Kyle (1985, 1989) which is used to show dynamics of risk sharing (DeMarzo and Urosevic, 2006; Brunnermeier and Pedersen, 2005). It has also by Glosten (1989) to demonstrate the conditions for market failure and further extended to incorporate different speeds of information revelation caused by risk averse agents (Baruch, 2002) , insiders (Chau and Vayanos, 2008) and the presence of regulation (Huddart et al., 2001). The issue of imperfect competition is even more important for heterogeneous and non-divisible goods like real assets. For example, small investors cannot obtain trading information which is only available to large fund managers, and they do not have access to investment opportunities because of diversification issues that these investments may cause relative to the dimension of other assets in the portfolio (Fuerst and Marcato, 2009).

Fifth, funding constraints do not allow agents to borrow freely hence restricting their capacity to invest in some markets or segments. This phenomenon may be linked to the uncertainty attached to the liquidation value (Hart and Moore, 1994, 1995; Schleifer and Vishny, 1992) and limits to financing applied on intermediaries offering liquidity (Gromb and Vayanos, 2002; Liu and Longstaff, 2004). Furthermore, a possible contagion (or spiral) effect is found for assets that would be otherwise unrelated as we have seen over the 2008 financial crisis (Brunnermeier and Pedersen, 2009) especially for agents with a short investment horizon (Scleifer and Vishny, 1997) and even for optimal contracts (Acharya and Viswanathan, 2011). Funding constraints are probably the one market imperfection which interacts most with all other imperfections. Hence Albagli (2011) and Bai et al. (2006) among others have focused on this interaction to tease out plausible amplifying effects.

Finally, search costs arise from a decentralised form of organization – the normal way OTC (over-the-counter) markets operate – and they are associated to the need of finding a counterparty (Duffie et al. 2002, 2005, 2008) and Vayanos and Wang (2007) among others. This market imperfection is particularly applicable to direct real estate and other unlisted financial products based on those assets (e.g. property derivatives and unlisted funds). A vast literature on this cause of liquidity has also been developed for the housing sector.

5.2 MEASURES OF LIQUIDITY

Liquidity itself is not observable and therefore, has to be proxied by different liquidity measures. Market microstructure and finance literature have identified several trading variables that measure different dimensions of liquidity, thus reflecting the need to capture all these facets separately. Moreover, some studies have shown that mixed results in liquidity premiums may be due to the use of different aspects of the overall liquidity risk (Baker, 1996; Bertin et al., 2005). As a consequence, we have decided to identify a series of measures which may be helpful to describe liquidity and compare results across assets and market segments.

In the following part of this chapter, we present several indicators used in the literature and we group them into four main categories:

(i) Transaction Cost Measures
(ii) Volume-Based Measures
(iii) Time-Based Measures
(iv) Price Impact Measures
(v) Return-Based Measures

Our classification is analogous to that of Sarr and Lybeck (2002) but we extend it by adding time-based measures, extensively used for real estate assets and isolating return-based measures as a separate category.

5.2.1 TRANSACTION COST MEASURES

Transaction cost measures are those that capture the cost of trading financial assets and the trading frictions in financial markets. Amihud and Mendelson (1986) state that "illiquidity can be measured by the cost of immediate execution." They go on to say "a natural measure of illiquidity is the spread between the bid and ask prices." Hence, larger bid-ask spreads are widely regarded as evidence of more illiquid securities. The difference between the ask and bid price and its related measures gives an approximation of the cost incurred when trading. In addition to fees and taxes, the trader has to pay the spread as cost for the immediate execution of a trade.

Demsetz (1968) was the first to analyse bid-ask spreads empirically, and numerous researchers have followed his path breaking work. Acker et al. (2002) for examined the determinants of bid-ask spreads and their behavior around corporate earnings announcement dates. The spread is used to determine where price discovery takes place in Harris et al. (2002), a study that compares trading at different stock exchanges. The smaller the spread-related liquidity measures are, the more liquid the market is. In the remaining part of this section, we present several measures of bid-ask spreads.

5.2.1.1 Absolute (Quoted) Spread

The absolute spread is the difference between the lowest ask price and the highest bid price. The absolute spread *(sabs)* is thus calculated as follows:

$$Sabs_t = p_t^A - p_t^B \qquad \textbf{5(1)}$$

where p_t^A is the lowest ask price and p_t^B the highest bid price.

This measure is always positive and its lower limit is the minimum tick size. For small orders, the quoted spread is a good indication of the execution cost for a trade. For large orders, however, it may not fully represent the cost.

Chordia et al. (2001) use this measure in their study of the NYSE and Grammig et al. (2001) with data on the German stock market. It is intensively investigated for the whole market and for single market makers in Barclay et al. (1999) who analyze the impact of the NASDAQ market reforms of 1997, which ended the collusion among market makers to artificially inflate the spreads. The absolute spread differs also across the NYSE specialist firms as Corwin (1999) shows. Another study using individual dealer's data is Christie and Schultz (1998) who investigate the liquidity provision during the 1991 market break, when the index fell over 4%. Karagozoglu (2000) divides the quoted spread by two but had to calculate it out of the average price reversals because quote data is not available in the futures market.

The absolute spread may be logarithmized to improve its distributional properties. It is used in Hamao and Hasbrouck (1995) because its distribution is closer to a normal than the absolute spread and, therefore, mathematically easier to use.

$$LogSabs_t = ln(p_t^A - p_t^B) \qquad \textbf{5(2)}$$

5.2.1.2 Relative Spread

The relative spread is the liquidity measure most extensively studied because it is easy to calculate and because it makes spreads of different stocks comparable to each other. Sometimes this measure is also referred to as "inside spread" as in Levin & Wright (1999). Another advantage is that it may be calculated even if no trade takes place, in contrast to the relative spread calculated with the last trade.

$$Srel\_mid_t = \frac{\left(p_t^A - p_t^B\right)}{\frac{p_t^A + p_t^B}{2}} \qquad \textbf{5(3)}$$

$$Srel\_last_t = \frac{p_t^A - p_t^B}{p_t} \quad \textbf{5(4)}$$

where p_t denotes the last paid price of the asset before time *t*.

5.2.1.3 Effective Spread

Bid–ask spread measures reflect the cost of transacting in the market, but these measures are subject to criticism. For example, Grossman and Miller (1988) and Lee et al. (1993) argue that the quoted bid–ask spread is a noisy and inadequate measure of liquidity, since a large number of transactions take place at prices other than the quotations. The effective spread better captures the cost of a round-trip order by including both price movement (dealers coming in to execute orders at a better price than previously quoted) and market impact (spread widening due to the size of the order itself). It is computed as follows:

$$Seff_t = \left| p_t - p_t^M \right| \quad \textbf{5(5)}$$

where p_t denotes the last traded price before time t and the mid-quote price p_t^M is obtained by:

$$p_t^M = \frac{p_t^A + p_t^B}{2} \quad \textbf{5(6)}$$

If the effective spread is smaller than half the absolute spread, this reflects trading within the quotes. Sometimes the effective spread and all the following related measures may be multiplied by two to make them better comparable to the other spread measures, as in Barclay et al. (1999), Bacidore (1997), Bacidore et al. (2002), Breedon and Holland (1997), Jones and Lipson (1999), or Lin et al. (1995). In Lee et al. (1993) this doubled effective spread is weighted with the trade size to get an average effective spread for a certain period. This yields similar results as weighting with the number of trades does. Using the effective spread, Battalio et al. (1998) calculate a liquidity premium: $LP_t = I \cdot (p_t - p_m^t)$ where *I* is the direction of trade indicator. *I* equals 1 for buyer initiated trades and -1 for seller initiated trades. This liquidity premium is positive if the buyer pays more or if the seller pays less than the spread midpoint.

5.2.1.4 Relative Effective Spread

The relative effective spread can be calculated with last trade or with mid-price. The relative measure allows comparability across different stocks. Also the relative effective spread may be doubled to compare it to other relative spread measures.

$$Sreleff\_mid_t = \frac{\left|p_t - p_t^M\right|}{p_t^M} \quad 5(7)$$

$$Sreleff\_last_t = \frac{\left|p_t - p_t^M\right|}{p_t} \quad 5(8)$$

where p_t denotes the last traded price before time t and the mid-quote price p_t^M is obtained from above.

5.2.2 VOLUME BASED LIQUIDITY MEASURES

Volume-based measures distinguish liquid markets by either the absolute or relative amount of transactions compared to the price variability, primarily to measure breadth and depth. Barclay et al. (1998) emphasize volume measures as better indicators of liquidity than price discounts. Volume of trading has been measured in a variety of ways, including the number of shares traded, dollar volume of shares traded and the number of transactions. Volume-based measures are most useful in measuring the breadth of the market and include: (i) Transaction Volume, (ii) Trading Frequency, (iii) Turnover Ratio, (iv) Quote Size and (v) Herfindhal Index

5.2.2.1 Transaction Volume

Trading volume is an indirect but widely cited measure of market liquidity. Its popularity derives from empirical evidence that more active markets such as treasury bonds markets tend to be more liquid, and from theoretical studies linking increased trading activity with improved liquidity through ease of access and decrease in transaction costs. The popularity of such a measure (sometimes represented by 'order flows' in equity markets) reflects its simplicity and availability, with volume figures regularly reported for most assets. A drawback, however, is its association with market volatility which may reduce market liquidity (Karpoff, 1987).

Transaction volumes for a given period *t* (i.e. the dollar volume traded Vol_t) are computed as the sum of individual *i* trades within the period (computed as prices P_{it} times quantities Q_{it}).

$$Vol_t = \sum_{i=1}^{n} P_{it} Q_{it} \quad 5(9)$$

Empirical investigations of common stock intraday patterns initially focused solely on trading volume. The first comprehensive theory to explain intraday trading behavior within the context of a strategic trader model including informed traders and both discretionary and non-discretionary liquidity traders was presented by Admati and Pfleiderer (1988). The informed and discretionary liquidity traders prefer to trade when they have the least effect on price, and this desire creates a strong incentive to trade when other traders are active. Their model suggests that the periods immediately after the open and before the close are unique for this purpose and will incur lower trading costs due to higher liquidity. Therefore traders may have a preference for trading during these high liquidity periods among nondiscretionary traders, and this may result in other traders gravitating to these time periods as well. Based on this explanation, Brock and Kleidon (1992) model the bid–ask spread during the day and conclude that the intraday pattern should be U-shaped, if the intraday pattern in volume is also U-shaped. Empirically, Jain and Joh (1988) found a U-shaped pattern in intraday volumes for stocks of the S&P 500 Index. Similarly, Foster and Viswanathan (1993) report that stocks with relatively low volume exhibit a more pronounced U-shaped pattern than high volume stocks.

5.2.2.2 Turnover Ratio

Turnover gives an indication of the number of times the outstanding volume of an asset changes hands within a specified time period:

$$Turn_n = \frac{Vol}{(S*P)} \qquad \textbf{5(10)}$$

where Vol is the transaction volume, S is the number of outstanding stocks of a certain asset and P is the average price of the *i* trades in the equation for transaction volumes. While its computation is easy for exchange traded securities, an adequate coverage of transaction volumes and estimation of existing stocks represent critical issues for assets traded over the counter (i.e. OTC products), such as real estate.

Amihud and Mendelson (1986) show that this measure is negatively related to illiquidity costs. In fact, when the turnover ratio is low, market makers tend to charge a higher transaction cost to cover the risk of holding their position – i.e. the higher the turnover ratio, the more liquid the stock is.

Turnover has been a popular liquidity measure in the previous literature (Rouwenhorst, 1999; Chordia and Swaminathan, 2000 and Dennis and Strickland, 2003). The theoretical motivation for using turnover as a liquidity proxy goes back to Demsetz (1968) who shows that the price of immediacy would be smaller for stocks with high trading frequency since frequent trading reduces the cost of inventory controlling. Glosten and Milgrom (1985) also show that stocks with high trading volume would have lower level of information asymmetry to the extent that information is revealed by prices.

Finally, Constantinides (1986) finds that investors would increase their holding periods (thus, reduce turnover) when a stock is highly illiquid.

5.2.2.3 Quote Size

Quote size refers to the quantity of securities tradable at the bid and offer prices. It accounts for market depth and complements the bid-ask spread. Market makers often do not reveal the full quantities they will transact at a given price so the measured depth underestimates the true depth.

$$Quote\ Size = \frac{Average\ No\ of\ Transacted\ Assets}{Average\ Size\ of\ the\ Market} \quad \mathbf{5(11)}$$

A related measure to quote size is the quantity of securities traded at the bid and offer prices, reflecting any negotiation over quantity i.e. the trade size. A drawback of this measure is the availability of such information as market makers may not reveal this amount. It can also underestimate market depth because the quantity traded is often less than the quantity that could have been traded at a given price.

5.2.2.4 Number of Bids

The number of investors who put in their bid for a particular asset can be used as a measure of liquidity in that market. The larger number of bids, the easier the trading should be because it should be easier to find a counterparty for the transaction. A more liquid fund interest is likely to generate greater buyer interest which should translate into a greater number of bids.

Kleymenova et al. (2002) uses the number of bids, computed as the natural logarithm of the number of individual spot or portfolio bids received for a particular asset in the first round of bidding, to find that this measure to be highly correlated with the number of bidders. Kleymenova et al. (2002) used this to gauge the liquidity of Private Equity Markets. This measure has also been used in the corporate bond market – see Gehr and Martell (1992) and Jankowitsch et al. (2002).

5.2.2.5 Market Depth

The market depth at time *t*, D_t is also referred to as "quantity depth" (Huberman and Halka, 2001) or "volume depth" (Brockman and Chung, 2000). It is computed as the sum of bid and ask volumes at time *t*. Corwin (1999) shows that market depth differs significantly among the NYSE specialist firms, and Corwin & Lipson (2000) investigate depth around trading halts. Greene & Smart (1999) look at abnormal depth due to liquidity trading.

$$Depth = q_t^A + q_t^B \quad \mathbf{5(12)}$$

To improve the distributional properties of this measure, the log depth (*Dlogt*) may be used, as in Butler et al. (2002). The log depth measure is computed as follows:

$$Log\ Depth = ln\left(q_t^A + q_t^B\right) \qquad \mathbf{5(13)}$$

As the market depth for bid and ask can be computed separately, the overall depth may also be obtained as an average between the two (Chordia et al, 2001; Goldstein and Kavajecz, 2000; Sarin et al., 1996). As the depth measures of the bid- and the ask-sides of the limit order book are not symmetrical and do not necessarily move in common, the computation of separate measures may be helpful to study both dimensions of liquidity (Kavajecz, 1999; Kavajecz and Odders-White, 2001).

5.2.3 PRICE IMPACT MEASURES

Price impact measures attempt to differentiate between price movements due to the degree of liquidity from other factors such as general market conditions or arrival of new information. Bernstein (1987) noted that, measures of liquidity when no information is hitting a stock must be more relevant than measures of liquidity when new information leads to new equilibrium values. They include: (i) Amihud measure (ii) Percentage of 0% return and (iii) Market efficiency coefficient.

5.2.3.1 Amihud measure

Amihud measure has been widely used in the literature (Avramov et al., 2006; Watanabe and Watanabe, 2008 and Karolyi et al., 2011) normally with a monthly frequency and it is computed as follows:

$$Amihud_t = \frac{1}{n}\sum_{i=1}^{n}\frac{|TR_i|}{Vol_i} \qquad \mathbf{5(14)}$$

where t and n respectively refer to the month and number of trading days in a month, while TR_i and Vol_i represent the total return and transaction volume of an asset/market on the day i of month t.

This liquidity measure has its advantage in solving the problem of nonlinear relation between transaction costs and trading volume since economies of scale sometimes do exist for institutional traders or for investors with large trading volume and commission discounts.

5.2.3.2 Regressed lambda

An alternative measure to the Amihud illiquidity is represented by the regression coefficient of returns on the signed volume of transaction activities as represented by the following:

$$TR_t = a + lVol_t + \sum_{j}^{m} \delta_j * Z_{jt} \quad 5(15)$$

where λ is the illiquidity measure which represents the price impact per unit of trade due to the existence of market imperfections, while Z_{jt} and δ_j represent respectively j control variables and their estimated coefficients.

5.2.3.3 Pastor-Stambaugh Liquidity Factor

This liquidity dimension is associated with temporary price changes accompanying order flow. Pastor and Stambaugh (2003) construct a measure of market liquidity in a given month as the equally weighted average of the liquidity measures of individual assets, using daily data within the month.

Particularly, the liquidity factor for asset i at time t is computed as γ_{it} coefficient estimated as follows:

$$r^e_{i,d+1,t} = \theta_{i,t} + \omega_{i,t} r_{i,d,t} + \gamma_{i,t} sign\left(r^e_{i,d,t}\right) * Vol_{i,d,t} + \epsilon_{i,d+1,t} \quad 5(16)$$

Where $r_{i,d,t}$ is the return of asset i in day d of the month t, while $r^e_{i,d,t}$ is the same return but in excess of the market return and $sign(.) * Vol_{i,d,t}$ represents the signed transaction volumes (positive if the excess return is positive and negative viceversa).

The liquidity measure γ_{it} is linked to the idea that the signed transaction volume should lead to an expectation of reversal in future returns and hence the estimated value should be negative and increasing in absolute value for assets/periods with higher illiquidity.

5.2.3.4 Percentage of 0% Return

Lesmond et al. (1999) developed a model to estimate transaction costs in which the only data requirement is the time series of daily stock returns. The basic assumption is that, on average, a zero return is observed if expected return does not exceed the transaction cost threshold. Therefore, high transactions costs result in zero return days. In addition, investors have relatively low incentive to obtain private information for stocks with high transaction costs and, as a results, most trades are noise trades which more likely lead to zero-return, and possibly positive volume, days. Bekaert et al. (2007) use the Zeros measure as one of liquidity measures in examining liquidity and expected return in emerging markets and find that this measure is able to significantly predict future returns. The measure is computed as:

$$ZR_{i,t} = \frac{N_{i,t}}{T_t} \quad 5(17)$$

where:

T_t=number of trading days in a month t

$N_{i,t}$=number of zero-return days of stock i in month t

Bekaert et al. (2007) demonstrate that this measure is highly correlated with more traditional measures of transaction costs for emerging equity markets. Lesmond (2005) provides a detailed analysis of emerging equity market trading costs, and confirms the usefulness of this measure. For the period from the mid-1990s over which the Trade and Quote (TAQ) data are available, Goyenko et al. (2005) compare various transaction cost measures for U.S. data, and find that those based on observed zero returns are correlated with effective costs obtained from high-frequency data.

The zero return measure has been widely used to evaluate the relation between market liquidity and political risks in emerging markets (Lesmond, 2005), the implication of liquidity on asset pricing in emerging markets (Bekaert et al., 2007), and the pricing of liquidity risks in global financial markets (Lee, 2011). Importantly, *ZR* is defined over zero-volume days as well as positive volume days since this measure assumes that a zero-return day with positive volume is a day when noise trading induces trading volume.

Goyenko et al. (2009) propose an alternative version of Zeros, Zeros2, which is the proportion of trading days with zero return but positive trading volume within one month. The argument is that stocks with higher transaction costs tend to have less private information acquisition so these stocks are more likely to have no-information-revelation zero returns even on positive volume days. The second component is about trading frequency. Since illiquid stocks are traded less frequently and, therefore, are more likely to have zero trading volume days, I propose another version of Zeros, *ZeroVol*, which is defined as:

$$ZeroVol = \frac{Number\ of\ days\ with\ zero\ volume}{Number\ of\ days\ in\ Trading\ Month} \qquad \textbf{5(18)}$$

5.2.3.5 Market efficiency coefficient

The Market-Efficiency Coefficient (MEC), or variance ratio, was developed by Hasbrouck and Schwartz (1988) and has been used extensively in the literature considering that price movements are more continuous and reflect new information timely in liquid markets. Thus, for a given permanent price change, the transitory changes to that price should be minimal in resilient markets. This measure is computed as follows:

$$MEC=\frac{Var(R_t)}{\left(T*Var(r_t)\right)} \quad \textbf{5(19)}$$

where:

$Var(R_t)$ and $Var(r_t)$ represent the variance of respectively long-period and short-period returns and T is the number of short periods within each long period.

The Market efficiency ratio tends to be close but slightly below one in more resilient markets, since a minimum of short term volatility should be expected. Indeed, prices of assets with low market resiliency may exhibit greater volatility (more transitory changes) between periods in which their equilibrium price is changing. Factors that foster excessive short-period volatility (overshooting) result in an MEC substantially below one. These factors include price rounding, spreads, and inaccurate price determination involving partial adjustment to news, cause prices to adjust relatively small, and positively correlated increments. This would dampen short-period price volatility relative to longer period price volatility (Sarr and Lybek, 2002).

5.2.4 TIME-BASED LIQUIDITY MEASURES

Time-based measures capture either the time that has elapsed between trades or the amount of time required to trade an asset once a decision to buy or sell has been made. It might be assumed that where a particular asset or type of asset is traded more often, then that asset or group of assets is more liquid. If so, then this would be captured by two of the measures examined in this section: (i) holding period and (ii) trading frequency. However, there could be instances where assets are held for a long period because they have particularly desirable characteristics and not because they are difficult or costly to trade. If so, then it may be possible to transact such assets very quickly once marketed and this would be captured by the third measure explored here: (iii) time on market.

Time on market could be split further, with the search for a counterparty forming one stage and the time to process a trade forming the other. In mainstream financial markets, both of these stages may seem trivial in length owing to the existence of centralised, public exchanges. In contrast, the decentralised and private nature of direct real estate markets means that time on market has been studied extensively for residential real estate, with more limited attention from the commercial real estate literature. Nonetheless, the time to execute trades is still of importance in financial markets. For instance, certain arbitrage strategies may need to be executed within minutes or even seconds, and so the possibility of being able to trade within such intervals becomes important.

5.2.4.1 Holding Periods (Inverse of Turnover Rates)

The standard way of incorporating market frictions into asset pricing models is to assume that trading involves some exogenous trading cost. The more often that investors plan to trade, the more important are such costs in terms of their impact on returns. In fact, the magnitude of any costs may influence investors' expected holding periods. If higher trading costs for a particular asset or market translate into longer holding periods, this in turn implies a reduced volume of trading for that asset or market, as fewer participants seek to sell assets in any given period.

A number of theoretical models use the concept of expected holding period to link liquidity to asset prices. For example, Amihud and Mendelson (1986) provide an early model that incorporates the expected holding period. However, it has been hard to investigate these theories empirically owing to a lack of data on actual holding periods. Instead, investigations have relied on proxies of investor holding periods constructed in the following way from data on turnover:

$$HP=\frac{(S*P)}{Vol}=\frac{1}{Turn_n} \qquad 5(20)$$

where T_n is turnover rate, Vol is the dollar volume traded, S is the outstanding stock of the asset and P is the average price of i trades. In contrast, the actual holding period for an asset held by an investor would simply be the time between the purchase date and the sale date for that asset.

In financial markets, even though high turnover stocks are likely to have many investors buying and selling that stock, it is by no means certain that all owners of the stock have short holding periods. For example, there may be a group of owners with very long holding periods, but high turnover among the remaining investors. The core of this problem is that, while turnover is a characteristic of an asset, holding period is a decision made by an investor. This is recognized in empirical work for real estate by Collett et al. (2003) where statistical models were deployed to correct the measurement of holding periods for the presence of untraded assets over the study period.

5.2.4.2 Trading Frequency

Trading frequency is also closely related to trading volume. Trading frequency equals the number of trades executed within a specified interval, without regard to trade size. Like trading volume, high trading frequency may reflect a more liquid market. However, it may be associated with volatility and lower liquidity. Jones et al. (1994) show that the positive volume-volatility relationship found in many equity market studies reflects the positive relationship between the number of trades and volatility, and that trade size has little incremental information content.

To obtain trading frequency, a count of the number of trades between time $t-1$ and t is required. Information on the timing of transactions may also be used to compute waiting time between trades, as studied by Peng (2001):

$$WT_t=\frac{1}{N-1}\sum_{i=2}^{N} tr_i-tr_{i-1} \qquad \textbf{5(21)}$$

where tr_i denotes the time of the trade and tr_{i-1} the time of the trade before. Therefore, waiting time for a specific time space has to be calculated as an average time between two trades.

5.2.4.3 Volumes Volatility

As real estate is not divisible and traded infrequently, a proxy one may use to represent the above dimension of liquidity is the volatility of transaction volumes. This measure should be inversely proportional to the trading frequency because the implication of this measure can be twofold: the average trading volume is lower (and hence similar swings show higher impact) and/or the swings in transaction volumes from one period to the next are higher. The Volumes Volatility measure and is computed as follows:

$$\sigma_{Vol_t}=\frac{\sum Vol_t-\overline{Vol_t}}{N-1} \qquad \textbf{5(22)}$$

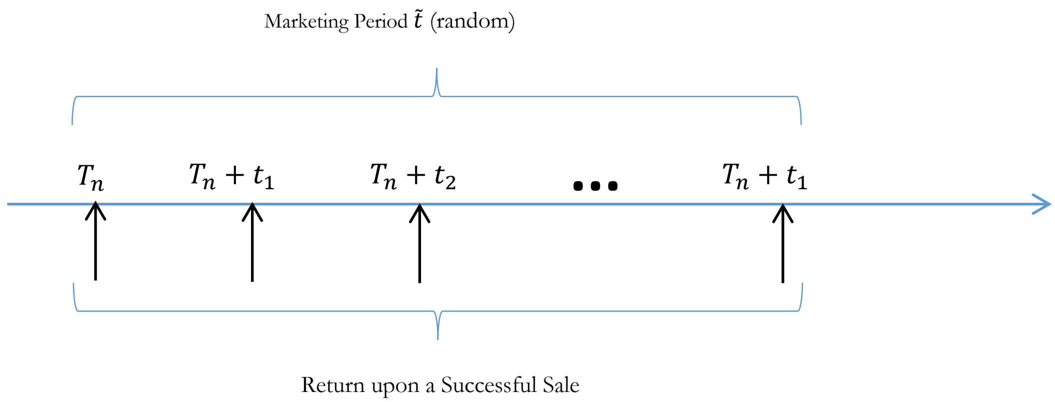
where Vol_t is the dollar volume traded and N is the number of observations within the period.

5.2.4.4 Time on Market (TOM)

A fundamental characteristic differentiating real estate investments from mainstream financial assets is the time involved in buying or selling once a decision to buy or sell has been made. Furthermore, the timescale is not only long, but it is also uncertain. This is because the private and decentralized nature of real estate markets requires search by participants for appropriate assets and/or willing counterparties, while the physical, legal and spatial heterogeneity of assets may necessitate extensive due diligence by purchasing parties.

This uncertainty is discussed by Lin and Vandell (2007), who provide a simple illustration of the real estate transaction process reproduced in Figure 5(2). In the figure, an investor purchases a real estate asset at time 0 and holds it until time T_n before placing it on the market for sale. $\tilde{t}$ is the potential marketing period, the actual length of which is a random variable. t_1, t_2 and t_i represent possible end points to the transaction process and $\tilde{P}_{T_n+\tilde{t}}$ is the price upon a successful sale.

Figure 5(2): The Transaction Process for Real Estate



A defining feature of this process is the sequential but random arrival of offering prices that characterizes the mutual search between sellers and potential buyers. During the search process, the seller receives offers over time from a stream of buyers whose offer prices and timing of arrival are stochastic in nature. Buyers make offers based on the information acquired from their search. Each time a buyer makes an offer, the seller evaluates the benefits of waiting for a potentially better offer and the cost associated with waiting, and then decides whether to sell the asset or not. If a deal is not reached, the search continues. Thus, there is uncertainty both around the length of the marketing period and the price that will eventually be agreed.

In terms of empirical measurement, time on market is often measured from the perspective of the seller, looking from the date when a property is listed for sale to the date when a sale is formally concluded. However, it is also relevant to consider time to transact from the perspective of buyers, which could be seen as commencing from the point at which search begins. Moreover, it is possible to also break the time to transact down into different stages. For instance, McNamara (1998) breaks the sales process into three periods: (i) the period between the decision to sell a particular asset and the date when heads of terms are agreed; (ii) a subsequent period up to exchange of contracts; and (iii) the last period up to when money is finally transferred. All three periods affect the liquidity risk, though the achieved sale price should not change during the third of these periods. These stages are further refined and then measured in Crosby & McAllister (2004), while Scofield (2013) concentrates on the buyer perspective.

5.2.5 RETURN-BASED MEASURES

Some liquidity indicators have been drawn theoretically from the impact that a lack of transaction activities may have on price movements and hence properties of return time series. These measures have then become popular because price indices exist for several assets and markets and no other information is required.

5.2.5.1 Roll Measure

Roll (1984) developed an implicit measure of the effective bid-ask spread based on the serial covariance of the changes in stock price. Two key assumptions are that the market is informationally efficient and the probability distribution of observed price changes is stationary. Let P_t be the last observed trade price on day *t* and assume that it evolves as:

$$P_t = V_t + \frac{1}{2} S Q_t \qquad \textbf{5(23)}$$

where:

V_t unobserved fundamental value of the stock on day t and it fluctuates randomly
S is the effective spread to be estimated
Q_t is a buy or sell indicator for the last trade on day t that equals 1 for a buy and -1 for a sell.

Assuming that Q_t is equally likely to be 1 or -1, is serially uncorrelated and is dependent on the public information shocks on day t, Roll shows that the effective spread can be estimated as:

$$S = 2 \times \sqrt{-cov(\Delta P_t, \Delta P_{t-1})} \qquad \textbf{5(24)}$$

where Δ is the change operator.

The beauty of this Roll measure is that it can be estimated easily since the only data requirement is daily price. However, this measure is not meaningful when the sample serial covariance is positive, which is more likely to happen in emerging markets with low market efficiency. Therefore, as in Goyenko et al. (2009) modified the Roll measure as follows:

$$\begin{cases} 2 \times \sqrt{-cov(\Delta P_t, \Delta P_{t-1})} & \textit{when } cov(\Delta P_t, \Delta P_{t-1}) < 0 \\ 0 & \textit{when } cov(\Delta P_t, \Delta P_{t-1}) \geq 0 \end{cases} \qquad \textbf{5(25)}$$

5.2.5.2 Run Length

Das and Hanouna (2010) developed an illiquidity proxy based on run length of returns, defined as the consecutive series of positive or negative returns without reversion. Empirically, they showed that run lengths are positively related to the price impact of trading and can explain cross-sectional variation of stock returns. Using daily stock returns, the monthly measure of run lengths is computed as follows:

$$RL_{i,m} = \frac{N^{run}}{N_m} \quad \mathbf{5(26)}$$

where N^{run} is the sum of the length of each run in a month m and N_m is the number of runs in a month m.

If the consecutive occurrence of positive or negative returns is not reversed right after the presence of zero return, the zero return day does not terminate the run. If any run is reversed after the presence of zero returns, then the run terminates with the last zero. The minimum possible run length of a stock in any month is one.

5.3 EMPIRICAL STUDIES IN REAL ESTATE MARKETS

After identifying the dimensions and causes of liquidity and introducing measures that can proxy for this risk, we discuss empirical research related to real estate markets/products. We begin by reviewing studies that explore public real estate before turning to the private real estate market and finally to work produced on unlisted real estate vehicles.

5.3.1 EMPIRICAL EVIDENCE IN LISTED REAL ESTATE MARKETS

Corgel et al. (1995), Zietz et all. (2003), and Feng et al. (2011) provide descriptive overviews of exchange-listed REITs. The liquidity of REITs relative to alternative investments linked to real estate has great appeal and this allowed the market to develop with a high institutional component in its ownership structure.

Nelling et al. (1995) find that the liquidity of real estate investment trusts (REITs) – daily closing bid-ask spread for securities listed in the NASDAQ – decreased during 1980s, making these products relatively expensive over that period. Following this work, but using market microstructure data, Bhasin et al. (1997) show that, during mid-1990s, the trend inverted and these products became more liquid, partly thanks to a significant growth in their number and market capitalization driven by the "new REITs era" (Cole, 1998). Bhasin et al. (1997) use an empirical model of spreads following Stoll (1978) and shed light on their determinants: price and dollar volume (positive relation) and return volatility (negative). Clayton & MacKinnon (2000) confirm these results for the early 1990s by decomposing the percentage spread into three components (depth, tightness and resiliency) following Kyle (1985) and find that most gains are driven by improvements in depth rather than tightness. Meanwhile, Cannon and Cole (2011) find significant improvements in the overall liquidity of REITs around 2000-2006.

Marcato and Ward (2007) develop the model in Clayton and MacKinnon (2000) to allow an estimation with daily rather than intra-day data. Similar results are found for the U.S., with improving liquidity measured for both estimated spreads and market depth. The choice of stock exchange is found to be significant, with even smaller REITs benefiting from listing in the NYSE as opposed to NASDAQ and AMEX, similar to Danielsen and Harrison (2000), who found the NYSE and AMEX to be preferable to the NASDAQ. Weaker results are also found for other markets (U.K. and Australia).

Characterizing the intraday-trading behavior. Below, Kiely, and McIntosh (1995) find that (1) REIT structures present a smaller amount of volumes and trades than nonREIT ones, (2) equity REITs present higher spreads than mortgage REITs, and (3) REITs with high institutional ownership trade at spread levels similar to those observed for non-REITs. However, Bertin et al. (2005) argue that using raw spreads fails to include transactions taking place inside the quoted spread. Therefore, they compute several liquidity proxies and show that REIT liquidity follows an intraday U-shaped pattern similar to that of common stocks.

Brounen et al. (2009) support the idea of studying several dimensions of liquidity in international markets and use three proxies for liquidity—dollar trading volume, turnover, and a version of the Amihud measure—to avoid misleading conclusions. They show that dividend yield, market capitalization, and non-retail share ownership are the main drivers of liquidity. Furthermore, Subrahmanyam (2007) finds liquidity risk to be priced in REITs. He is the first to explore order flow spillovers across NYSE stocks, finding that this phenomenon occurs from REITs to non-REITs and that liquidity measures of the latter are a good predictor for the former.

Benveniste et al. (2001) compare asset replacement value with company value and show that the securitization process of assets obtained through the REIT structure enhances the underlying asset value by IO%-20%. Yet, they do not find that the market value of equity provides explanatory power for liquidity when they include control variables such as sector and institutional ownership. Following from the evidence that REITs partly reflect equity and partly private real estate performance, Bond and Chang (2012) study the cross-asset liquidity between these three markets/assets. In line with theoretical expectations, they find liquidity risk and commonality in liquidity to be generally lower for REITs than for other equities and causality going from public to private markets.

Finally, a recent by Glascock and Lu-Andrews (2014) sheds light on the macroeconomic factors driving REIT funding liquidity and its linkages with market liquidity across the business cycle. The authors use the Amihud measure and turnover ratio for market liquidity and LTV ratio, debt service coverage ratio, and number of loans for funding liquidity. This study shows that both contemporaneous and lagged macroeconomic factors have a significant impact on REIT funding liquidity; negative for inflation, default spreads, and term spreads and positive for the banks' willingness to lend.

5.3.2 EMPIRICAL EVIDENCE IN DIRECT REAL ESTATE MARKETS

There are fewer studies of liquidity for private real estate than for either financial assets or REITs. In part, this stems from the decentralized and private nature of real estate markets that has created difficulties in obtaining data and creating liquidity measures. Yet, liquidity issues have been subject to more extensive study in recent years, including work that considers the impact of liquidity on real estate price series. This has resulted in the creation of liquidity indices in the U.S., although the assumptions and models required to produce such indices are methodologically complex. Meanwhile, other research has occurred using more traditional liquidity indicators such as volumes and time-on-the-market.

Fisher, Ling, and Naranjo (2009) and Ling et al. (2009) have explored the relation between volumes and returns in private real estate investment markets. They examine the relation between capital flows and investment returns in the U.S. and the U.K., respectively, to see whether they affect each other. Both studies use a vector autoregressive (VAR) approach where institutional capital flows and returns are specified as endogenous variables in a two-equation system. Fisher, Ling, and Naranjo (2009) find that lagged capital flows have a statistically and economically significant relationship with returns, which suggests weight-of-money effects in pricing. They do not find evidence for return chasing. Ling et al. (2009) find positive contemporaneous correlations between returns, absolute and percentage capital flows, and turnover, but their results did not support the idea that capital flows exert a "price pressure" effect in the U.K.

The composition of transaction volumes is studied in Fisher, Gatzlaff, Geltner, and Haurin (2004). They examined sales out of the population of private real estate investments monitored by the National Council of Real Estate Investment Fiduciaries (NCREIF) in the U.S. They tested whether specific property, owner or market characteristics affected the probability of an asset being sold. The results might indicate when properties are more liquid and which assets are more liquid than others, but it is possible that some buildings with desirable characteristics are held for longer by owners and would trade rapidly if offered for sale. Fisher and Young (2000) studied holding periods using the NCREIF database whiles Collett et al. (2003) examined holding periods for institutional grade U.K. real estate. The latter find that holding periods have reduced over time, and vary with market state and by type of property.

In contrast to volumes, tightness, as captured by bid-ask spreads, is much more difficult to measure for private real estate than for many financial assets as there is not an observable bid-ask spread for different assets in the real estate investment market. However, there is a distinction between the reservation price of a seller (at which they are prepared to sell) and that of a buyer. The distance between these determines the likelihood of a sale taking place: where reservation prices meet or overlap, a buyer and seller can conclude a trade, but, where they do not, the asset concerned will remain unsold.

More generally, a distribution of reservation prices that reflects the views of potential buyers of real estate assets can be inferred as can a similar distribution of reservation prices that reflects views of potential sellers. Such distributions are proposed by Fisher et al., (2003). They describe how the shape and extent of overlap between these distributions influences the number of assets likely to trade (Clayton et al., 2008). They argue that variations in liquidity in the real estate market over time make the interpretation of real estate price series more difficult. This is because prices tend to adjust slowly to changes in real estate market conditions. In fact, the nature of real estate markets causes adjustments to occur in prices, volumes, and time to transact when market conditions change, as well as in the mix of assets being traded. As such, Fisher et al. (2003) argue that real estate indices need to be adjusted to reflect the differential ability to enter and exit the market at different points of the real estate cycle.

Adjustments to create constant liquidity real estate price series for the U.S. are tested by Fisheret al. (2003), Goetzmann and Peng (2006), and Fisher et al, (2007). Subsequently, the relation between constant liquidity and uncorrected price series has been used by Clayton et al. (2008) to derive a measure of market-wide liquidity, while Buckles (2008) proposes a liquidity index based on a more complicated procedure. This strand of research resulted in the publication of a liquidity series by the MIT Center for Real Estate, alongside the U.S. transaction-based price series resulting from the work of Fisher et al. (2007). However, similar, constant-liquidity transaction price indices do not exist in other countries and are a prerequisite for creating a liquidity index of this nature.

The other major area of examination has been in regard to the time it takes to transact assets in the private real estate investment market. As noted earlier, a substantial body of research has explored time-on-the-market for residential property, but there are far fewer studies for commercial real estate. McNamara (1998) conducted survey work to estimate average transaction times for U.K. real estate investments. For sales, he reported a marketing period of four to eight weeks and a due diligence period of four to twelve weeks depending on property type. However, IPF (2004) found actual times to be longer, with a median sale time of 190 days and considerable dispersion in transaction times as well. Scofield (2013), who considers the transaction process from the buy side, finds that time to transact is time varying and that transactions were conducted more rapidly during the boom phase of the U.K. real estate cycle. This is reinforced by Devaney and Scofield (2015), who also suggest that features of the asset and counterparties involved are influential in explaining why some transactions take longer than others.

The nature of real estate markets (heterogeneous assets with limited numbers of buyers and sellers operating under various economic constraints) means that the length of the time-on-the-market is likely to be affected by many factors. Thus, when real estate investors come to sell a property, they face uncertainty not only in regard to transaction price (price risk), but also around the time it will take to sell (marketing period risk). In contrast, many financial assets can be sold instantaneously through public exchanges and so investors do not bear marketing period risk.

The nature and behavior of marketing period risk is investigated by Lin and Vandell (2007), who highlight the importance to investors of the hidden risk exposure that occurs during the extended marketing period of a commercial real estate asset. They estimate the extent to which ex post data on real estate performance understates the ex-ante risk exposure taken by real estate investors, because it does not take into account the asset risk exposure during the marketing period or the uncertainty of the marketing period itself. This work is extended by Bond, Hwang, Lin, and Vandell (2007), who calibrate such models using the transaction times reported in IPF (2004). They suggest that the ex ante level of risk exposure for a commercial real estate investor is around one and a half times that obtained from historical statistics. Meanwhile, Lin and Liu (2008) consider how the level of risk might vary with the financial circumstances and investment horizons of different types of sellers, while the analysis has been extended still further in more recent work by Cheng et al. (2010, 2013a, 2013b).

This work provides evidence of the importance of liquidity in private real estate markets and, to some extent, the degree of liquidity for different types of property or in different periods. However, the range of measures produced and tested in a private real estate context is much narrower than for either REITs or financial assets and is less developed for commercial real estate than for residential property, where data have traditionally been much richer.

5.3.3 EMPIRICAL EVIDENCE ON OTHER REAL ESTATE VEHICLES

A descriptive overview of the public non-listed REIT sector is provided by Corgel and Gibson (2008) for U.S. funds and by Brounen et al. (2009) for European funds. New empirical work on the estimation of liquidity premiums for investment vehicles different from REITs has started to be developed in recent times and this area is likely to be further analyzed in the future. So far, however, only a few articles have focused on European unlisted funds, debt products, and U.S. real estate mutual funds.

Schweizer et al. (2013) discuss open-ended property funds, which offer apparently perfect daily liquidity, but failed to do in market conditions when liquidity was most required (redemptions are suspended if a threshold of requests is passed). They found that these vehicles offer a liquidity premium (measured as discount to NAV) of about 6% in the short run, but are not affected by liquidity risk in the long run and represent an attractive investment tool for long-term investors such as pension funds and other institutional players.

Marcato and Tira (2015) build upon the issue of suspended redemptions and estimate the impact of traded volumes on the price of such vehicles. Interestingly, if no effect is seen for aggregate transaction volumes, in line with previous findings in the finance literature, an opposite effect is found for money flows entering and exiting such funds. In fact, a smart money effect is estimated for outflows (i.e., capability of disinvesting timely), suggesting that current investors have access to better information. In contrast, a return-chasing behavior seems to drive inflows (i.e., investors enter funds that performed well in the past), also thanks to the persistence of fund returns over time.

As a further step in the analysis of indirect causes of liquidity for unlisted funds, Wiley (2014) links the problem of suspended redemptions to managerial incentives and finds that an increase in compensation increases illiquidity risk indirectly because it reduces the ability to generate revenues and to raise equity capital to be used to fulfil redemption requests.

Finally, as far as debt products are concerned, we clearly see a shift in the pricing of liquidity risk for such products. If, before the last economic crisis, Nothaft et al. (2002) estimated a very small liquidity premium for agency (e.g., Freddie Mac, Fannie Mae) products, Kim (2009) later found that a liquidity shock is more likely for mortgage-backed securities (MBSs) than for government bonds if there is a sudden and significant drop of trading activities (as observed in 2008). Work from the Federal Reserve Bank of New York and Atlanta reinforces these results, linking the premium to vintage and a common factor (along with credit rating and an idiosyncratic factor) (Dungey et al., 2013). It shows the positive effect (around 10 to 25 bps) of the trading method on a "to-be-announced" (TBA) basis and no effect of the presence of a government credit guarantee.

5.4 MANAGING LIQUIDITY WITHIN DC PENSION PORTFOLIOS

In the preceding sections, we identified a number of approaches that have been developed to help quantify or measure liquidity within asset markets. In this section, we will offer a discussion of various approaches that exist for institutional investors such as pension funds to manage liquidity within investment portfolios. Kathuria and Myer (2013) identified five main approaches for managing liquidity: (i) Spending policy rate (ii) Asset allocation and Rebalancing (iii) Use of derivative securities (iv) Sensitivity or stress test analysis and (v) Loan program or the issuance of debt.

5.4.1 SPENDING POLICY AND RATE

There are two variables that go into determining an institutional investor's cash outflows: (i) The targeted proportion of the portfolio spent per time period e.g. 5% per annum and (ii) The method by which the rate is calculated i.e. the spending policy. Both variables need to be taken into account when determining the liquidity needs of the investor. When the spending rate is low, the liquidity needs of the portfolio would not be impacted too much, particularly during normal market environments. However, if the expected draw from the portfolio is high, this may impact the investor's choice of liquidity profile, especially in stressed market conditions. A well designed spending rule would give enough flexibility to the institutional investor to accommodate unforeseen decreases in portfolio value and to avoid forced liquidation and permanent loss of value. A well designed spending rule also helps the investor to stabilise spending.

The cash inflow for pension funds is made up of the contributions from active employees and the transfer payments from newly recruited employees. The returns on investment can also be classified as cash inflows. The cash outflows include benefit payments to retired or disabled employees or the vested benefits to resigned worker. Cash outflows also include payments to beneficiaries of a deceased worker. (Mettler, 2005). It is important to make a projection of the pension fund's cash inflows and outflows. The derivation of future cash flow profile often involves a specification of both demographic and economic variables.

Within the realm of actuarial science, the projection of the expected cash flows for pension funds generally involves two steps. First, the future state of the contributors or group of contributors is forecasted by employing some stochastic process. Secondly, a reward of some type is triggered upon the attainment of a certain state (Papadopoulou et al., 2002). Mettler (2005) used four different models to estimate the projected cash flows of a life-insurance/pension fund provider i.e. population model, salary model, savings model and a cash flow model. The population model follows the evolution of the insured or group of insured in terms of their physical characteristics such as age and health status. A salary model describes the future salary distribution of active workers. Given that contributions and some element of benefit payments for some products are based on a given percentage of the insured's salary, a salary model is appropriate for determining future cash flow profile. A savings model follows the accumulation process of contributions and the returns on invested contributions. The future level of savings becomes the basis for the calculation of various benefit payments. The cash flow model reassembles the results of the other three models, thereby integrating the applicable contributions and benefit rates.

A significant change that has occurred within the UK pension landscape is the introduction of the Freedom and Choice Legislation. Two pieces of legislation in particular paved the way for what has become known as the 'pensions freedoms' viz. the Taxation of Pensions Act 2014 and the Pensions Act 2014. This legislation makes it possible for DC members to withdraw their pension funds as they wish after their 55th birthday. The two main options open to them are the (i) Flexi-access drawdown and (ii) Uncrystallised funds pension lump sum. Chapter 2 contains a full discussion of these various modes of access. Clearly, this affects the cash flow pattern of DC pension funds.

Commenting on the liquidity situation of Australian DC pension funds, Jones (2008) observed that although the cash flows of DC pension funds have been cash flow positive, the issues of portability and the retirement of a large cohort of DC pension contributors has heightened the concerns over liquidity within Australian DC pension funds. Among the measures put in place to manage liquidity risk, he observed that there is the need for DC funds to strike a good balance between member investment choice and the ability to meet payment request within the context of choice.

5.4.2 ASSET ALLOCATION AND REBALANCING

Although traditional asset allocation focuses on the types of assets, increasingly, portfolio allocation takes into consideration different risk factors such as interest rate risk, inflation risk, currency and liquidity risk. A substantial amount of research has also been devoted to the relation between liquidity and the conditional distribution of returns. However, the question of how liquidity influences portfolio allocations is not easy to address.

Modelling portfolio allocations should take into account the illiquid nature of the investments. Not all securities within each asset class share the same liquidity profile. Different vehicles have different liquidity constraints (Myers, 2009). This would help to foresee shifts in the strategic asset allocations and enable investment management committees to set the allocations to those assets appropriately. Kathuria and Myers (2013) also recommend that those firms that invest in private market assets should employ laddering of their allocations to reduce the potential for liquidity squeezes.

As part of their asset allocation process, investment managers should not only determine the parameters for allocation to broad asset classes but also seek to understand the impact of investment vehicles on the near-term liquidity pool.

Another way in which institutional investors can manage liquidity is to consider the possible declines in the market values of illiquid assets when rebalancing portfolios at policy-determined intervals. Without a deliberate and periodic rebalancing, liquidity constraints could cause a portfolio to stray from its intended target asset allocation. As it is often easier to add money to illiquid assets than to redeem, alternative allocations should be monitored and proactively reduced to avoid the situation where allocations stray from their targets. A rebalancing program or continuously monitored redemption request could help mitigate this risk. Many institutions have indicated that they regularly rebalance their portfolios to maintain or enhance liquidity in those portfolios. (Kathuria and Myers, 2013).

Lo et al. (2003) identified three methods for incorporating liquidity directly into the mean-variance portfolio construction process. The three approaches for doing so are: (a) imposing a liquidity "filter" for securities to be included in a portfolio optimization program; (b) constraining the portfolio optimization program to yield a mean-variance efficient portfolio with a minimum level of liquidity; and (c) adding the liquidity metric into the mean-variance objective function directly.

5.4.3 USE OF DERIVATIVE AND HYBRID ASSETS

Derivatives allow investors to increase the exposure of their portfolios to certain asset classes without actually owning the assets. In using derivative securities, investors must be mindful of the fact that they can directly lead to liquidity squeezes if margin calls occur. Derivatives can increase the complexity and risk of portfolios and hence care should be taken when using them (Kathuria and Myers, 2013).

Passive replication products have become very common within the hedge fund and private equity market. MSCI has for example created a liquid private equity index for US real estate investors based on an approach developed by Pegliari et al. (2005) and Ang et al. (2013). Kat & Palaro (2005) used the FundCreator approach has been used by a number of product developers and institutional investors to replicate hedge fund performance.

Factor models are by far the most common approach used by product developers and academics to try and replicate the performance of these illiquid assets (Hasanhodzic & Lo, 2006; Amenc et al., 2008; Amenc et al., 2010 and Bollen & Fisher, 2013). Factor models estimate the target fund's exposure to a number of factors and then use the estimated coefficients to determine the allocations in the replication portfolio. Despite their popularity, factor models have been criticised on a number of basis. Due to the lack of transparency in the investment management process, it is difficult to identify the factors that drive the performance of different hedge fund or private equity strategies. Consequently, the tracking error of the portfolios constructed using the factor approach tend to exhibit a poor out-of-sample tracking error relative to the performance of the target portfolios. Also, products developed based on the estimates obtained from factor models have been found to underperform the target portfolios. Kat & Palaro (2005) however explained that the goal of the replicated funds is not to match the returns of the target portfolios but rather to attempt to create portfolios that have statistical properties similar to the fund being replicated.

In order to enhance the liquidity of investments such as real estate, private equity and hedge funds, some investment managers blend different strategies. In response to the to the growth in the DC market and the increasing emphasis on liquidity by these funds, many real estate investment managers have developed products to enable DC funds gain access to the real estate market. These funds typically combine direct real estate and significant proportion of liquid assets, mostly listed real estate and/or cash. The attractiveness of these funds is that they offer daily pricing and liquidity. In this section, we provide evidence on the existence of these funds. Later in the section, we discuss the extent of usage of these funds among DC pension funds, especially within master trust pension funds.

5.4.3.1 TR Property Investment Trust

TR Property Investment Trust is perhaps the most widely known property investment company that combines direct and listed real estate within the same portfolio (Moss & Baum, 2013). Founded in 1905, the company invests in UK direct property as well as shares and securities of property companies and property related businesses. The fund is managed by Thames River Capital and F&C Investment Business Limited and is benchmarked against the FTSE/EPRA NAREIT Developed Europe Capped Net Total Return Index in Sterling. Although the company aims to diversify internationally, a pan-European benchmark means that most of its investment are domiciled in Europe. Direct property investment is limited to the United Kingdom. The limits set for the various assets are 5 – 20% for direct UK property, 45 – 75% European listed equities, 25 – 50% in UK listed equities, 0 – 5% in other listed equities and 0 – 5% in bonds. The current (2016) allocations of the fund currently stand at: 8.5% direct UK property, 26.4% UK securities, 65.3% European securities.

5.4.3.2 Legal and General Property Fund

The fund was launched in 2011, being the first hybrid real estate fund targeted at Defined Contribution Pension Schemes. The managers of the fund believe that it meets the optimum investment criteria of UK Defined Contribution Pensions, having being designed in consultation with leading investment managers. The hybrid property portfolio is made up of 70% direct commercial property and 30% global REITs. This combination is more diversified and provides greater liquidity along with lower expenses, compared to a direct investment in property. The 70:30 ratio can be adjusted by the fund manager within an agreed range. The fund is designed to provide returns that are broadly in line with the AREF/IPD UK Quarterly Balanced Property Funds Index.

5.4.3.3 HSBC Open Global Property Fund

This fund aims to provide investors with a property portfolio that is diversified both geographically and offering investors an exposure to real estate through both the direct and listed market. Listed real estate currently makes up about 60% of the portfolio whiles direct real estate receives an allocation of around 30%. A cash buffer made up of cash deposits and money market securities such as Treasury bills makes up the remainder of the portfolio. Geographically, the fund invests about 40% in the UK, 30% in North America and the remaining in continental Europe. A fund of fund strategy is employed to ensure that there is better diversification, access to local managers and increased liquidity. In particular, the fund believes that partnering with local property investment managers gives them a leverage especially in the selection of quality assets.

5.4.3.4 Evidence of UK DC Pension Fund Investment in Hybrid/Blended Real Estate

As an asset manager and Master Trust Pension Fund, Legal and General, offers a number of property funds targeted at pension funds. Those funds targeted at DC pension funds are constructed with liquidity being a key consideration. The L&G UK property Fund for example invests in UK property in a concentrated manner as opposed to a broad based approach. The fund invests 60 – 80% in direct property, depending on the market conditions. The fund also invests 20 – 30% in cash and marketable securities and about 5% in REITs. In 2011, Legal and General launched the hybrid property fund which it hopes would give UK DC pension funds an innovative way to invest in direct real estate in a cost efficient way.

NEST, the largest DC Pension investor in the UK announced in 2013 that it has selected the Legal and General Investment Management and its property platform, Legal and General Property (LGP) as the manager of its two real estate mandates. The allocation of 20% to real estate that NEST announced represents a sizable allocation to real estate for a DC pension fund. Hitherto, NEST invested just over 3% in listed real estate through its diversified beta fund. Like NEST, Standard Life Pension invests in the L&G Hybrid (70:30) Real Estate Fund.

The Pension Trust (TPT) gains its property exposure through three different funds provided by CBRE and Standard Life. TPT invests in CBRE's UK Property Fund which invests exclusively in UK direct property and a Europe (ex UK) property fund which invests in private equity style real estate funds. In addition to the two funds, TPT also invests in the Standard Life long lease property fund which targets institutional investors who require regular, increasing cash flows. The Standard Life long lease property fund also invests about 6% in cash and money market securities. The overall performance objective for TPT's property investment is to outperform the returns on the IPD monthly index over an annualised rolling seven-year period. This benchmark is not applied to each of the funds but to TPT's property portfolio in general.

5.4.4 SENSITIVITY/STRESS TEST ANALYSIS

It is important to evaluate the liquidity profile of investment portfolios in both normal and stressed environments. For each asset class, the liquidity expectation in normal market environments or conditions should be identified and compared to the estimated downside experience in stressed market environments.

In normal market environments, assets such as hedge funds and core real estate funds provide quarterly liquidity. However, in stressed market environments, the actual redemption could take one or two years. The winding down period of private equity funds could take about two years in normal market environments. However this could be much longer in stressed market environments.

The investment structure, as well as the terms of the private capital investments such as core real estate and hedge fund investments, including any lock-ups and redemption constraints need to be carefully considered. The better investors understand what drives lock-up periods for example, the better would be their ability to analysed liquidity. Stress testing and scenario analysis would also help the institutional investors to determine their illiquidity tolerance, as well as their ability to meet spending targets in stressed market environments.

5.4.5 USE OF LEVERAGE (DEBT)

Although some institutions such as pension funds may have restriction on the use of loans, this may represent a good way of managing liquidity when the need arises. A proactive loan programme means that the firm agrees a credit line in advance with banks. Interest is only paid on the amount the firm actually uses. Having a credit line creates a funding capacity for short-term liquidity needs. This allows the institution to better deploy its funds in more long-term profitable investments. Also, during stress market environments, having access to credit would ensure that the institution does not have to sell off its investments at inopportune times (Kathuria and Myers, 2013).

Occupational pension schemes in the United Kingdom that are defined benefit or defined contribution could borrow from a bank. The occupational Pension Schemes Regulation (2005) prescribes that pension funds may only borrow money for the purposes of providing liquidity for the scheme on a temporary basis. Occupational pension schemes with fewer than a hundred members do not have a restriction on borrowing but can only borrow if the Trust Deed and rules grants them permission to do so. For smaller schemes, the powers for trustees to borrow are included in the investment provision of the Pension Trust Deed and Rules although technically speaking, borrowing is not an investment activity. For larger funds, the Statement of Investment Principles must allow borrowing, otherwise banks may not lend any money to the fund.

Schemes are also limited in the value of their borrowing. Generally, pension funds are not allowed to take out loans that exceed 50% of their assets, measured on the day the loan is granted. Going beyond this limit could have tax implications for the pension fund.

5.5 CONCLUSION

In this chapter, we have examined the literature on liquidity over recent decades and highlight the multi-faceted dimension of this phenomenon, the market imperfections causing it, the different measures used to estimate its significance empirically, and the main results obtained for real estate investment markets and products. We distinguished two types of liquidity. Trading (or market) liquidity refers to the nature of different assets and the markets in which they are traded. Funding liquidity is related to investors and their ability to gain funding to execute trades of those assets. The focus of this review was trading liquidity, several dimensions of which are presented and related to the time and costs of trading and its potential impact on prices: (1) tightness, (2) depth, (3) resilience, (4) breadth, and (5) immediacy. Different liquidity measures spring from the presence of six main market imperfections and we attempt to map these measures against the identified dimensions. This helps investors to understand market activity and their behavior in response to liquidity shocks. For each individual measure considered, both the formula for calculation and notes on its use in financial markets are set out.

The applicability of different measures to real estate markets and their occurrence in the real estate literature are examined. While this exercise shows that some measures may be impractical for private real estate markets, it also reveals their suitability and relevance for alternative investment vehicles in real estate, such as REIT shares, private equity funds or real estate debt. Aside from REITs, we find that the liquidity of alternative forms of real estate investment has received surprisingly little attention. We also identify other measures that are yet to be used with private real estate data, but which have potential and should be explored. A clear example is represented by Marcato (2015), who estimates liquidity premia using volume-based, time-based, and price-impact measures to improve confidence in final outcomes and the estimation process.

The estimation of liquidity premia for private real estate assets or funds is an area that requires more investigation. Liquidity is often suggested as a factor that can explain the risk premium puzzle for private real estate alongside issues concerning measurement of real estate returns. However, the extent of any liquidity premium is rarely quantified. Furthermore, there is a long history of trying to reconcile theoretical allocations to real estate from portfolio modelling with actual allocations by institutional investors. If liquidity could be incorporated formally into such models, more realistic solutions for portfolio weights to different assets, including private real estate, might be forthcoming. The time it takes to transact commercial real estate is also rarely researched, in contrast to the large amount of literature on this issue for residential real estate assets.

In the last section of this chapter, we discussed a number of ways that institutional investors such as DC pension funds can manage liquidity within their investment portfolios. These approaches include the use of asset allocation techniques that consider the illiquidity of the various assets. Another common approach to managing liquidity which we have highlighted is the use of derivative and hybrid instruments. Rather than investing directly in assets considered illiquid, managers of institutional portfolios are increasingly turning to passive replication products and hybrid products that contain a mix of the illiquid asset and some other assets, mostly liquid ones. We have provided examples of these assets and funds within the hedge fund and direct real estate markets. Other liquidity management approaches we have touched on include the use of debt (leverate) and sensitivity/stress test analysis.

This work represents a comprehensive review of studies on liquidity and its impact on pricing. We hope that empirical work might spark from this review, improving the debate on such an important issue for markets with real as opposed to financial assets. In the next chapter, we take a closer look at the design of hybrid products within the direct real estate markets. The motivation for this exercise is the increasing popularity of blended/hybrid real estate products that are being targeted at DC pension funds in an effort to attract these funds to invest in the real estate asset class without having to compromise on the daily liquidity requirement which most of these funds have in place.

CHAPTER SIX – OPTIMAL COMPOSITION OF HYBRID/BLENDED REAL ESTATE PORTFOLIOS

6.0 INTRODUCTION

Unlisted real estate funds are an important part of many mature property markets around the world and have grown significantly in number and assets under management in the last two decades. Yet, despite this, there is still relatively little academic research on such funds, either on the structure and operation of the funds themselves or as an option for gaining exposure to real estate as an asset class. Open-ended funds, in particular, are a potentially attractive route for investors that desire exposure to a diversified pool of real estate investments while holding units that are reasonably liquid. However, the performance and liquidity of such funds has come into sharper focus in recent years. For instance, in the UK, the ability of investors to exit some open-ended funds has been restricted following market shocks (Forbes and Cartwright, 2012; 2017).

This makes questions around the degree of liquidity that such funds can offer, and the means by which they can do so, important issues for research. Open-ended fund units are not normally traded on a secondary market. Instead, units are normally bought or sold directly from the fund itself. In order to facilitate such trades, open-ended funds typically hold significant amounts of cash in the portfolio, for which Appendix 6(A) provides evidence in respect of UK funds. In most market conditions, though, cash acts as a drag on fund performance, reducing the returns achieved and thus the ability of the fund to match the underlying real estate market (Frodsham, 2012). So, while holding more cash would enable a fund to redeem units more easily in downturns or following shocks, it also reduces its attractiveness to investors seeking real estate exposure.

In this context, this study examines the implications of open-ended real estate funds holding different types of liquid assets in their portfolios alongside direct real estate. Such portfolios are called either blended or hybrid real estate portfolios, as they do not consist solely of direct real estate investments. Formal optimisation procedures are used to determine an optimal mix of liquid assets that might be held, with the aim of finding portfolios that replicate closely the performance of the underlying direct real estate market. The performance of these optimal portfolios is then compared to that of portfolios which use only a single predetermined liquid asset, such as cash, to provide the liquidity necessary for operation of the fund. The findings suggest that holding a mix of liquid assets could be more effective than holding cash in isolation. A version of this chapter has been has been published in the Journal of Property Investment and Finance. [2]

This discussion does not imply that liquidity is a priority for all investors in real estate, not even for all investors in open-ended funds. For some investors in funds, restrictions on liquidity through minimum notice periods and exit fees are perceived to offer protection (Timmermans, 2009). Nonetheless, there has been increased emphasis on liquidity by numerous parties such as regulatory agencies, investment managers, pension trustees and consultants following the 2007-2008 global financial crisis. At the same time, the low yield environment following the crisis has raised interest in real estate and alternative asset classes as a means of meeting performance objectives. Thus, investors have been faced with the challenge of increasing their exposure to less liquid asset classes without sacrificing liquidity.

This study contributes to the discussion of how real estate funds need to be structured to deal with the increased emphasis on liquidity while retaining the essential performance attributes of real estate as an asset class. The goal is to add liquid, tradable assets to a direct real estate portfolio but without altering the risk-return profile of the portfolio significantly. The chapter begins by discussing literature on blended solutions in both real estate and other private asset markets before outlining the methods adopted to find optimal blended portfolios in a real estate context. The data used are then discussed before results and findings are presented, with the final section concluding on the implications of the findings and the areas for further research.

6.1 LITERATURE REVIEW

Liquidity is a multi-faceted concept for which a variety of proxy measures exist, none of which capture all of its dimensions (Ametefe et al., 2016). Here, liquidity refers to the ability of investors to buy or sell assets quickly, at low cost and with minimal loss in value from executing the trade. Liquidity is also a relative concept, with direct real estate investments seen as comparatively illiquid owing to their high transaction costs, lengthy and uncertain trading times, and low frequency of transactions. Thus, in the absence of active secondary markets, real estate funds that want to offer greater liquidity to investors must do so by holding other assets in addition to direct real estate. This has been achieved traditionally through holding cash balances, but the use of public (or listed) real estate investments to facilitate greater liquidity has been explored recently by several studies.

[2] Frank Kwakutse Ametefe, Steven Devaney, Simon Andrew Stevenson, (2018) "Optimal composition of hybrid/blended real estate portfolios", Journal of Property Investment & Finance, https://doi.org/10.1108/JPIF-04-2018-0022

6.1.1 BLENDING DIRECT AND LISTED REAL ESTATE INVESTMENTS

Early studies into the benefits of including listed real estate in US direct real estate portfolios included Giliberto (1990), Giliberto and Testa (1990) and Stevenson (2001). These studies showed that there was potential to diversify by investing in both direct and listed real estate markets, with listed real estate assets acting as timing devices that enabled investors to observe market movements which take time to be reflected in direct real estate values. Stevenson (2001) conducted sector level analysis using three REIT sectors – equity, mortgage and hybrid REITs – as well as non-US listed real estate assets. He noted that, in addition to enhanced diversification, listed real estate also made it possible for an investor to quickly alter the exposure of their portfolio, as well as infuse the portfolio with liquidity as an alternative to cash.

NAREIT (2011) also examined the benefits of blending private and listed real estate investments. They found that optimal blends of private real estate funds and listed real estate assets produced significantly better risk-adjusted returns than investing in private vehicles alone. This was again driven by the diversification and timing benefits of listed real estate investments. They suggested that the optimal composition of blended real estate portfolios should be around one-third listed real estate and two-thirds private real estate. The optimal blended real estate portfolio was found to produce positive annual returns, with not a single period of negative return over the entire sample period, which remarkably encompassed the 2007-2008 global financial crisis.

Lee (2014) analysed portfolios containing a blend of private and public real estate using the 70:30 allocation suggested by NAREIT (2011). His study employed the percent contribution to risk measure of Holman and West (2013) to see whether the additional return generated by including listed real estate in the blended portfolio justifies the additional risk which it adds to the portfolio. The results showed that a blended public and private real estate portfolio produced a higher Sharpe ratio than any direct real estate fund type. Listed real estate was however found to be the main driver of volatility in the blended portfolios. Lee (2014) concluded that although listed real estate enhances the returns of real estate portfolios, the returns were not sufficient to justify the risk they contribute to the portfolio.

The findings of NAREIT (2011) were confirmed by Moss and Farrelly (2014). They analysed a 70:30 blend of UK unlisted real estate funds and global listed real estate funds over the period 1998-2013, as well as a portfolio split 75:25:5 between UK unlisted real estate, global listed real estate and cash. They found that adding global listed real estate to the portfolio resulted in return enhancement of about 19% over the full period. It also led to a significant increase in volatility, though they found that the Sharpe ratio only declined modestly due to the high increase in returns. They argued that this decline was acceptable given the additional liquidity benefits that were obtained by adding listed real estate.

Meanwhile, the motivation for the cash allocation was to service the day-to-day liquidity requirements of the portfolio, so that the return enhancement benefits of listed real estate would not be lost through frequent trading of this element (see also Farrelly and Moss, 2014; Moss & Farrelly, 2015).

Nonetheless, Moss and Farrelly (2014) noted that, although many asset managers are aware of the benefits of including a proportion of listed real estate in their direct real estate portfolios, most were reluctant to implement this strategy. One of the main concerns was the increase in tracking error that would result from adding listed real estate to the direct real estate portfolio. For example, allocating 30% to listed real estate, as recommended by NAREIT (2011), resulted in a per-annum tracking error of 5.2% relative to the UK IPD direct real estate index. So, while listed real estate might offer a diversification benefit relative to direct real estate, if the aim in a multi-asset context is to obtain direct real estate returns, then adding listed real estate might be detrimental to that wider aim.

This raises the question of the extent to which listed and direct real estate could be considered as substitutes or complements from a multi-asset perspective, or even whether listed real estate should simply be considered part of the broader equity market. The earliest studies to examine these questions utilised simple correlation based tests, which often revealed a low contemporaneous correlation between direct and listed real estate, and a high correlation between listed real estate and equities. More recent contributions have used cointegration and other advanced techniques to understand the linkages better.

Ling & Naranjo (1999) examined whether the direct real estate market and the REIT market in the US were integrated with the common equity market. While REITs were found to be integrated with the equity market, direct real estate markets were not. However, other studies have found evidence of integration between direct and listed real estate (for example, Wang et al., 1997; Tuluca et al., 2000; Morawski et al., 2008; Oikarinen et al., 2011). Most of these studies have found that returns in the listed real estate market lead direct real estate returns, implying that information is incorporated into the prices of listed real estate investments more quickly, and that the two types of real estate will not track each other closely in the short-term as a result.

Hoesli & Oikarinen (2012) examined the short-term and long-term dynamics between listed and direct real estate. Their analysis was based on sector level data from Australia, the UK and USA. The study also adjusted for the absence of leverage in direct real estate indexes. They show that over the long run, the returns of listed real estate were much closer to the direct real estate market than they are to the general stock market. Similarly, Yunus et al. (2010) found a long-term relationship between the listed and direct real estate markets, and that listed real estate leads the direct real estate market in the

UK, US, Australia and the Netherlands. Meanwhile, Ang et al. (2013) studied the US market and found a common and highly persistent real estate cycle across both the direct and listed real estate markets. Both were broadly exposed to pro-cyclical market factors.

The foregoing suggests that direct and listed real estate might be good long-term substitutes, but, to the authors' knowledge, only (Farrelly and Moss, 2014; Moss & Farrelly, 2015) have considered the question of tracking error when combining direct and listed real estate into a blended portfolio, though low short-run correlations between direct and listed real estate imply that significant tracking error will be present. Meanwhile, none of the studies reviewed so far have addressed the question of which liquid assets beyond cash and listed real estate could be included within a blended real estate portfolio or the optimal combination of such assets. Given that many property funds have fixed, pre-determined allocation to various liquid assets, sometimes with a tolerance level, this study considers the optimal mix of liquid assets within the liquid asset component and examines the effects on returns, risk and tracking error in relation to a direct real estate benchmark.

6.1.2 REPLICATING RETURNS OF ILLIQUID ASSETS - EVIDENCE FROM OTHER MARKETS

The issue of enhancing liquidity within asset portfolios is not limited to the real estate market. O'Doherty et al. (2015) note a very high demand among institutional investors for passive replication products that track the performance of illiquid assets such as private equity and hedge funds. An example are Liquid Alternative Beta funds, which seek to replicate the risk and return characteristics of hedge fund indexes through investment in liquid, tradable instruments (see Drachman and Little, 2010). The use of factor models to replicate hedge fund performance with more liquid investments is perhaps the most popular approach among product developers and academics (Hasanhodzic and Lo, 2007; Amenc et al., 2008; Amenc et al., 2010; Bollen & Fisher, 2013). These models estimate the target fund or index exposure to certain factors and use the information to determine asset allocations within the replicated portfolios. For instance, Hasanhodzic and Lo (2007) constructed a factor model and used it to replicate the returns of 1,610 hedge funds. These funds covered all the major hedge fund investment strategies.

Although intuitively appealing, factor models have some drawbacks that limit their effectiveness in replicating hedge fund returns. The lack of transparency in the investment process of hedge funds makes it difficult to identify an appropriate set of factors. This leads to poor out-of-sample performance of these models in tracking hedge fund returns, while products based on them have also been found to underperform the target portfolios (Amenc et al., 2010; Bollen & Fisher, 2013). Kat and Palaro (2005) advocate an alternative approach that does not seek to generate identical period-to-period returns, but generate returns with the same statistical properties as the hedge fund being replicated. Meanwhile, other alternatives to factor models are the algorithmic approach and the payoff distribution approach. O'Doherty et al. (2015) used an algorithm that combines information from several pre-selected models and use this to create a cloned hedge fund.

Private equity funds are perhaps the most illiquid alternative asset class, as capital in these funds can be locked up for as long as twelve years (Timmermans, 2009). Nonetheless, such funds appeal to institutional investors as they can offer higher returns and diversification opportunities. A few studies have examined the possibility of replicating the risk and return features of private equity funds using more liquid investments. Axelson et al. (2013) documented factors that determine the financial structure of private equity funds and compared these with publicly traded funds. Using the factors identified in Axelson et al. (2013), Stafford (2017) then explored the possibility of replicating private equity fund performance using a passive portfolio of similar public equity investments. A similar approach was taken by Ang et al. (2013), and MSCI has since created a liquid private equity index for US real estate investors based on their analysis.

6.2 APPROACH

Different strategies are employed in this study for the creation of blended or hybrid real estate portfolios. The aim is to construct blended real estate portfolios whose out-of-sample returns best replicate the risk and return features of the underlying direct real estate market over time. The types of blended portfolios constructed here are set out in Table 6(I).

Table 6(I) Composition of Various Blended Real Estate Portfolios

Fund A (DRE-CASH)	Direct real estate and cash
Fund B (DRE-LRE)	Direct real estate and listed real estate
Fund C DRE-ALL)	Direct real estate, cash, listed real estate, aggregate stocks, bonds of various maturities (No minimum return constraint)
Fund D (DRE-ALL1)	Direct real estate, cash, listed real estate, aggregate stocks, bonds of various maturities (With minimum return constraint)

Note: The minimum return constraint is that the target return should be equal to or greater than the average return on the IPD All Property Index. See text for further discussion.

The first strategy employs the use of cash as a liquidity buffer. This approach is referred to as Fund A and it is common among UK real estate funds as can be seen from Appendix A. The second strategy adds listed real estate to a portfolio of direct real estate investments. This is referred to as Fund B and is used in funds such as Legal & General's Pension Property Fund. Two further strategies are then examined using formal optimization procedures. In each case, portfolios are constructed by combining direct real estate with a wider selection of liquid assets; cash, listed real estate, aggregate stocks and bonds of various maturities. The third strategy, which is referred to as Fund C (DRE-ALL), does not have a minimum return requirement, while the fourth strategy, labelled Fund D (DRE-ALL1), includes a requirement that the returns of the portfolio equal at least the average total return on the IPD UK real estate index over the same period.

For the first and second portfolios, once the investment manager determines the proportion of cash or listed real estate that should be included in the blended real estate portfolio, the blending process consists of adding this proportion of liquid asset to the direct real estate portfolio. The return of the blended/hybrid portfolio can be obtained from the Equation 1 below:

$$R_p=[r_{DRE}*w_{DRE}]+[r_{LA}*w_{LA}] \qquad \textbf{6(1)}$$

Where:

R_p= Return of the blended real estate portfolio

r_{DRE} and r_{LA} = return of the direct real estate portfolio and selected liquid asset, respectively

w_{DRE} and w_{LA} = weight of direct real estate and the selected liquid asset in the blended portfolio

For the portfolios that include a wider selection of liquid assets, the optimal combination of such assets is determined as follows. First, an optimal allocation to the various liquid assets is determined using an extension of the mean-variance optimisation procedure of Markowitz (1952). The extension is made to accommodate the practice of evaluating the performance of managers relative to a benchmark (Rudd & Rosenberg, 1980; Roll, 1992; Rudolf et al., 1999). The optimisation problem is formulated in terms of tracking error and its volatility as opposed to absolute returns and its volatility. Tracking error is defined as the standard deviation of the difference between the portfolio returns and the benchmark return. In this context, it measures how closely the blended portfolio follows the returns on the benchmark index. Mathematically:

$$TE_P=\sigma(r_{Pt}-r_{bt}) \qquad \textbf{6(2)}$$

Another common approach to measuring the relationship between two variables is the correlation coefficient. However, tracking error is preferred here for the optimization procedure because the correlation coefficient is not a measure of congruence, but the strength of linear relationship. Thus, a high level of correlation is necessary but not a sufficient condition for minimising the tracking error variance of a portfolio. Given the variance of the portfolio returns and benchmark returns as well as the correlation between a portfolio and the benchmark, the tracking error can be estimated using the relation below:

$$TE_P=\left(\sigma_P^2+\sigma_b^2-2\rho\sigma_p\sigma_b\right)^{0.5} \qquad \textbf{6(3)}$$

Where:

TE_P is the tracking error of a portfolio

σ_P^2 is the variance of portfolio returns

σ_b^2 the variance of benchmark returns and

ρ represents the correlation between the returns of the portfolio and the returns on the benchmark.

A general form of the tracking error optimisation model seeks to minimise the tracking error variance for a given expected excess return. The following numerical optimisation model is implemented:

$$\min_{w_k} \sum_{k=1}^{T}\left(r_{index,t}-\sum_{k=1}^{N} w_k r_{k,t}\right)^2 \qquad \textbf{6(4)}$$

Subject to:

$\sum_{t=1}^{T}\left(r_{index,t}-\sum_{k=1}^{N} w_k r_{k,t}\right)=0$

$\sum_{k=1}^{N} w_k=1$

$L<w_k<U$

Where:

$r_{index,t}$ = the return on the direct real estate benchmark at time t

$r_{k,t}$ = the return on the kth asset at time t

w_k = the weight assigned to the kth asset

The optimizer selects a combination of assets that provide the lowest tracking error relative to the IPD UK index returns, subject to the constraints of zero expected tracking error, unit sum of weights and a set allocation to direct real estate. The weight set for direct real estate ranged from 0% to 90%, in 10% intervals. The optimal combination of liquid assets was then determined for the remainder of the portfolio in each case. Discussion in this chapter focuses on liquid asset allocations of 10 to 30% which represents the range of allocation by UK hybrid real estate funds. For example, the Legal and General Hybrid Property Fund consists of a 30% liquid asset allocation whereas typical open-ended real estate funds contain a 10% liquid asset allocation.We also include a pure replication portfolio that is made up entirely of liquid assets to demonstrate the possibility of using liquid assets alone to proxy the direct real estate market.

Tracking error optimisation models are subject to limitations. As they minimise in-sample tracking error with respect to a benchmark, this could lead to over-fitting the data in-sample at the expense of additional out-of-sample tracking error. The in-sample over-fitting may also result in an unstable portfolio structure that requires frequent rebalancing and incurs significant transaction costs (Gregoriou et al., 2005). The models also make use of the covariance matrix, which means that they suffer from the weaknesses generated by the use of correlation as a measure of dependency. Correlation is a short-term statistic which lacks stability. Its estimation is sensitive to outliers, non-stationarity and volatility clustering. Some authors have suggested using vector autoregressive (VAR) models to measure the relationship between variables. For example, Alexander and Dimitriu (2004) compared the theoretical and empirical properties of the classic mean tracking error models with an enhanced MTE model that has an additional feature allowing for use of the cointegration between the tracking portfolio and the index. They found no clear advantages in using the enhanced version of the MTE model.

Nonetheless, it has been shown that tail events exist where parameters such as correlation change drastically. It is, therefore, better to calculate a conditional correlation which estimates correlation based on all information available up to a particular time point. Several approaches can be used to estimate the conditional correlation. A rolling correlation is easy to estimate and is capable of capturing time-variation and clustering of cross asset returns. However, there is no clear theoretical or empirical basis for selecting a window length. Furthermore, Anderson and Romaindo (2008) observed that, since all the windows in a rolling correlation analysis are given the same weight, they tend to adjust very slowly to new information. This problem becomes greater with longer window lengths. There could be huge changes in correlation estimates when there are abnormally small or large return observations, especially when these observations enter or leave the window. Forbes & Rigobon (2002) found that rolling correlation coefficients tend to be prone to bias. They explained that, as volatility increases in one asset market, heteroscedasticity in returns may cause the correlation coefficient to be biased upward (see also Chong et al., 2012).

To make up for the drawbacks of the rolling correlation method, Engle (2002) suggests using the Dynamic Conditional Correlation (DCC) model. Many studies have used the DCC model within the real estate literature (Cotter and Stevenson, 2007; Chong et al., 2009; Liow et al., 2008; Fei et al., 2010; Case et al., 2012; Heaney & Sriananthakumar, 2012; Sing and Tan; 2013). The DCC model calculates the conditional correlations as a function of past volatilities of assets and the covariance between them. Given that all past information is used in the optimisation process, there is no difficulty in selecting a window length as with rolling correlations. Engle (2002) found that the multivariate and univariate volatility forecasts are consistent with each other. The volatility forecasts and the correlations of the original assets remain unchanged when new variables are added to the system, depending on the way the model is revised. Also, when applied to typical financial applications, it was found that DCC models revealed important time varying features that might otherwise be difficult to quantify.

The Dynamic Conditional Correlation model estimates a GARCH (1,1) specification, employing the resulting standardized residuals to estimate the time varying correlation matrix. In order to accomplish this, the residuals are transformed by their estimated standard deviations $\Xi_t = \varepsilon_t / \sqrt{h_t}$.

The covariance matrix can be expressed as $H_t \equiv D_t R_t D_t$, where D_t is a diagonal matrix of univariate GARCH volatilities. $R_t = Q_t^{*-1} Q_t Q_t^{*-1}$ is the time varying correlation matrix, with Q_t as described by:

$$Q_t = (1 - a - b)\overline{Q} + a\left(\Xi_{t-1}\Xi'_{t-1}\right) + Q_{t-1} \qquad \textbf{6(5)}$$

$\overline{Q}$ is the unconditional covariance of standardized residuals resulting from the first stage estimation, and Q_t^* is a diagonal matrix composed of the square root of the diagonal elements of Q_t. As with the standard GARCH (1, 1) model, the coefficients of the DCC(1, 1) model are estimated by maximum likelihood using the algorithm of Broyden–Fletcher–Goldfarb–Shanno (BFGS). The log-likelihood function, under the assumption of conditional multivariate normality can be displayed as follows:

$$L(\vartheta) = -\frac{1}{2}\left[TN \ln(2\pi) + \sum_{t=1}^{T} \ln\left|H_t + \Xi'_t H_t^{-1} \Xi_t\right|\right] \qquad \textbf{6(6)}$$

where Ξ_t is an $N \times 1$ vector stochastic process, with $H_t = E_{t-1}\left(\Xi_t \Xi'_t\right)$, being the $N \times N$ conditional variance-covariance matrix.

6.3 DATA

This study uses UK data to analyse the effects of adding different combinations of liquid assets to a direct real estate portfolio over the period 1987 to 2015. Quarterly total return rates for direct real estate investments were sourced from MSCI IPD (splicing the IPD UK monthly index with the larger IPD UK quarterly index when latter begins in Q1 2000), while total returns for listed real estate, government bonds, equities and cash were all sourced from DataStream.[3] The in-sample portfolios were estimated from Q1 1987 as this was the earliest date from which quarterly return rates for direct real estate were available. Out-of-sample portfolios were estimated from the start of 1991, based on a five-year window. So the first out-of-sample portfolio is estimated using data from Q1 1987 to Q1 1991, then the next is estimated by rolling the window forward by one quarter, repeating this process up to the second quarter of 2015. In total, 78 out-of-sample portfolios are estimated.

One of the issues with direct real estate return series is that they are appraisal based, which means they tend to understate the risk of the underlying asset class. This leads, in turn, to an over-allocation to direct real estate in multi-asset optimisation studies (see Marcato & Key, 2007). In this study, the weight allocated to direct real estate has been set at particular thresholds and does not interfere with the relative allocation to different liquid assets in the portfolio. This is shown later by the results, as allocations within the liquid asset component remain stable, irrespective of the proportion allocated to direct real estate. However, the direct real estate index also serves as a benchmark against which the performance and tracking error of each portfolio is assessed, which is a potential limitation of the analysis conducted here.

Another criticism of direct real estate indexes is the difficulty in passively replicating their returns. The reason for this criticism is the belief that an investor must hold a large number of properties to diversify unsystematic risk. For example, while Callender et al. (2007) found that investing in 30 to 50 properties could achieve a large amount of risk reduction, they found that more properties were necessary to achieve very low levels of tracking error against the market index. However, their study was based on the use of naïve diversification, which ignores the potential gains from deliberate structuring of a portfolio to reduce systematic risk. Moreover, Boudry et al. (2013) have subsequently found that real estate portfolios do a good job of tracking index returns when these portfolios contain at least 20 assets.

The most common liquid assets in the portfolios of UK open-ended property funds are cash and listed real estate, but the liquid asset universe is expanded in this study to include the two main classes of liquid, publicly traded assets; bonds of various maturities and aggregate stocks. While many investors view the stable income flows of real estate to be bond-like, Shepard et al. (2015) found the long-run behavior of real estate returns to be more equity-like, i.e. cyclical and growth sensitive. Thus, the role that both bonds and general equities could play in replicating direct real estate returns is investigated. The UK FTSE all share index is used to represent the aggregate equity market while returns for bonds

[3] Note that the opportunity set has been limited to UK assets to avoid the added complications of currency fluctuations. This omission does not detract from the general points that the study seeks to make.

of various maturities are drawn from the Thomson Reuters DataStream bond indexes. The 3-month UK Treasury bill return is used as the proxy for cash.

Table 6(II) Summary Statistics and Correlation Coefficients for Quarterly Total Return Rates (Q1 1987 – Q1 2015)

	Direct Real Estate	**Listed real estate**	**General stocks**	**Bonds 10yr+**	**Bonds 10yr**	**Bonds 7yr**	**Bonds 5yr**	**Bonds 3yr**	**Bonds 2yr**	**Cash**
Panel A: summary statistics										
Mean	2.31	2.90	2.70	2.40	2.24	2.06	1.89	1.75	1.60	1.36
Median	2.59	4.72	3.77	2.14	2.34	1.99	1.73	1.64	1.30	1.31
Maximum	9.92	43.98	27.11	15.96	15.12	9.45	10.66	7.32	5.92	3.48
Minimum	-12.96	-34.18	-30.61	-9.38	-8.26	-5.91	-4.77	-2.12	-1.12	0.09
Std. Dev.	3.06	12.03	8.44	4.67	3.99	3.11	2.64	1.81	1.45	0.90
Sharpe ratio	0.31	0.13	0.16	0.22	0.22	0.22	0.20	0.21	0.16	0.00
TE w.r.t. DRE	0.00	11.00	8.27	5.76	5.41	4.83	4.46	3.94	3.74	3.26
Panel B: Correlation Coefficients										
Direct real estate	1.0000									
Listed real estate	0.4514	1.0000								
General stocks	0.2388	0.0637	1.0000							
Bonds 10yr +	-0.0704	0.0848	0.0662	1.0000						
Bonds 10yr	-0.1637	0.0501	0.0751	0.9613	1.0000					
Bonds 7yr	-0.2235	0.0536	0.0792	0.9082	0.9757	1.0000				
Bonds 5yr	-0.2218	0.0472	0.0816	0.8542	0.9475	0.9765	1.0000			
Bonds 3yr	-0.2624	0.0159	0.1136	0.7498	0.8604	0.9163	0.9591	1.0000		
Bonds 2yr	-0.2850	-0.0279	0.0846	0.6318	0.7556	0.8220	0.8850	0.9668	1.0000	
Cash	-0.0787	-0.0675	0.0288	0.0404	0.1057	0.1499	0.2248	0.3584	0.5140	1.0000

Note: Bonds 10yr+ = Bonds with maturity greater than 10 years; Bonds 10yr = 10 year bonds; Bonds 7yr = 7 year bonds; Bonds 5yr = 5 year bonds; Bonds 3yr = 3 year bonds; Bonds 2yr = 2 year bonds; TE w.r.t. DRE = Tracking error with respect to IPD All Property index; Sharpe ratio = Risk-adjusted returns with respect to the risk-free rate i.e. 3-month UK T-bill rate; Std. Dev. = Standard deviation of returns.

Table 6(II) shows the quarterly return and risk characteristics of the various assets that are used to estimate optimal hybrid real estate portfolios. Listed real estate had the highest return and variability of all the selected liquid assets. Meanwhile, the returns for shorter-term bonds were found to be lower than those for longer-term bonds – implying an upward sloping yield curve over the majority of the period analysed.

Concerning the relationship between direct real estate returns and the returns of the liquid assets, the correlation coefficient between direct real estate and listed real estate is the highest, followed by the correlation between direct real estate and stocks (Table 6(I)). It is interesting to note that the correlation between direct real estate and listed real estate is far greater than the correlation between the two stock series - listed real estate and general stocks. This may be indicative of the fact that listed real estate is more associated with the direct real estate market than the general stock market. Negative correlation between is observed between direct real estate all the bond maturities. However, the absolute value is higher for shorter maturity bonds than longer maturity bonds. The correlation between the various bond maturities themselves is quite high, often more than 0.70. The correlation between cash and bonds is also higher for shorter maturity bonds than longer-maturity bonds.

Although the correlation coefficient between direct real state and listed real estate was the highest of all the selected liquid assets, due to the very high standard deviation, the tracking error with respect to direct real estate turned out to be very high. A high tracking error implies that, compared to the returns of returns the other liquid assets, the returns of listed real estate does not does not have a close association with the returns on the IPD direct real estate benchmark portfolio. This implies that adding general stocks or listed real estate to a blended real estate portfolio may result in the resulting portfolio exhibiting a risk and return profile that is quite different from those of the real estate benchmark. The tracking error between cash and direct real estate was the lowest, implying that cash may be the most suitable asset to be added to the direct real estate portfolio. The returns of shorter-term bonds exhibited lower tracking errors to direct real estate than longer-term bonds.

6.4 RESULTS

The optimal allocations for the blended real estate portfolios are now discussed, looking first at the in-sample allocations and then the out-of-sample results. Funds A and B were made up of pre-determined allocations to direct real estate and either cash or listed real estate, with no optimization as per Moss & Farrelly (2015). Funds C and D were then constructed using the tracking error optimisation approach, with the aim of finding the combination of direct real estate and the selected liquid assets that produced the lowest tracking error. Fund C had no minimum return constraint and Fund D was constrained to produce returns that matched the average total returns on the direct real estate benchmark.

6.4.1 IN-SAMPLE ALLOCATIONS, RISK AND RETURNS OF BLENDED REAL ESTATE PORTFOLIOS

Prior to comparing risk and return for the various approaches, the allocations from the in-sample optimization exercise were as follows. Without minimum return constraints, Table 6(III) shows that about 80% of the allocation to liquid assets in Fund C went to cash, while the remaining allocation was to listed real estate and to general equities. Although the reported proportions change in line with the overall allocation to liquid assets, once the allocations are rescaled to reflect only the liquid component, the mix of liquid assets remains constant. The allocation to cash remains at 80%, while listed real estate and general stocks made up 12% and 8%, respectively. The high allocation that cash receives is broadly in line with the investments made by existing UK open-ended real estate funds. However, the addition of some listed real estate and general stocks could still improve the tracking error of these portfolios relative to the direct real estate market.

For Fund D, with a constraint that the returns of the portfolio should at least equal the average return of direct real estate, long-term bonds with maturities greater than 10 years gain significant allocations (33% of the liquid asset component). Again, the proportion of each liquid asset to the total liquid asset allocation is very consistent. The allocation to cash dropped from 80% to about 25% of the liquid asset component, while the allocation to general stocks increased from 8% to about 24%, and listed real estate increased to 19%. This suggests that, to remove the negative performance impact of the so called cash drag, other types of liquid assets are likely to be required within a blended real estate portfolio.

An examination of the returns of the various blended real estate funds presented in Table 6(III) shows that the in-sample tracking error of Fund C (DRE-ALL) with respect to direct real estate was the lowest. This is followed by Fund A (DRE-CASH). However, the returns of the two portfolios that have the lowest tracking error were also quite low when compared to the direct real estate index. For example, with just a 10% allocation to liquid assets, there is a significant drop in return from 2.31% to 2.22% for Fund A and 2.25% for Fund C. In contrast, although Fund B (a mix of direct and listed real estate) produced the highest tracking error, it generated consistently higher returns than the direct real estate index, matching the findings of Farrelly and Moss (2014) and NAREIT (2011). The in-sample returns of Fund D, which includes the minimum return constraint, were also higher than the return on the direct real estate index, but with a far lower tracking error than the portfolios where listed real estate was used in isolation.

Table 6(III) In-Sample Statistics of Blended/Hybrid Real Estate Portfolios

PERFORMANCE STATISTICS					ALLOCATIONS									
Portfolio Return	Excess return wrt DRE	Portfolio Standard Deviation	Tracking Error	Correlation with Real Estate	Stocks	Bonds (10+ years)	Bonds (10 year)	Bonds (7 years)	Bonds (5 years)	Bonds (3 years)	Bonds (2 years)	Listed real estate	Cash	Direct real estate
Fund A Direct real estate and cash														
1.3624	-0.9505	0.9028	3.3561	-0.0787	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00
2.0278	-0.2851	2.1387	1.0068	0.9920	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.30	0.70
2.1228	-0.1901	2.4415	0.6712	0.9973	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.80
2.2178	-0.0950	2.7495	0.3356	0.9946	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.90
Fund B Direct real estate and listed real estate														
2.9025	0.5897	12.0337	11.0032	0.4433	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00
2.4976	0.1847	5.0047	3.3010	0.7627	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.30	0.00	0.70
2.4397	0.1268	4.1977	2.2006	0.8578	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.80
2.3819	0.0690	3.5517	1.1003	0.9527	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.00	0.90
Fund C Direct real estate and all liquid assets (No minimum return constraint)														
1.6611	-0.6287	1.7745	2.7989	0.4332	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.80	0.00
2.1174	-0.1886	2.4215	0.8397	0.9802	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.24	0.70
2.1872	-0.1257	2.6316	0.5598	0.9925	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.16	0.80
2.2477	-0.0629	2.8365	0.2799	0.9984	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.08	0.90
Fund D Direct real estate and all liquid assets (with minimum return constraint)														
2.3129	0.0000	3.6384	3.7454	0.3828	0.23	0.33	0.00	0.00	0.00	0.00	0.00	0.19	0.25	0.00
2.3162	0.0033	2.7587	1.1236	0.9293	0.07	0.10	0.00	0.00	0.00	0.00	0.00	0.06	0.07	0.70
2.3151	0.0022	2.8128	0.7491	0.9703	0.05	0.07	0.00	0.00	0.00	0.00	0.00	0.04	0.05	0.80
2.3140	0.0011	2.9153	0.3745	0.9931	0.02	0.03	0.00	0.00	0.00	0.00	0.00	0.02	0.02	0.90

The foregoing discussion indicates that cash is the most suitable standalone asset to be included in direct real estate portfolios to improve liquidity without significantly altering the risk-return profile. However, adding listed real estate and a small amount of general stocks represents the optimal strategy. This optimal strategy still leads to a loss in returns because the unconstrained portfolios contain a large amount of cash, so the so-called cash drag remains. Thus, if concerned with return as well as tracking error, an investment manager may have to also include long-term bonds, especially those with maturities longer than ten years. More would have to be invested in listed real estate and general equities as well. The investor must accept a slightly higher tracking error if they require returns that are closer to direct real estate returns.

6.4.2 OUT-OF-SAMPLE ALLOCATIONS, RISK AND RETURNS OF BLENDED REAL ESTATE PORTFOLIOS

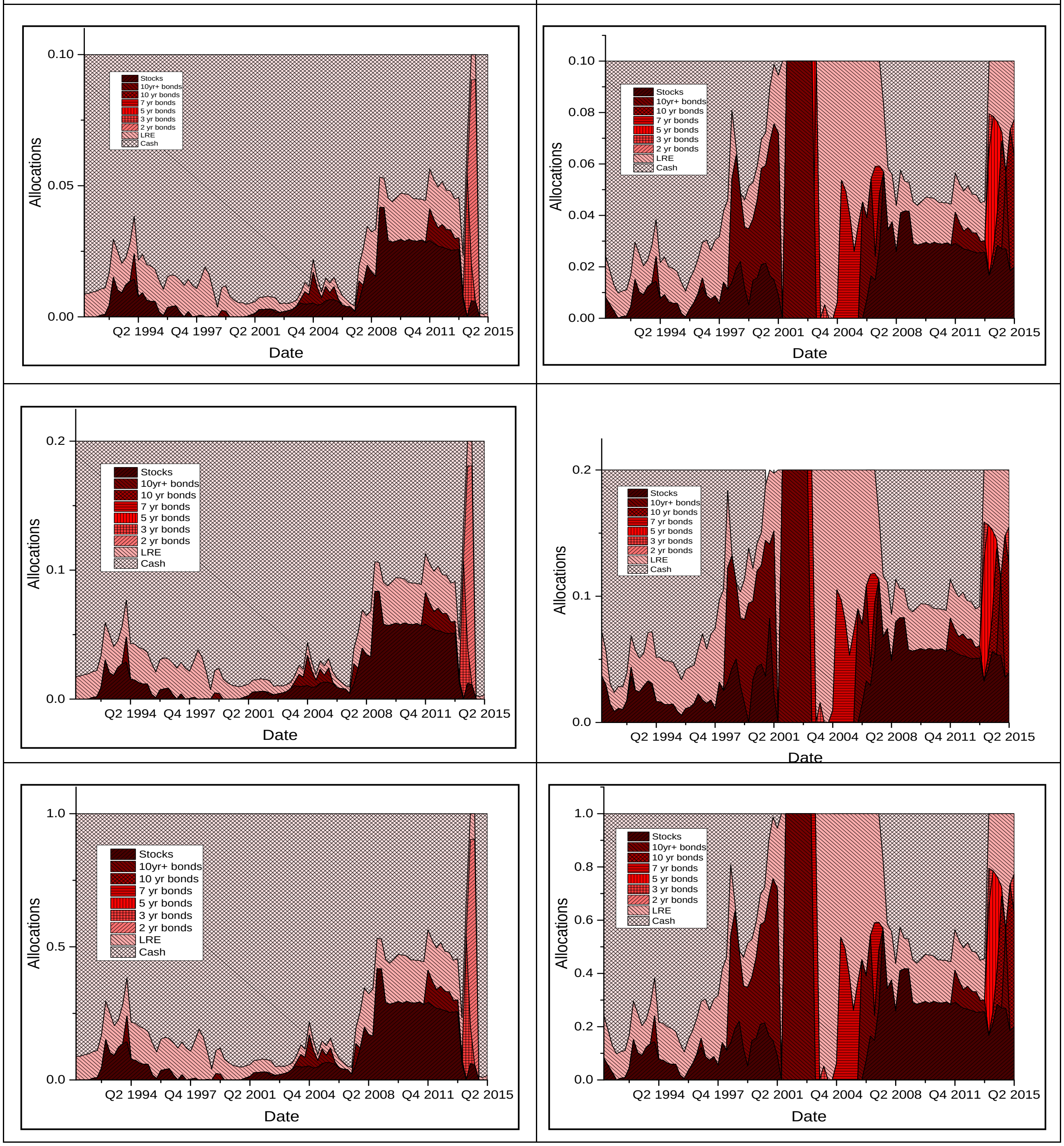
As noted earlier, a shortcoming of the tracking error optimisation model is that the in-sample estimates may be over-fitted, which could result in higher out-of-sample tracking errors. How well the model performs depends on whether out-of-sample outcomes corroborate the in-sample results. Hence, in this section, the allocations and subsequent performance of blended real estate portfolios over different five year windows is studied. This analysis of the out-of-sample portfolios also enables us to see whether the composition of the optimal portfolios remains the stable across different windows or whether some rebalancing would be required.

As with the allocations obtained in-sample, the out-of-sample allocations for the various combinations of liquid assets remain similar, irrespective of the overall weight to liquid assets in the portfolio. This consistency implies that, once the optimal allocation is obtained, there is no need to re-run the allocation if the liquid asset weight is to be increased or decreased. All that is required is to rescale the allocations to individual liquid asset classes to reflect the new overall weight of liquid assets relative to direct real estate.

Figure 6(1) shows the liquid asset allocations within the blended real estate portfolios. The portfolios that have a 10%, 20% and 100% allocation to liquid assets are used as examples. It can be seen that the pattern of allocation remains the same irrespective of how much liquid asset is contained therein. The left hand panel of Figure 6(1) shows the results for the unconstrained optimal portfolios. The liquid component of these blended portfolios is invested heavily in cash, especially prior to 2007. The only assets that had a significant allocation in the liquid component apart from cash is listed real estate. After 2007, though, general stocks and listed real estate together received allocations averaging about 40% of the liquid asset allocations.

Figure 6(1) Allocations within Blended Real Estate Portfolios (Out of Sample)

Fund C: No minimum return constraint	Fund D: With minimum return constraint



Notes: Bonds 10yr+ = Bonds with maturity greater than 10 years; Bonds 10yr = 10 year bonds; Bonds 7yr = 7 year bonds; Bonds; 5yr = 5 year bonds; Bonds 3yr = 3 year bonds; Bonds 2yr = 2 year bonds; Stocks = General stocks; LRE = Listed real estate; Cash = 3-month T-bills; Fund C = Optimisation is done without any minimum return constraint; Fund D = Optimisation is done with a constraint that target return should be equal to or greater than the average return on the IPD All Property Index.

The right-hand panel of Figure 6(1) shows the allocation in the constrained optimal portfolios. Clearly, these portfolios are more diversified than those in the left panel. The four assets that received significant allocations here are cash, listed real estate, general stocks and long-term bonds. Long-term bonds (10+ years) dominate the allocations between 1997 and 2003. Cash dominated the portfolio prior to 2000 and after 2007 but does not gain any allocations between 2000 and 2007. Short and medium term (3, 5 and 7 year) bonds also received allocations at various points within these portfolios.

Figure 6(2) shows the returns of the various blended real estate series alongside the returns on the IPD UK index. It can be seen that the returns of the blended Fund A (containing cash) and Fund C (unconstrained portfolio drawing on all liquid assets) track the benchmark more closely than their counterparts. This is also apparent from Table 6(IV), where the tracking error reported for Fund C (DRE-ALL) is the lowest, followed by that of Fund A (DRE-CASH). The combination of listed and direct real estate (Fund B) had the highest tracking error. This result was consistent across all levels of liquid asset allocation. The tracking error per quarter for Fund C ranges from 0.29% for the portfolio with only 10% weighting to liquid assets to 2.90% for that which contains only liquid, publicly traded assets. For Fund A, the tracking error ranges from 0.32% for the portfolio with 10% liquid assets to 3.16% where cash is the only asset in the portfolio.

With only 10% allocated to listed real estate, the tracking error for Fund B is 1.06%. This increases to 10.56% tracking error per quarter where only listed real estate is held. Imposing a minimum return requirement on the minimum tracking error model also increases the tracking error, but not as much as observed for the listed real estate and direct real estate mix. The tracking error ranged from 2.64% to 8.82%.

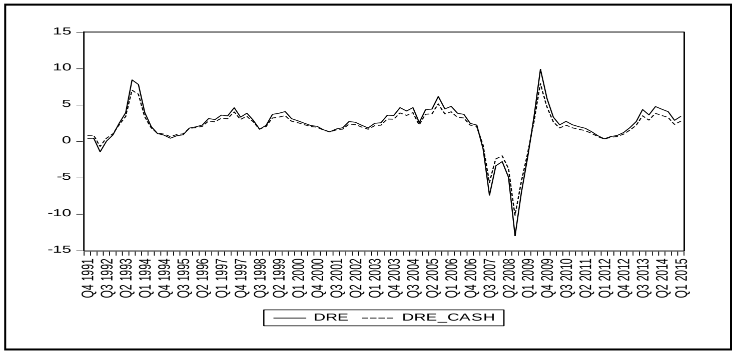
Table 6(IV) shows that of the different blended portfolios, the only one that recorded return enhancement when the allocation to liquid assets was increased was Fund B. However, there are differences when compound growth is considered instead of arithmetic average return rate. This shows that using listed real estate alone only enhanced returns up to a certain threshold. This was due largely to the volatility in listed real estate returns. Listed real estate also has the highest drawdown – a measure of risk which indicates how much an investment value would fall from peak-to-through until a new maximum is reached. Consequently, the portfolios for Fund B recorded the highest standard deviations among all the portfolios constructed.

None of the other portfolios showed an increase in return with the addition of liquid assets. On the contrary, the returns for Fund A (which contains cash and listed real estate) falls with every increase in the liquid asset allocation. Table 6(IV) shows that as much as 53% can be lost by substituting direct real estate for cash. This means that the lower tracking error observed earlier for the blended portfolio containing cash often comes at the cost of significant losses in return. The challenge then is to find a way of reducing tracking error without sacrificing significant returns.

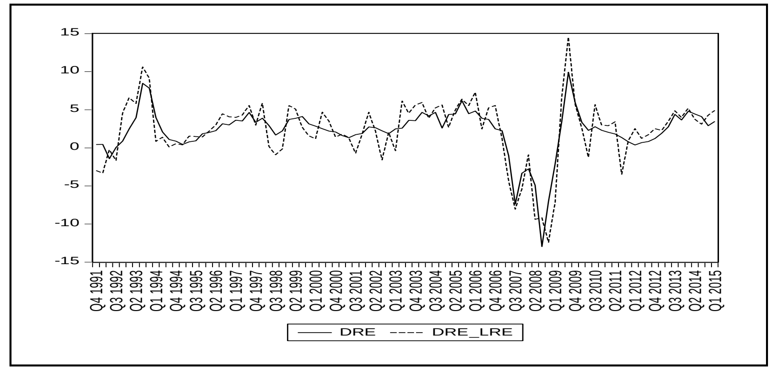
Including a wider selection of liquid assets and employing the Minimum Tracking Error optimisation procedure results in lower tracking error than simply adding cash to a direct real estate portfolio. From Table 6(IV), it can be seen that Fund C (DRE-ALL) produced lower tracking errors than Fund A (DRE-CASH), while providing returns that were higher. The loss in return required to achieve this low tracking error was 37%, compared to the 53% observed for Fund A. Meanwhile, in the case of Fund D (DRE-ALL1), unlike the in-sample results – which were subject to the minimum return constraint – the out-of-sample returns fell short of the returns on the IPD benchmark. This notwithstanding, the returns obtained from Fund D were higher and closer to direct real estate returns than those obtained for Fund C (DRE-ALL). Yet the tracking error increased slightly with the imposition of the minimum return constraint.

Figure 6(2) Out of Sample Returns of Blended Real Estate Portfolios (20% Allocation to Liquid Assets)

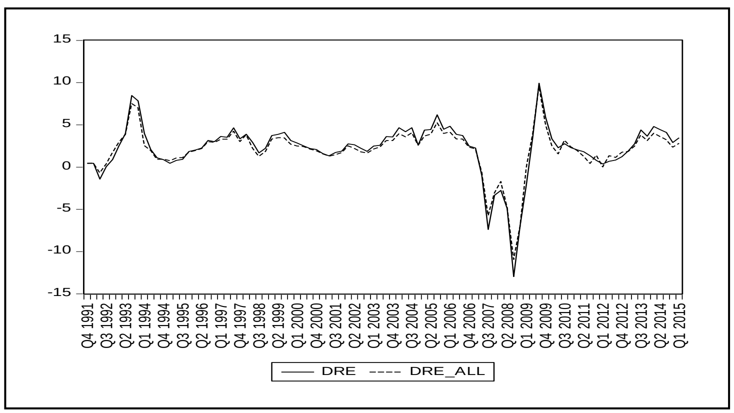
Fund A (DRE-CASH)



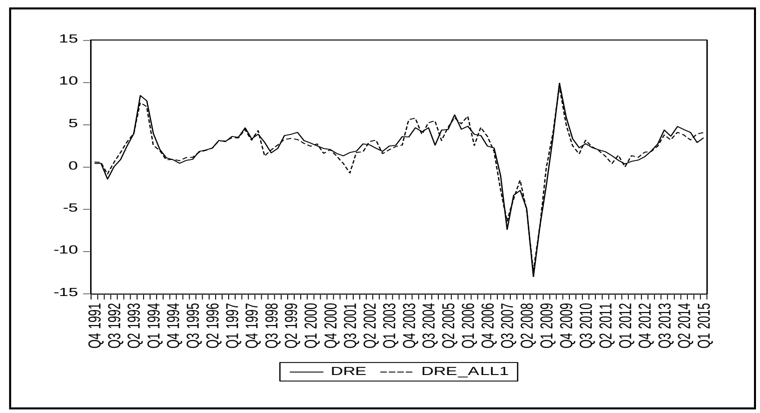
Fund B (DRE-LRE)



Fund C (DRE-ALL)



Fund D (DRE-ALL1)



Notes: DRE = IPD All Property Index; Fund A = A naïve mix of cash and the IPD All Property Index; Fund B = A naïve mix of listed real estate and the IPD All Property Index; Fund C = An optimised blend of the IPD All Property Index and selected liquid assets. Fund D = An optimised blend of the IPD All Property Index and selected liquid assets. Optimisation is done with a constraint that target return should be equal to or greater than the average return on the IPD All Property Index.

Table 6(IV) Quarterly Out-Of-Sample Summary Statistics of Blended Real Estate Portfolios

Liquid asset percentage	Selection of liquid assets				
10 percent liquid (90% direct real estate)	**FUND A (DRE_CASH)**	**FUND B (DRE_LRE)**	**FUND C (DRE_ALL)**	**FUND D (DRE_ALL1)**	**DRE**
Tracking error with respect to DRE (%)	0.3157	1.0561	0.2909	0.4037	0.0000
Average return (%)	2.0885	2.2462	2.1249	2.1882	2.2065
Average excess returns (%)	-0.1180	0.0397	-0.0816	-0.0183	0.0000
Standard deviation (%)	2.7127	3.4542	2.8128	2.9565	3.0216
Sharpe ratio	0.3825	0.3461	0.3819	0.3847	0.3825
Index value	670.05	773.36	692.37	731.03	742.18
Maximum drawdown	0.3145	0.4003	0.4110	0.3877	0.3886
Change in return with respect to DRE (%)	-5.3471	1.8013	-3.6981	-0.8283	0.0000
20 percent liquid (80% direct real estate)					
Tracking error with respect to DRE (%)	0.6315	2.1122	0.5794	0.8039	0.0000
Average return (%)	1.9705	2.2860	2.0428	2.1780	2.2065
Average excess returns (%)	-0.2360	0.0795	-0.1637	-0.0285	0.0000
Standard deviation (%)	2.4056	4.1186	2.6226	2.9467	3.0216
Sharpe ratio	0.3823	0.2999	0.3782	0.3825	0.3825
Index value	604.28	797.66	644.99	723.49	742.18
Maximum drawdown	0.2771	0.4482	0.4642	0.4173	0.4219
Change in return with respect to DRE (%)	-10.694	3.6026	-7.4190	-1.2899	0.0000
30 percent liquid (70% direct real estate)					
Tracking error (%)	0.9472	3.1683	0.8690	1.2063	0.0000
Average return (%)	1.8525	2.3257	1.9611	2.1616	2.2065
Average excess returns (%)	-0.3540	0.1192	-0.2454	-0.0449	0.0000
Standard dev. (%)	2.1010	4.9220	2.4503	2.9905	3.0216
Sharpe ratio	0.3816	0.2590	0.3715	0.3714	0.3825
Index value	544.37	814.27	600.56	711.33	742.18
Max drawdown	0.2381	0.4940	0.5153	0.4518	0.4507
Change in return wrt DRE (%)	-16.041	5.4040	-11.124	-2.0345	0.0000
100% liquid (pure replication)					
Tracking error with respect to DRE (%)	3.1574	10.5609	2.8967	4.0173	0.0000
Average return (%)	1.0267	2.6040	1.3884	1.9938	2.2065
Average excess returns (%)	-1.1798	0.3975	-0.8181	-0.2128	0.0000
Standard deviation (%)	0.6237	11.7270	2.1409	4.4406	3.0216
Sharpe ratio	-0.0388	0.1324	0.1577	0.2123	0.3825
Index value	254.44	693.23	355.74	581.39	742.18
Maximum drawdown	0.0000	0.7580	0.7358	0.6301	0.5708
Change in return with respect to DRE (%)	-53.471	18.013	-37.077	-9.6420	0.0000

Notes: DRE = IPD All-Property Portfolio; Fund A = A naïve mix of cash and the IPD All Property Portfolio; Fund B = A naïve mix of listed real estate and the IPD All Property Portfolio; Fund C = An optimised blend of the IPD All Property Portfolio and the all selected liquid assets. Optimisation is done without any minimum return constraint; Fund D = An optimised blend of the IPD All Property Portfolio and the all selected liquid assets. Optimisation is done with a constraint that target return should be equal to or greater than the average return on the IPD All Property Portfolio

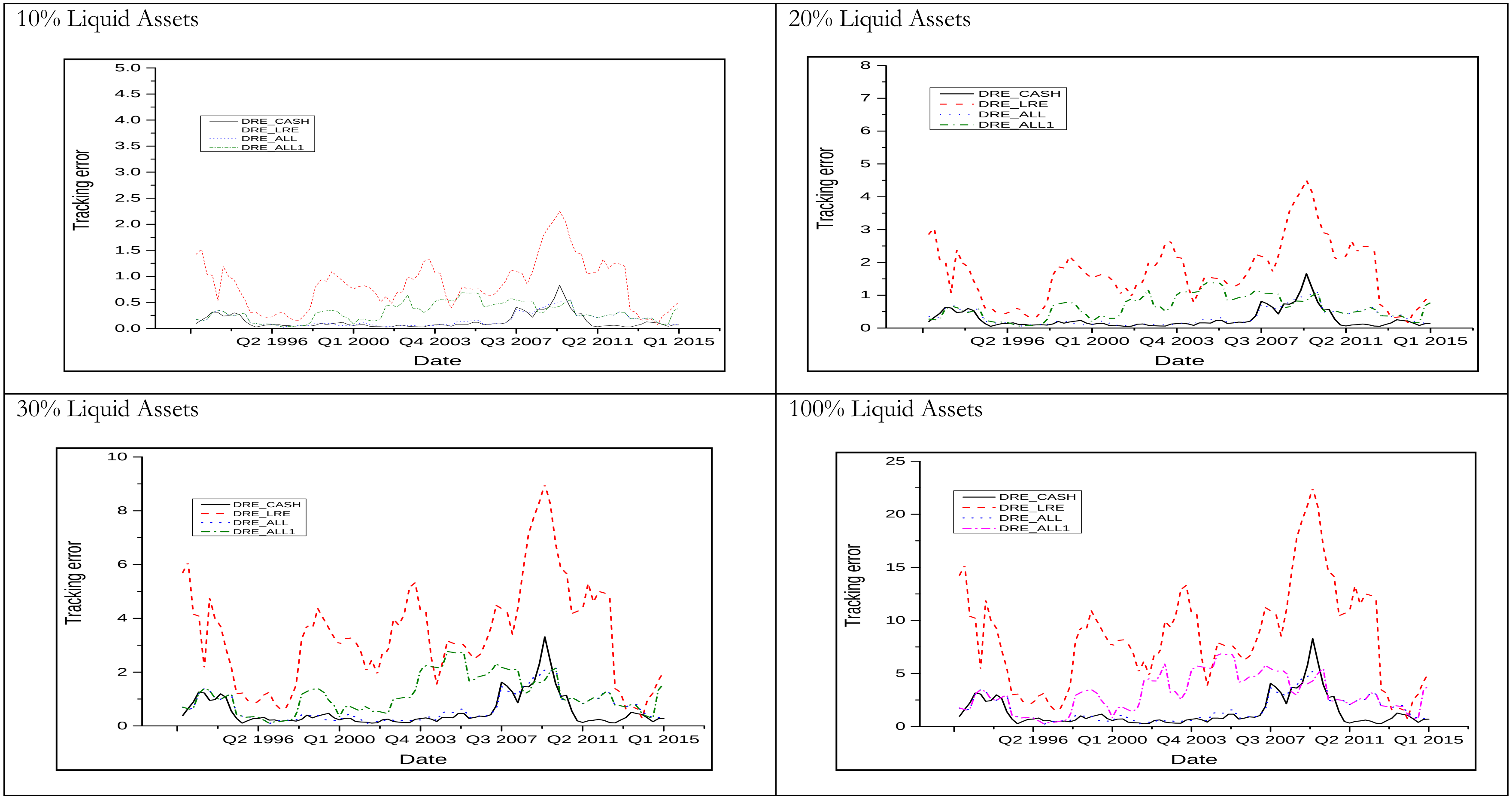
6.4.3 ANALYSIS OF THE TIME VARYING RELATIONSHIP BETWEEN HYBRID FUND RETURNS AND DIRECT REAL ESTATE

To account for potential temporal instability in relationships, rolling tracking errors are estimated using a 20-quarter (five year) window. As can be seen from Figure 6(3), the Portfolio containing direct real estate and listed real estate consistently had the highest tracking error relative to the direct real estate benchmark over the whole period. This confirms the results of previous studies and concerns raised by industry practitioners regarding the incorporation of listed real estate in direct real estate portfolios and also the results of the static tracking error presented earlier. The best combination remains cash and the blended real estate Fund C – which contains all liquid assets.

Tracking error generally increased for all the hybrid real estate funds during the periods around the recent Global Financial Crisis (2007 – 2008). Appendix 6(C) contains the summary statistics for the 20 quarter rolling tracking error for the four blended real estate funds. As indicated earlier, the blended real estate fund C (containing all liquid assets) recorded the lowest tracking errors which ranged from a minimum of 0.0162% per quarter (containing a 10% allocation to liquid assets) to a maximum of 5.4733 per quarter (for the pure replication fund). This means that even with no allocation to direct real estate, the maximum tracking error recorded for blended real estate fund C was less than 6% per quarter. This compares to a minimum of 0.0695% to a maximum of 22.49% tracking error for the blended real estate fund B (listed real estate – direct real estate mix). Blended real estate Funds A and D recorded a range of 0.0256% – 8.29% and 0.0256% - 6.92% respectively.

Different estimates of correlation are presented in Table 6(V). The average dynamic conditional correlation was identical to the 20 quarter rolling correlation for most funds. As observed by Chong et al. (2012) and Forbes & Rigobon (2002), where there were differences, the average conditional correlation was mostly lower than the average rolling correlation. At lower levels of direct real estate allocation, the correlation between Fund A (DRE-CASH) was very low, even negative at times. However, with very little allocation to direct real estate, the correlation between hybrid real estate Fund A and direct real estate increases remarkably. Fund A mostly had a higher correlation to direct real estate than all the other funds. This is attributable to the very low volatility of cash which makes it less likely to significantly alter the return pattern of the direct real estate portfolio when added to this portfolio.

Figure 6(3): 20-Quarter (5 year) Rolling Tracking Error



Notes: DRE = IPD All-Property Portfolio; DRE-CASH = A naïve mix of cash and the IPD All Property Portfolio; DRE-LRE = A naïve mix of listed real estate and the IPD All Property Portfolio; DRE-ALL = An optimised blend of the IPD All Property Portfolio and the all selected liquid assets. Optimisation is done without any minimum return constraint; DRE-ALL1 = An optimised blend of the IPD All Property Portfolio and the all selected liquid assets. Optimisation is done with a constraint that target return should be equal to or greater than the average return on the IPD All Property Portfolio

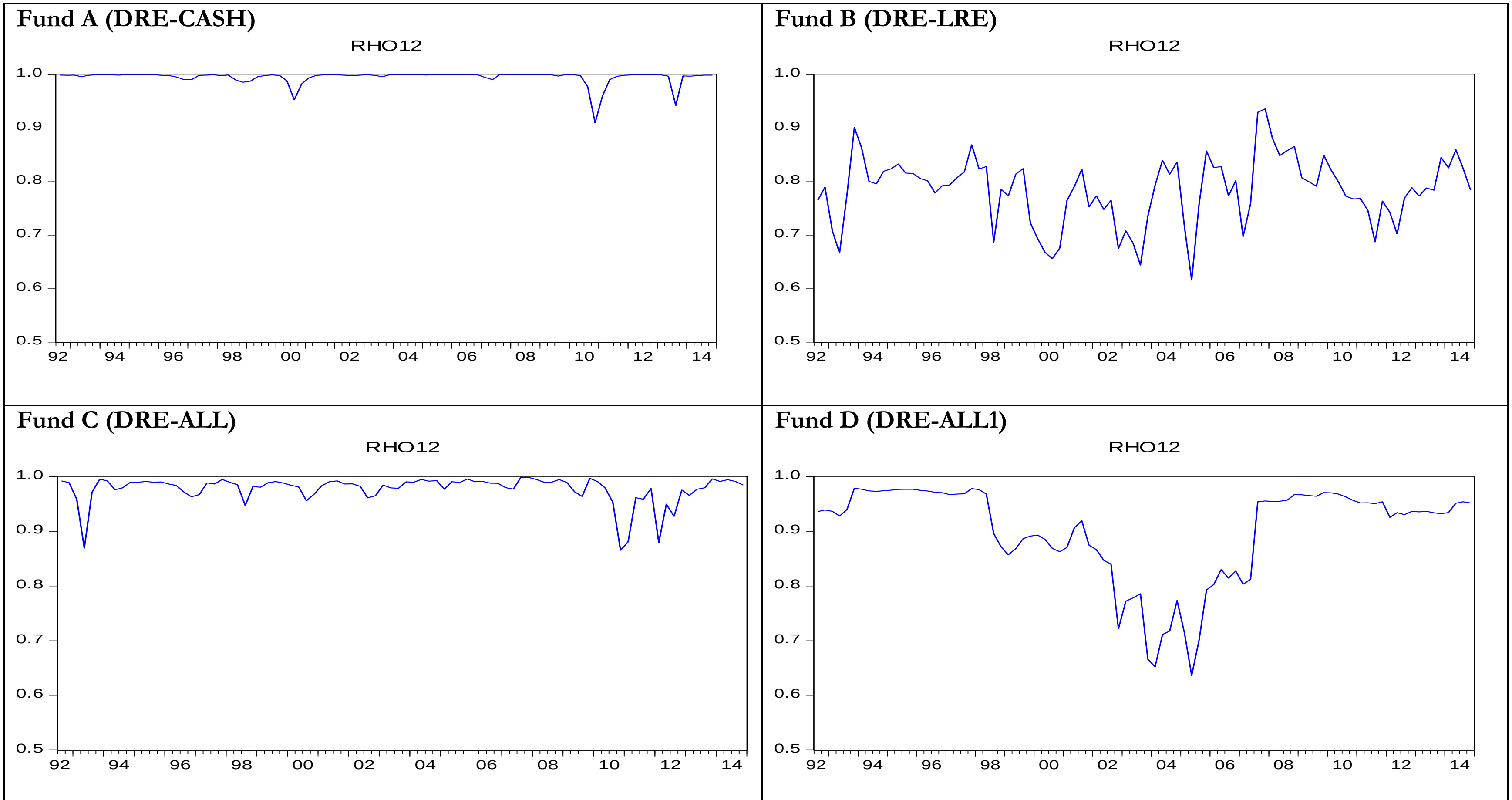
Interestingly, blended real estate fund B (LRE-DRE) recorded very stable correlation pattern relative to direct real estate. Even for the pure replication portfolio, containing no allocation to direct real estate, the correlations coefficients were above 0.45 over the entire sample period. This is due to the fact that as a stand-alone asset, listed real estate had a very high correlation with direct real estate. Consequently, when correlation is used as the main measure of association, blended portfolios containing listed real estate show a stable correlation pattern with direct real estate. What this result implies is that for investors who wish to have real estate portfolios that have significant allocations to liquid assets, especially more than 50%, listed real estate may represent a good choice of asset than any other stand-alone asset. However, it is clear from the foregoing discussion that a multi-asset approach is best at producing the best blended or hybrid real estate portfolios.

Table 6(V) Comparison of Static, 4 and 20 Quarter Rolling, and DCC Estimates

10% liquid	**Fund A (DRE-CASH)**	**Fund B (DRE-LRE)**	**Fund B (DRE-ALL)**	**Fund C (DRE-ALL1)**
Dynamic conditional correlation	0.9989	0.8931	0.9941	0.9629
Static correlation	0.9997	0.9555	0.9976	0.9911
4 quarter rolling correlation	0.9999	0.7013	0.9823	0.9010
20 quarter rolling correlation	0.9999	0.8918	0.9966	0.9663
20% liquid				
Dynamic conditional correlation	0.9950	0.7839	0.9772	0.8992
Static correlation	0.9987	0.8691	0.9889	0.9640
4 quarter rolling correlation	0.9996	0.4911	0.9422	0.7356
20 quarter rolling correlation	0.9993	0.7663	0.9843	0.8969
30% liquid				
Dynamic conditional correlation	0.9864	0.6959	0.9504	0.8280
Static correlation	0.9961	0.7839	0.9710	0.9195
4 quarter rolling correlation	0.9987	0.3684	0.8880	0.6098
20 quarter rolling correlation	0.9980	0.6763	0.9600	0.8206
100% Liquid				
Dynamic conditional correlation	-0.1067	0.4558	0.2146	0.3387
Static correlation	-0.1194	0.4956	0.4114	0.4736
4 quarter rolling correlation	-0.2505	0.1328	0.0755	0.0263
20 quarter rolling correlation	-0.1934	0.4369	0.3671	0.3824

Notes: DRE = IPD All-Property Portfolio; Fund A = A naïve mix of cash and the IPD All Property Portfolio; Fund B = A naïve mix of listed real estate and the IPD All Property Portfolio; Fund C = An optimised blend of the IPD All Property Portfolio and the all selected liquid assets. Optimisation is done without any minimum return constraint; Fund D = An optimised blend of the IPD All Property Portfolio and the all selected liquid assets. Optimisation is done with a constraint that target return should be equal to or greater than the average return on the IPD All Property Portfolio; DCC = Dynamic Conditional Correlation

Figure 6(4) Dynamic Conditional Correlations between Direct Real Estate and Hybrid Real Estate Returns (20% Liquid)



Notes: DRE = IPD All-Property Portfolio; DRE-CASH = A naïve mix of cash and the IPD All Property Portfolio; DRE-LRE = A naïve mix of listed real estate and the IPD All Property Portfolio; DRE-ALL = An optimised blend of the IPD All Property Portfolio and the all selected liquid assets. Optimisation is done without any minimum return constraint; DRE-ALL1 = An optimised blend of the IPD All Property Portfolio and the all selected liquid assets. Optimisation is done with a constraint that target return should be equal to or greater than the average return on the IPD All Property Portfolio; RHO 12: Dynamic Conditional Correlation

6.5 CONCLUSION

Managers of open-ended real estate funds have typically used cash, and sometimes listed real estate, to enhance the liquidity profile of their portfolios. Focus on the performance and liquidity of such funds has increased in the wake of market shocks and with the increased emphasis on liquidity by institutional investors, including the rising number of Defined Contribution pension funds. DC pension funds have been offering daily traded funds to contributors as opposed to monthly or even quarterly traded funds, raising the question as to whether real estate is a possible option in such a framework. Thus, with these developments, there is a need to design real estate funds with adequate liquidity to meet the requirements of such investors.

The inclusion of listed real estate in direct real estate portfolios has been found to enhance the returns of such portfolios, along with providing more liquidity. However, many investment managers are reluctant to use listed real estate within blended real estate portfolios owing to the fact that its inclusion can result in a high tracking error relative to a direct real estate benchmark – implying that the resulting portfolio fails to provide the investor with property-like returns. Meanwhile, the use of cash has been found to result in significant drags on portfolio return. The challenge for real estate funds then is to find a way of minimising tracking error with the direct real estate market without significant loss of returns or alteration to the fundamental performance features of direct real estate assets.

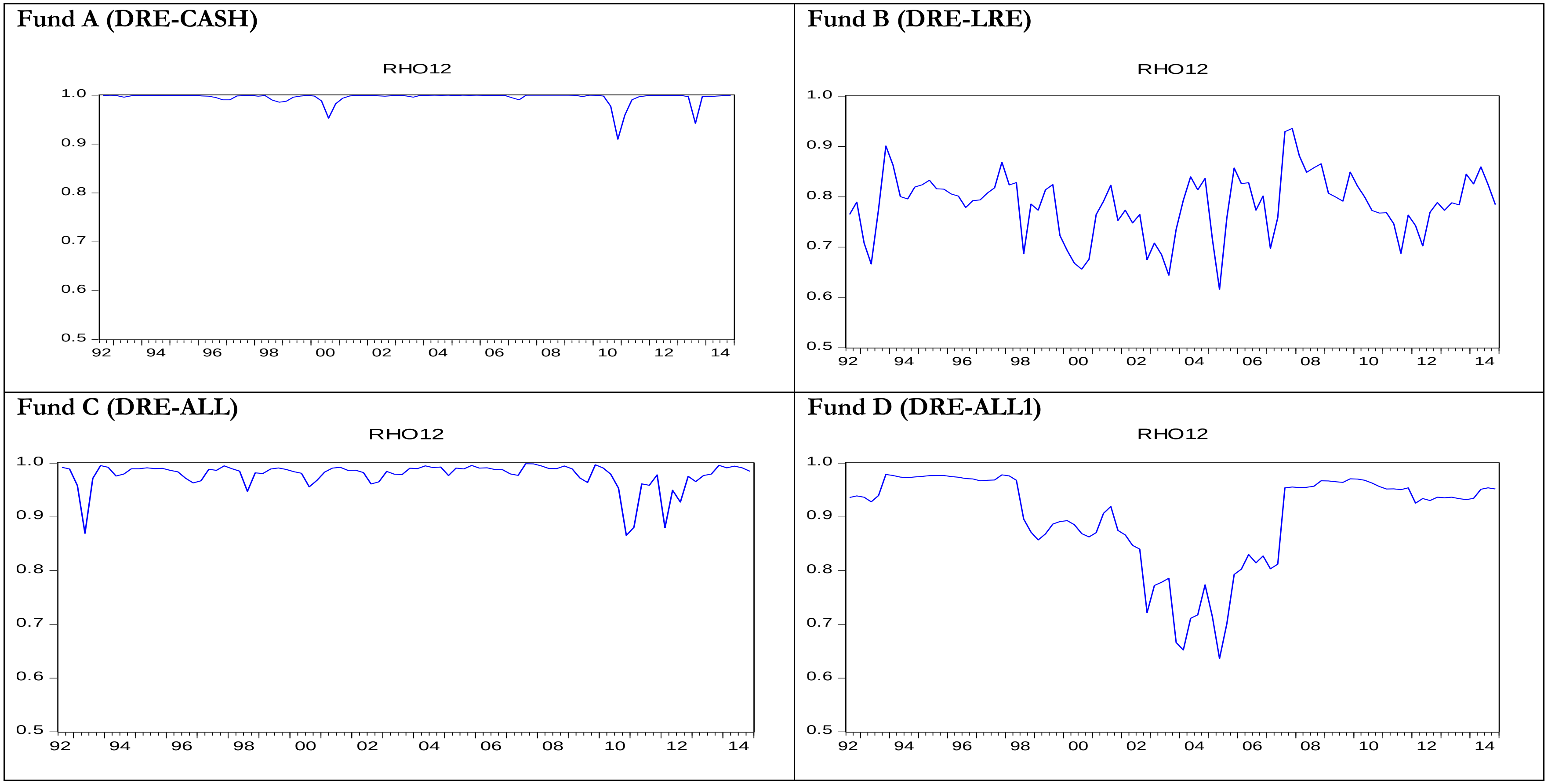
This study explores the possibility of expanding the asset universe beyond cash and listed real estate to see if it is possible to produce portfolios that deliver property-like returns along with enhanced liquidity. In addition to cash and listed real estate, general stocks and bonds of various maturities were used as options for addition to direct real estate portfolios. To create the blended real estate portfolios, Minimum Tracking Error optimisation procedures were utilised. This procedure is an extension of the classic Mean-Variance optimisation procedure and was implemented with and without a minimum return constraint in order to observe the most effective combinations of liquid assets in meeting portfolio objectives.

The results show that using a wider array of assets produced lower tracking errors than those obtained by using a cash-only liquidity buffer. The returns obtained were higher than those obtained through a direct real estate and cash mix, without significant increase in tracking error. In comparison, the returns of the direct real estate and listed real estate combination did not perform well in replicating the performance of the underlying direct real estate market. As in other studies, the direct-listed real estate combination produced enhanced returns, but this study shows that the terminal value obtained over the period for this strategy was lower if a certain threshold allocation to listed real estate was crossed. This is due to the high volatility and drawdown of listed real estate as a stand-alone asset.

One key question which this study seeks to answer is which assets should be included in the blended/hybrid real estate portfolio. The results from this study shows that the answer depends on whether the fund manager is concerned solely with tracking direct real estate returns as closely as possible or is also concerned with earning returns that are not significantly lower than direct real estate returns. A pure, unconstrained tracking error minimization portfolio consists largely of cash along with a limited amount of listed real estate and general stocks. The dominance of cash in this portfolio lends some credence to the current allocation within UK unlisted real estate fund portfolios. However, imposing a minimum return constraint where the portfolio must at least match the average return of the direct market resulted in a more diversified portfolio, with cash playing a limited role. These constrained portfolios had significant allocations to long term bonds, listed real estate and general stocks.

A number of future studies could be conducted in this area. The asset universe could be expanded further to include non-UK real estate and liquid assets. This would result in additional challenges stemming from foreign exchange risk and the difficulty in finding foreign assets that can be incorporated without significantly changing the risk and return profile of the underlying direct real estate portfolio. The use of factor models, as done in hedge fund and private equity markets, could also be explored to determine how direct real estate returns might be replicated to enable investors take advantage of the benefits of direct real estate investments with minimal liquidity risk. Finally, this study used historical returns in the estimation of the portfolio weights. Hence, another area that could be explored is the use of forward looking risk and return measures in the construction of the blended real estate portfolios.

Figure 6(5) Dynamic Conditional Correlations between Direct Real Estate and Hybrid Real Estate Returns (20% Liquid)



Notes: DRE = IPD All-Property Portfolio; DRE-CASH = A naïve mix of cash and the IPD All Property Portfolio; DRE-LRE = A naïve mix of listed real estate and the IPD All Property Portfolio; DRE-ALL = An optimised blend of the IPD All Property Portfolio and the all selected liquid assets. Optimisation is done without any minimum return constraint; DRE-ALL1 = An optimised blend of the IPD All Property Portfolio and the all selected liquid assets. Optimisation is done with a constraint that target return should be equal to or greater than the average return on the IPD All Property Portfolio; RHO 12: Dynamic Conditional Correlation

APPENDICES

Appendix 6(A) Allocation within Balanced UK Unlisted Real Estate Fund Portfolios as at March 2017

Name of Fund	Fund Type[4]	Retail	Offices	Industrials	Others	Cash	Total
AEW UK - Core Property Fund	PAIF	33.40	28.60	23.50	9.60	4.80	100
AEW UK Real Return Fund	PAIF	37.80	4.90	0.00	54.50	2.80	100
Aviva Investors Pensions Limited	MPF	29.90	38.80	15.30	8.80	7.30	100
BlackRock UK Property Fund	PUT	28.00	25.70	23.20	16.90	6.40	100
CBRE UK Property PAIF	PAIF	35.90	23.50	26.40	9.30	4.90	100
COIF Charities Property Fund	PUT	23.10	44.30	30.80	1.60	0.10	100
Fidelity UK Real Estate Fund	EPUT	16.30	39.20	34.50	-	9.90	100
UK Property Fund	PUT	32.30	30.80	31.90	2.60	2.40	100
Hermes Property Unit Trust	EPUT	22.30	38.10	22.70	12.50	4.40	100
Kames Active Value Property Fund	MPT	45.10	25.50	15.50	4.20	9.70	100
Kames Capital UK Active Value Property Unit Trust	PUT	34.40	36.30	13.50	2.80	13.00	100
Keills Property Trust	EPUT	16.90	24.70	11.40	42.80	4.30	100
Legal and General Assurance (Pensions Management) Ltd	MPF	22.80	34.30	16.10	12.70	14.10	100
Lothbury Property Trust	PUT	47.40	25.80	15.30	7.10	4.40	100
Mayfair Capital Property Income Trust for Charities	EPUT	22.40	28.80	32.70	11.10	5.00	100
Mayfair Capital Property Unit Trust	PUT	26.60	42.30	27.70	1.50	2.00	100
Rockspring Hanover Property Unit Trust	PUT	26.80	26.80	45.20	-	1.10	100
Royal London Property Fund	PAIF	33.20	29.40	20.40	11.00	6.00	100
Savills IM UK Income & Growth	PUT	36.90	6.00	40.30	13.40	3.40	100
Schroder UK Real Estate Fund	PAIF	24.50	38.00	19.10	10.00	8.40	100
Standard Life Investments Pooled Pension Property Fund	MPF	39.10	31.60	20.10	0.20	8.90	100
The Charities Property Fund	CIF	28.80	20.80	22.70	23.30	4.50	100
The Local Authorities Property Fund	EPUT	26.30	39.90	25.10	1.00	7.70	100
The M&G UK Property Fund	FCP	35.70	23.10	22.70	10.80	7.90	100
Threadneedle Pensions Ltd	MPF	38.00	25.80	19.30	6.20	10.60	100
Threadneedle Property Unit Trust	PUT	32.80	33.30	24.80	5.10	3.90	100
UBS Triton Property Fund	PNP	34.50	20.00	32.70	12.60	0.20	100

Source: AREF (2017)

[4] Fund type abbreviations: PUT - Property Unit Trust; EPUT - Exempt Property Unit Trust; MPF - Managed Pension Fund; PNP - Balanced Property Partnership; LP - Limited Partnership; CIF - Common Investment Fund; ICVC - Investment Company with Variable Capital; APUT - Authorised Property Unit Trust; PAIF - Property Authorised Investment Fund; SCA - Société en commandite par actions (Luxembourg)

Appendix 6(B) In-Sample Statistics of Blended/Hybrid Real Estate Portfolios (Rescaled)

All liquid assets and direct real estate (without minimum return constraint)

Stocks	Bonds (Aggregate)	Bonds (10+ years)	Bonds (10 year)	Bonds (7 years)	Bonds (5 years)	Bonds (3 years)	Bonds (2 years)	Listed real estate	Treasury bills	Total weight of liquid assets
0.23	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.19	0.25	1.00
0.23	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.19	0.25	0.90
0.24	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.19	0.24	0.80
0.24	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.19	0.24	0.70
0.24	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.19	0.24	0.60
0.24	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.19	0.24	0.50
0.24	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.19	0.24	0.40
0.24	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.19	0.24	0.30
0.24	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.19	0.24	0.20
0.24	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.19	0.24	0.10

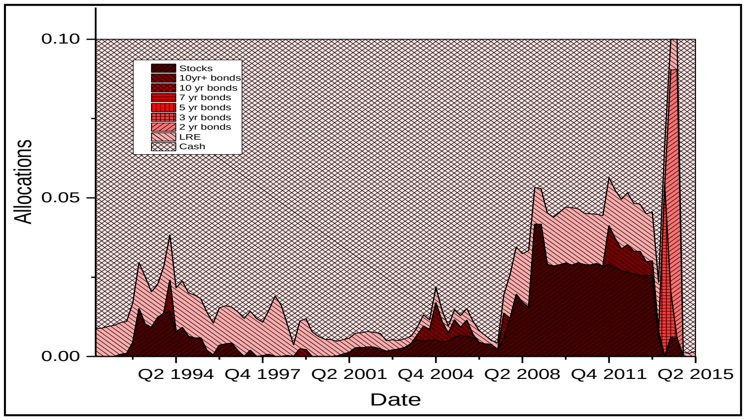
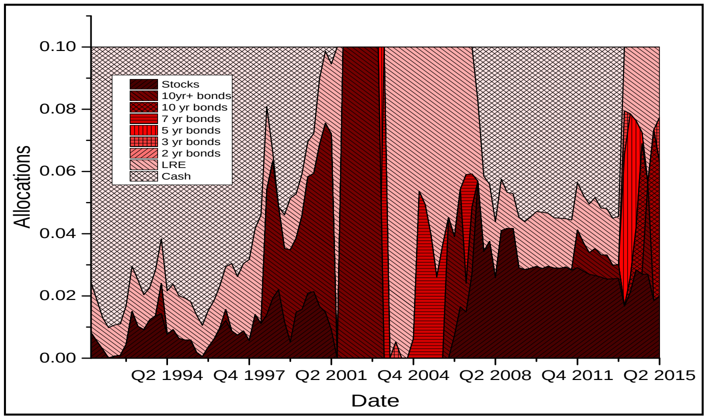
All liquid assets and direct real estate (with minimum return constraint)

Stocks	Bonds (Aggregate)	Bonds (10+ years)	Bonds (10 year)	Bonds (7 years)	Bonds (5 years)	Bonds (3 years)	Bonds (2 years)	Listed real estate	Treasury bills	Total weight of liquid assets
0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.80	1.00
0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.80	0.90
0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.80	0.80
0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.80	0.70
0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.80	0.60
0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.80	0.50
0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.80	0.40
0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.80	0.30
0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.80	0.20
0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.80	0.10

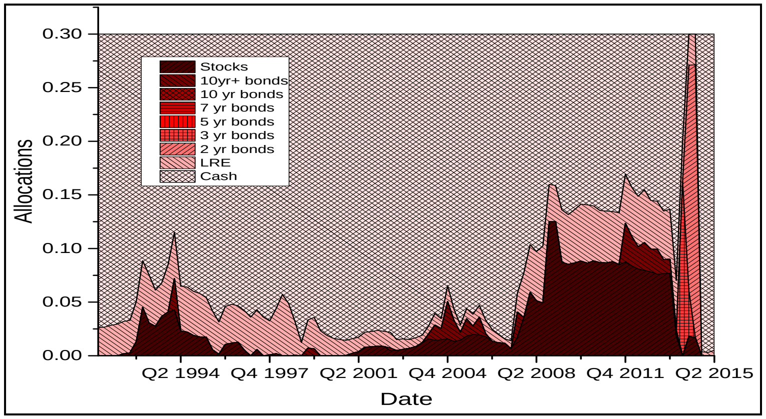
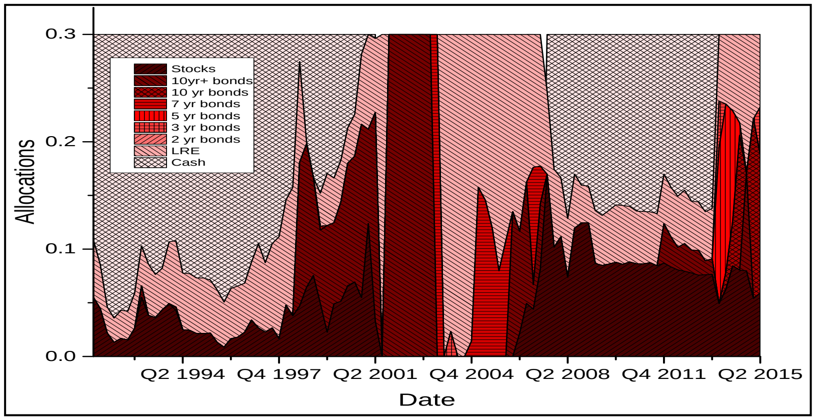
Appendix 6(C) Summary Statistics – 20 Quarters Rolling Tracking Error

Date	DRE_CASH	DRE_LRE	DRE_ALL	DRE_ALL1
10% Liquid				
Average	0.1355	0.8416	0.1653	0.3113
Standard deviation	0.1438	0.4779	0.1277	0.1752
Maximum	0.8286	2.2492	0.5473	0.6917
Minimum	0.0256	0.0695	0.0162	0.0256
20% Liquid				
Average	0.2710	1.6831	0.3295	0.6208
Standard deviation	0.2876	0.9558	0.2537	0.3496
Maximum	1.6572	4.4984	1.0947	1.3959
Minimum	0.0513	0.1391	0.0324	0.0599
30% Liquid				
Average	0.4065	2.5247	0.4943	0.9307
Standard deviation	0.4313	1.4337	0.3806	0.5244
Maximum	2.4857	6.7475	1.6420	2.0939
Minimum	0.0769	0.2086	0.0487	0.0898
40% Liquid				
Average	0.5421	3.3663	0.6591	1.1571
Standard deviation	0.5751	1.9116	0.5074	0.6898
Maximum	3.3143	8.9967	2.1893	2.7669
Minimum	0.1025	0.2782	0.0649	0.1022
50% Liquid				
Average	0.6776	4.2079	0.8238	1.5519
Standard deviation	0.7189	2.3895	0.6342	0.8740
Maximum	4.1429	11.2459	2.7367	3.4898
Minimum	0.1282	0.3477	0.0811	0.1497
60% Liquid				
Average	0.8131	5.0494	0.9886	1.9694
Standard deviation	0.8627	2.8674	0.7610	1.2498
Maximum	4.9715	13.4951	3.2840	5.2902
Minimum	0.1538	0.4173	0.0973	0.1533
70% Liquid				
Average	0.9486	5.8910	1.1534	2.1812
Standard deviation	1.0065	3.3453	0.8879	1.2176
Maximum	5.8001	15.7443	3.8313	4.8858
Minimum	0.1794	0.4868	0.1136	0.2096
80% Liquid				
Average	1.0841	6.7326	1.3181	2.4927
Standard deviation	1.1503	3.8232	1.0148	1.3915
Maximum	6.6286	17.9934	4.3787	5.5837
Minimum	0.2051	0.5564	0.1298	0.2396
90% Liquid				
Average	1.2196	7.5742	1.4829	2.7772
Standard deviation	1.2940	4.3010	1.1416	1.5679
Maximum	7.4572	20.2426	4.9260	6.2256
Minimum	0.2307	0.6259	0.1460	0.2300
100% Liquid				
Average	1.3551	8.4157	1.6477	3.0921
Standard deviation	1.4378	4.7789	1.2684	1.7492
Maximum	8.2858	22.4918	5.4733	6.9173
Minimum	0.2563	0.6955	0.1622	0.2556

Appendix 6(D) Allocations within Blended Real Estate Portfolio With 10% Liquid Assets (Out Of Sample)

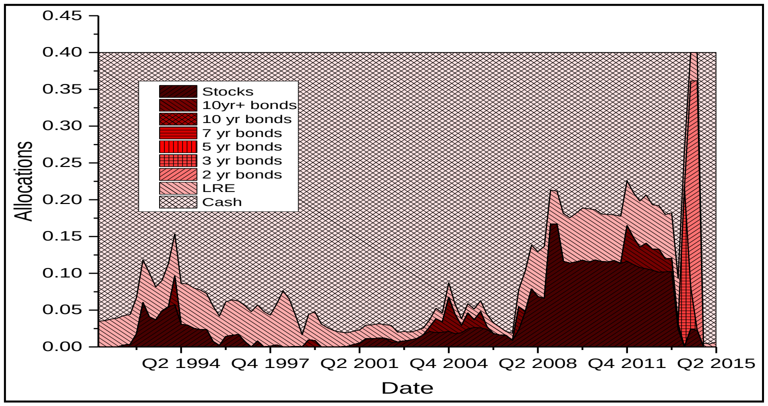
All liquid assets (No minimum return constraint)	All liquid assets (With minimum return constraint)
	

Appendix 6(E) Allocations within Blended Real Estate Portfolio with 30% Liquid Assets (Out Of Sample)

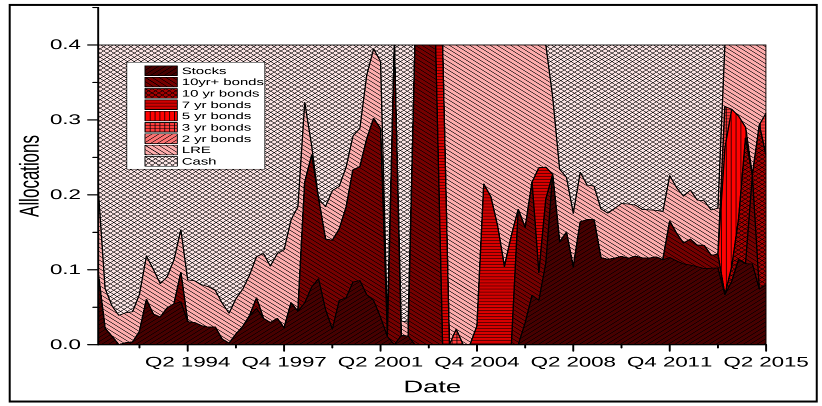
All liquid assets (No minimum return constraint)	All liquid assets (With minimum return constraint)
	

Appendix 6(F) Allocations within Blended Real Estate Portfolio with 40% Liquid Assets (Out of sample)

All liquid assets (No minimum return constraint)

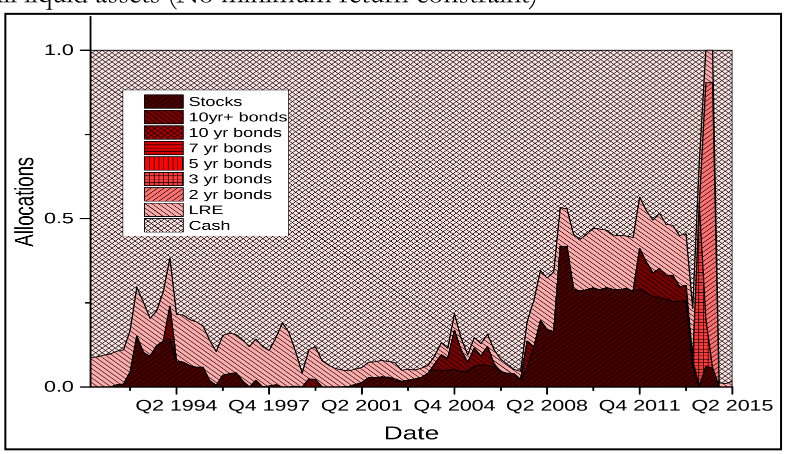


All liquid assets (With minimum return constraint)

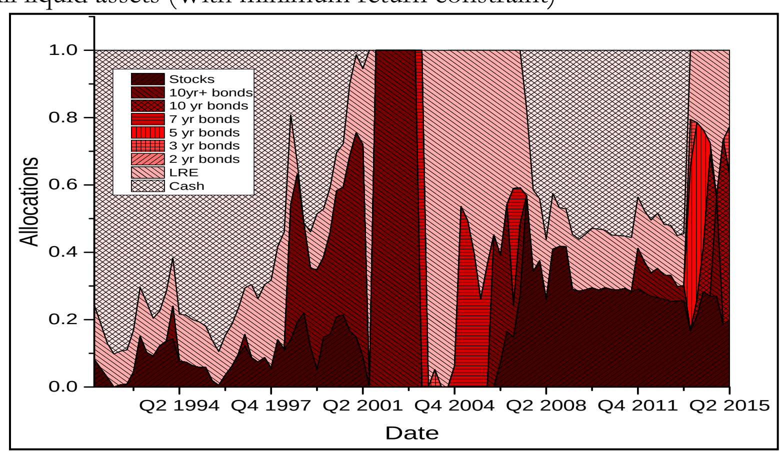


Appendix 6(G) Allocations within Blended Real Estate Portfolio with 100% Liquid Assets (Out Of Sample)

All liquid assets (No minimum return constraint)

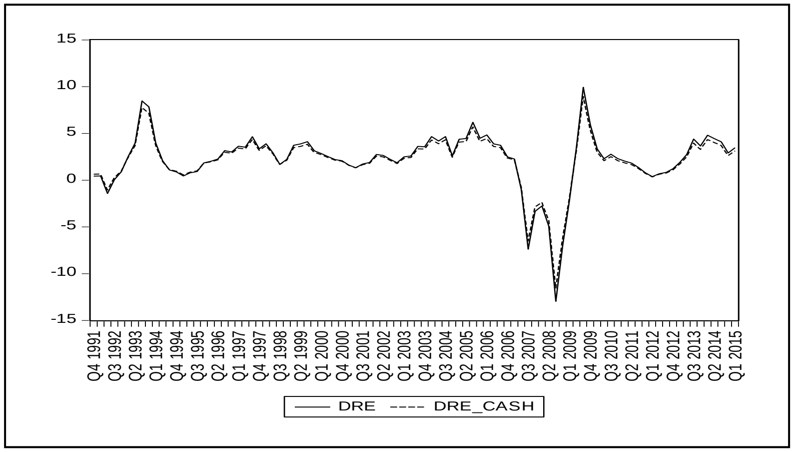


All liquid assets (With minimum return constraint)

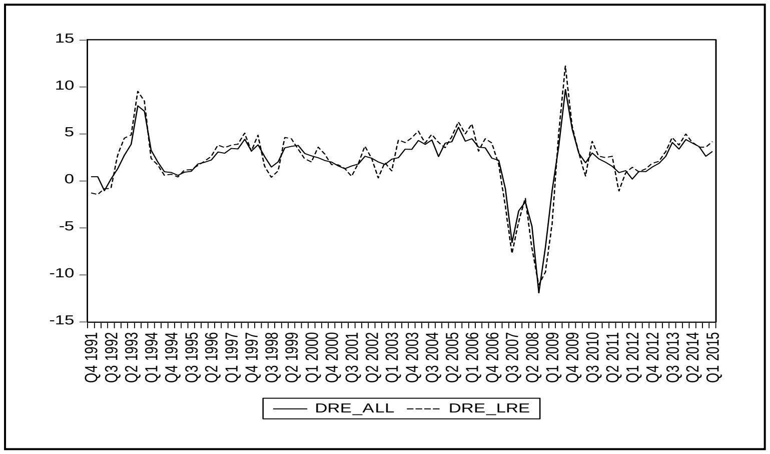


Appendix 6(H) Out of Sample Returns of Blended Real Estate Portfolios – 10% Liquid Asset

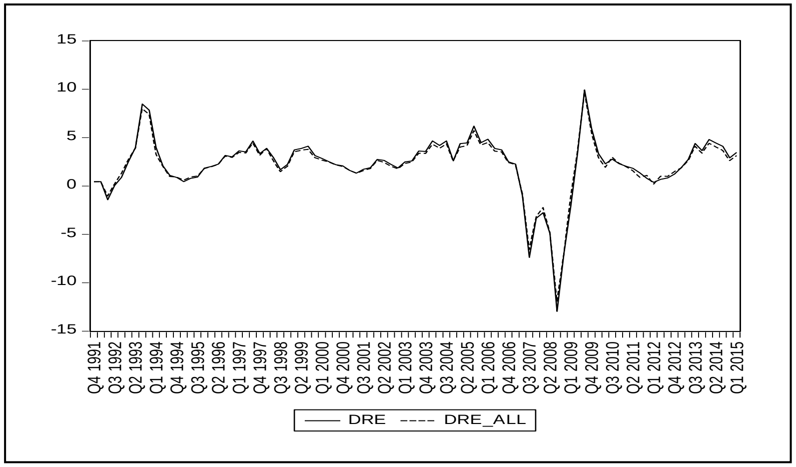
DRE-CASH



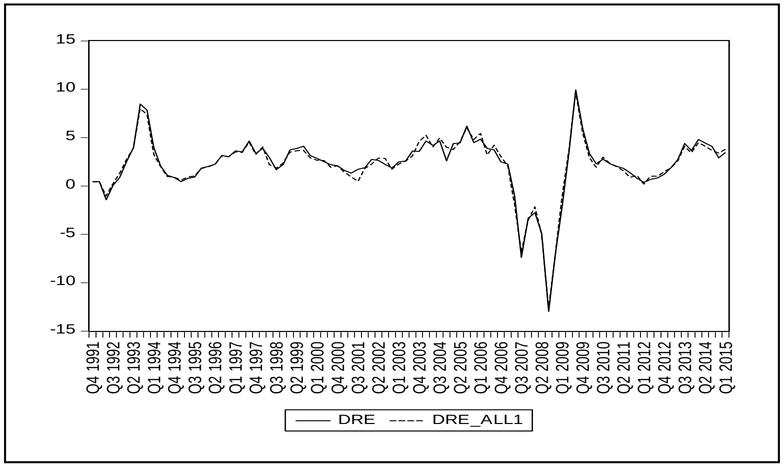
DRE-LRE



DRE-ALL

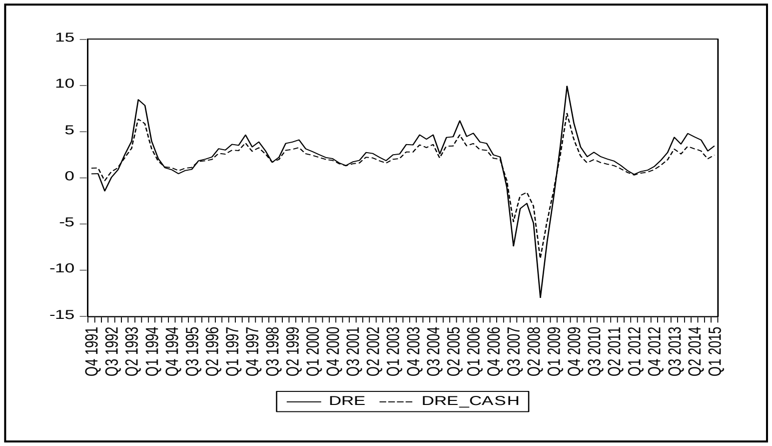


DRE-ALL1

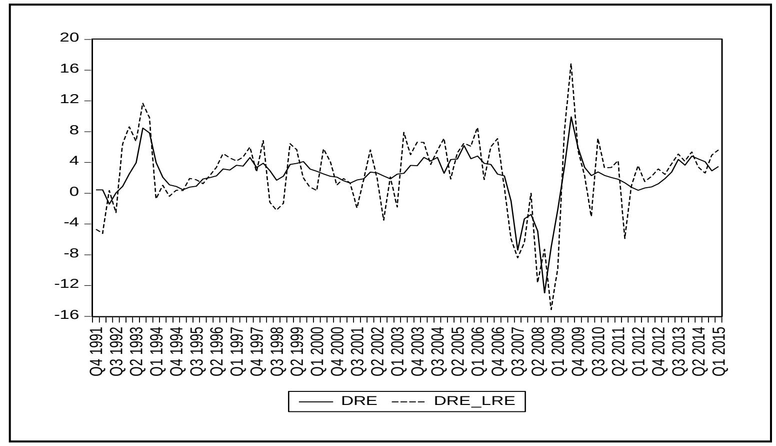


Appendix 6(I) Out of Sample Returns of Blended Real Estate Portfolios – 30% Liquid Asset

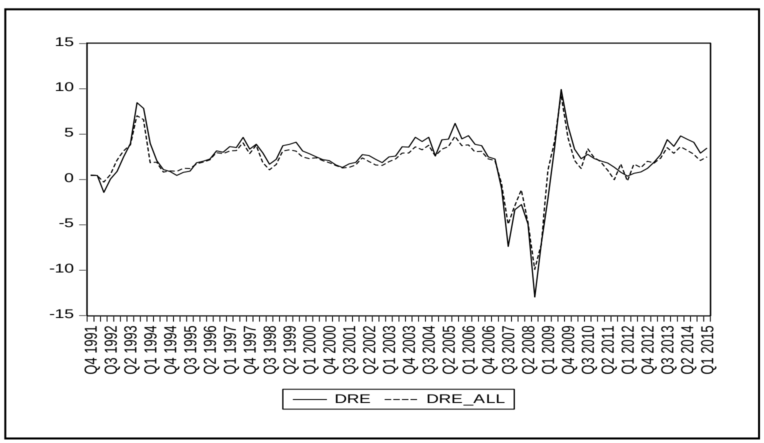
DRE-CASH



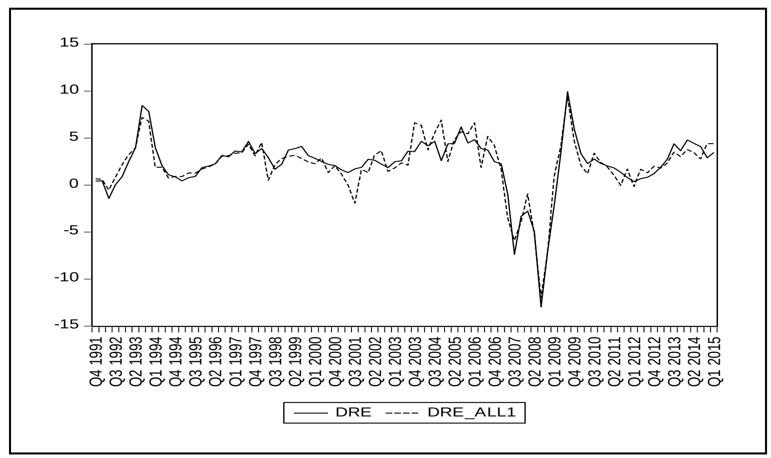
DRE-LRE



DRE-ALL

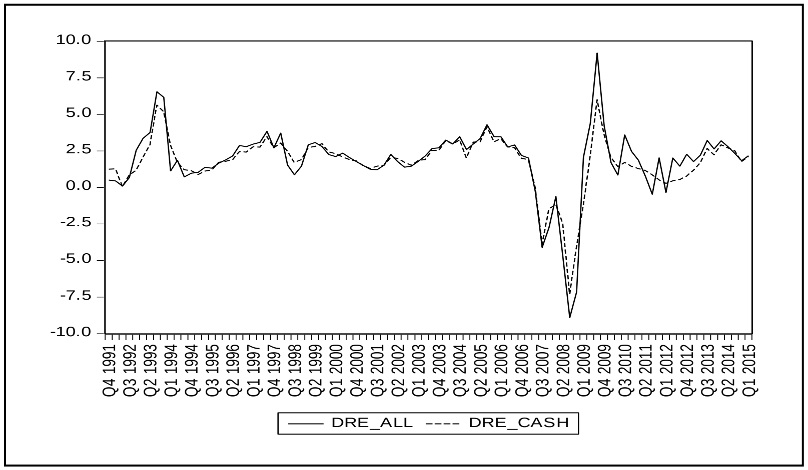


DRE-ALL1

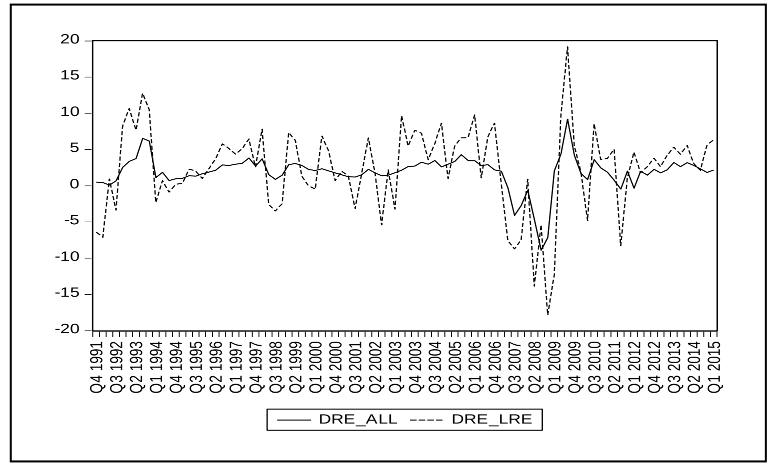


Appendix 6(J) Out of Sample Returns of Blended Real Estate Portfolios – 40% Liquid Asset

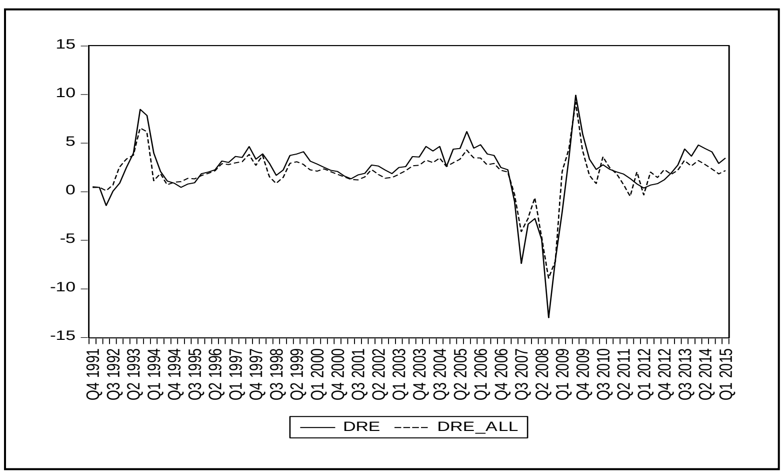
DRE-CASH



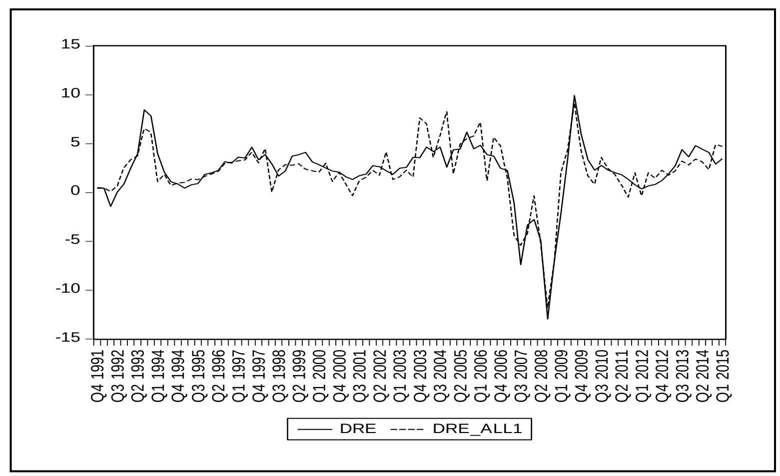
DRE-LRE



DRE-ALL

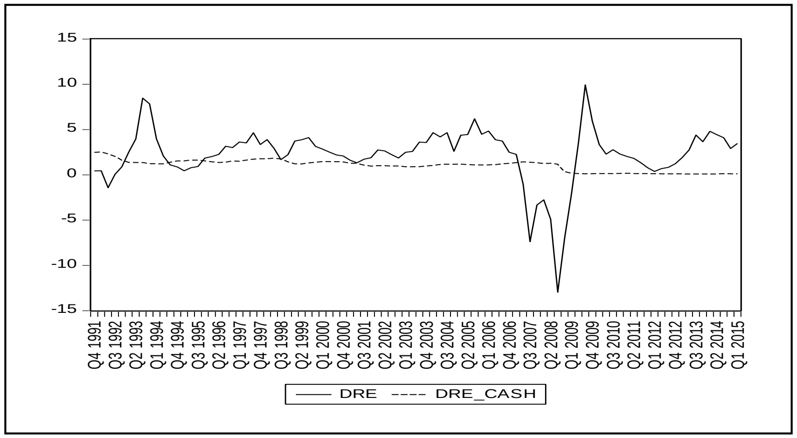


DRE-ALL1

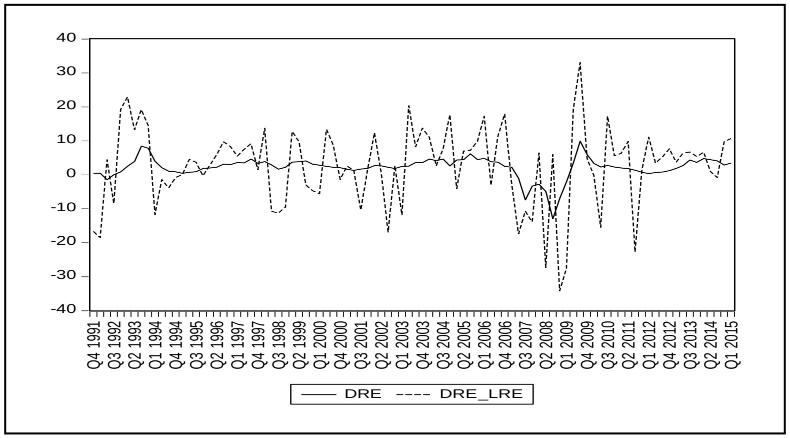


Appendix 6(K) Out of Sample Returns of Blended Real Estate Portfolios – 100% Liquid Asset

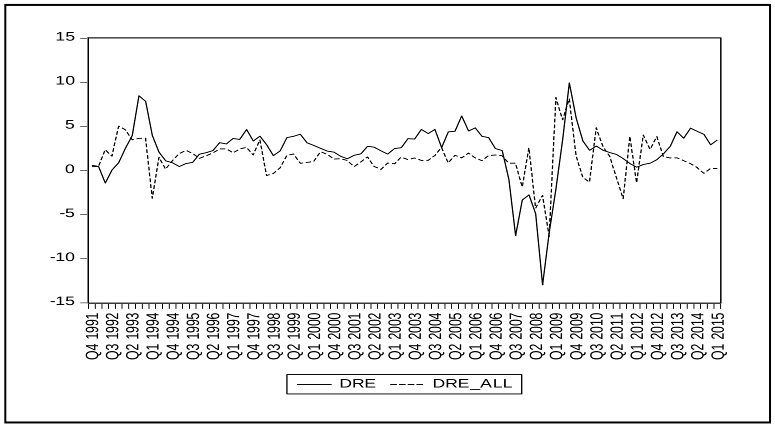
DRE-CASH



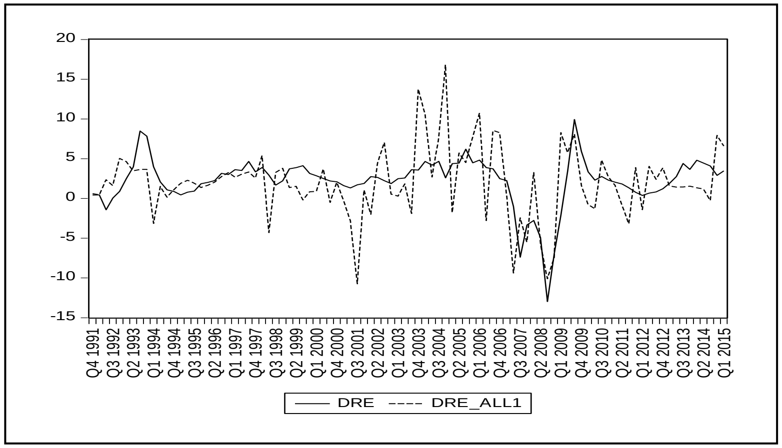
DRE-LRE



DRE-ALL

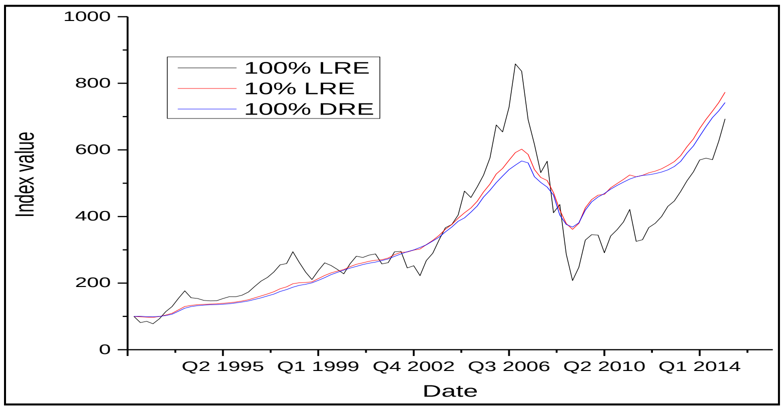


DRE-ALL1

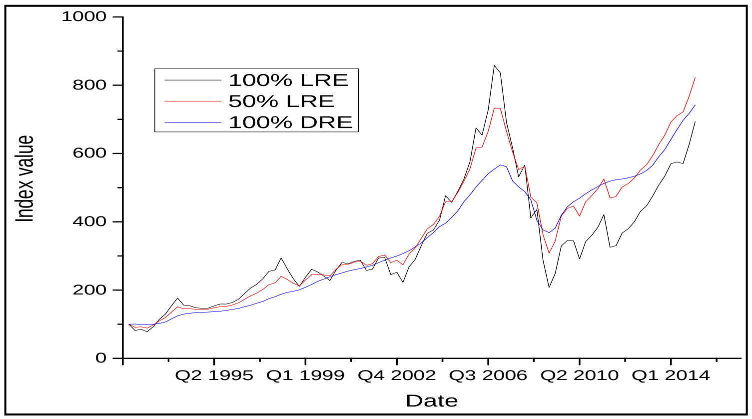


Appendix 6(L) Historical Returns of Blended Real Different Real Estate Series

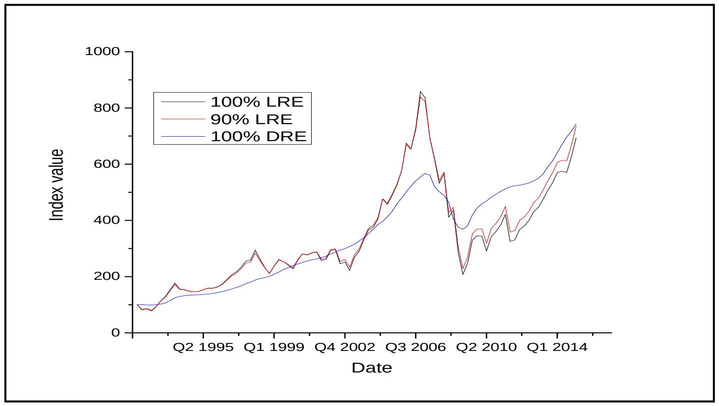
10% Listed Real Estate



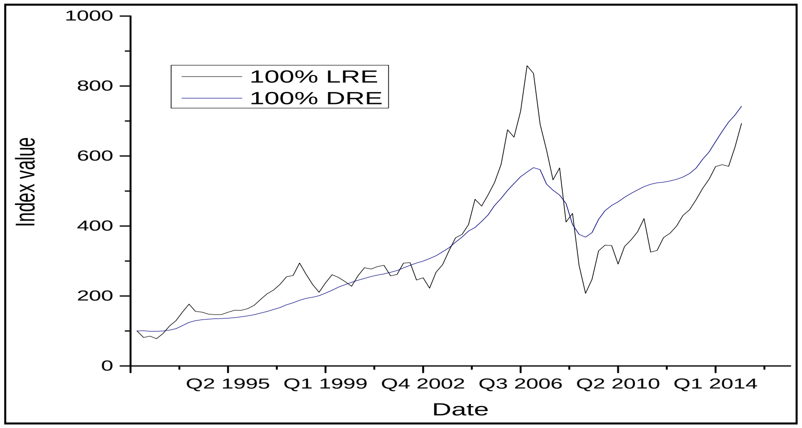
50% Listed Real Estate



90% Listed Real Estate

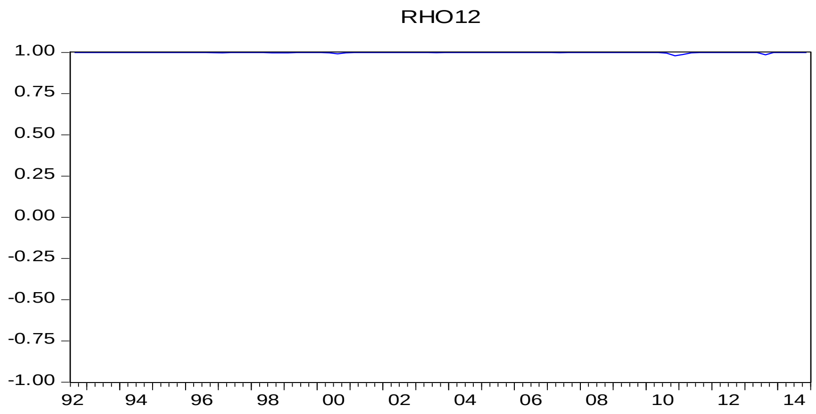


100% Listed Real Estate

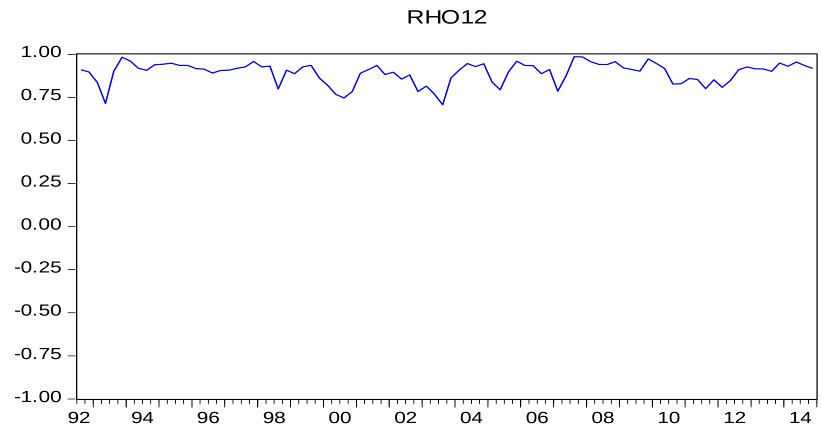


Appendix 6(M) Conditional Correlations – 10% Liquid Assets

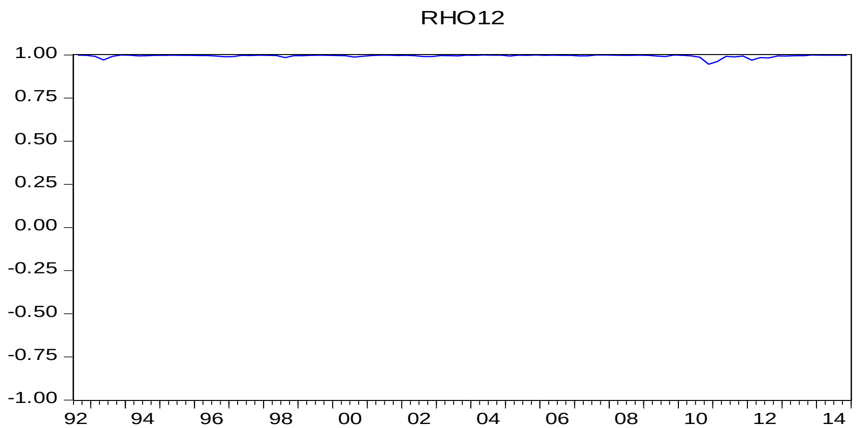
DRE-CASH



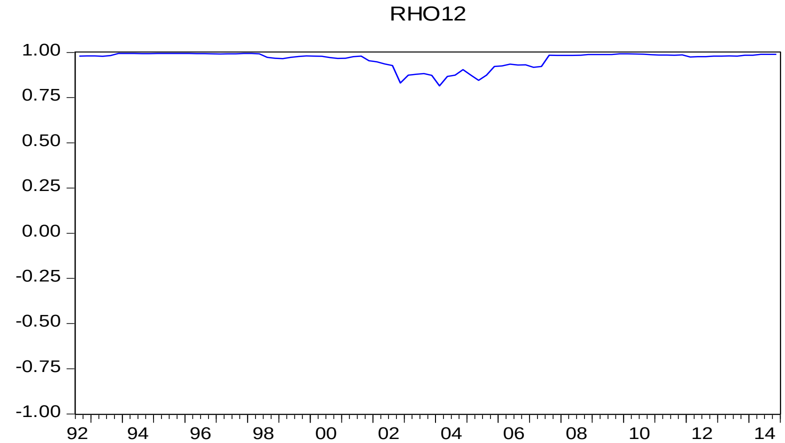
DRE-LRE



DRE-ALL

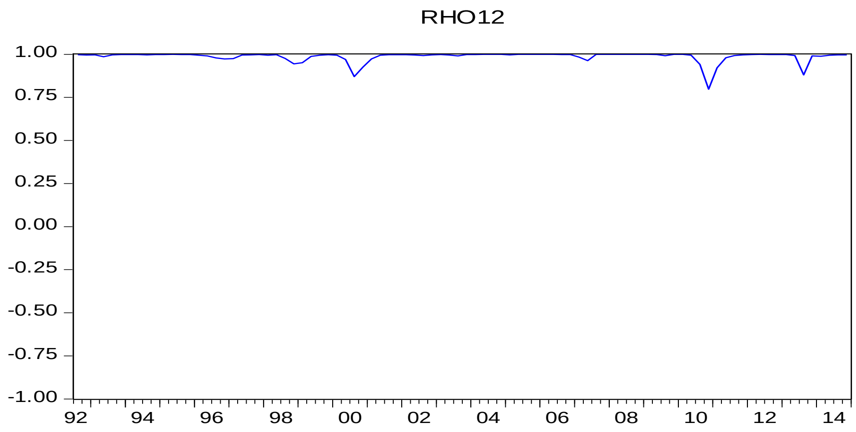


DRE-ALL1

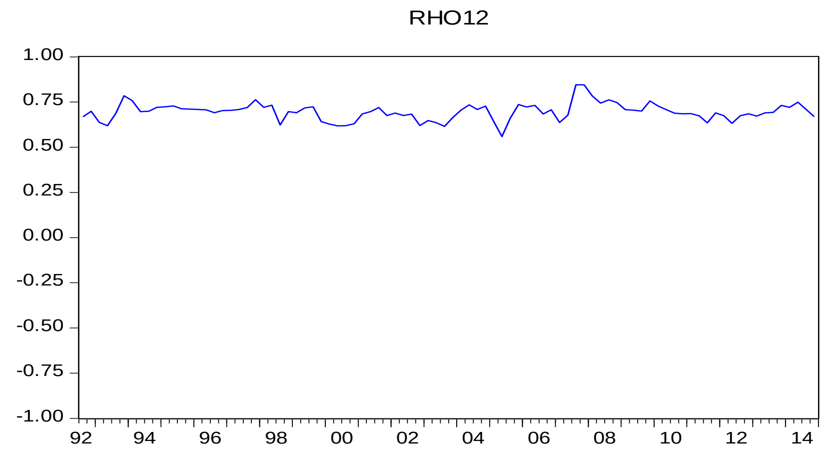


Appendix 6(N) Conditional Correlations – 30% Liquid Assets

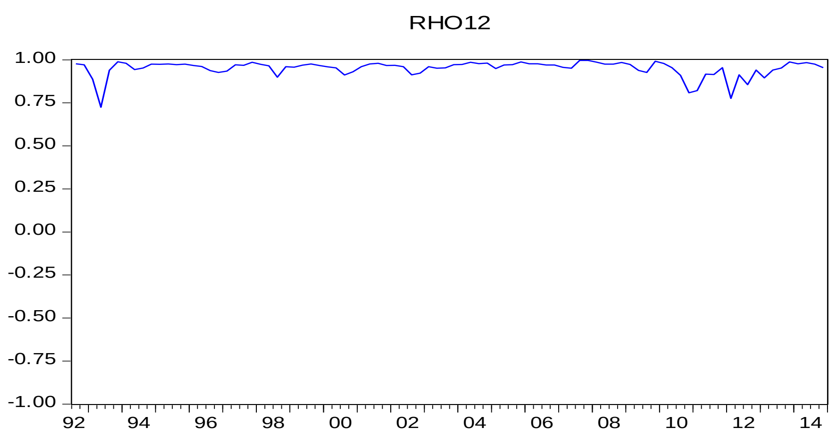
DRE-CASH



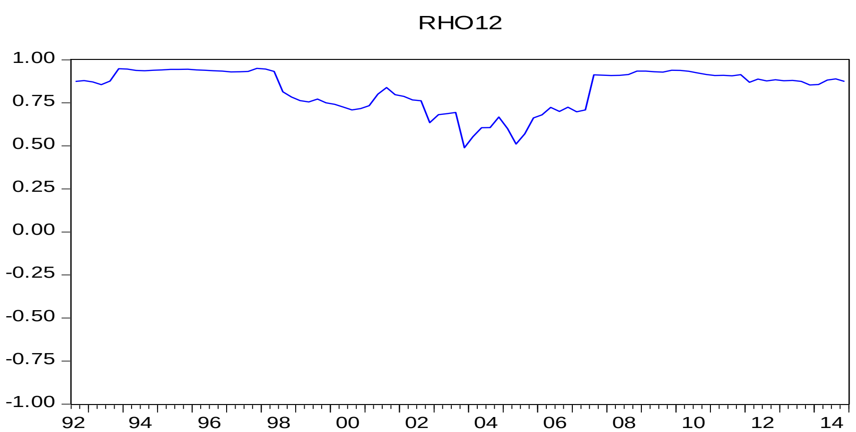
DRE-LRE



DRE-ALL

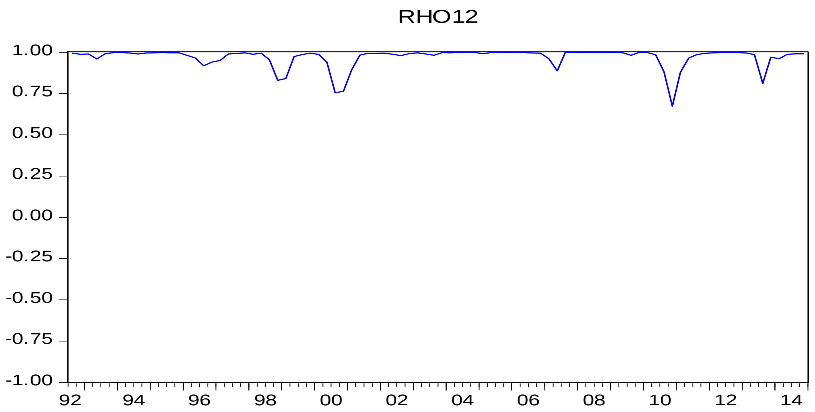


DRE-ALL1

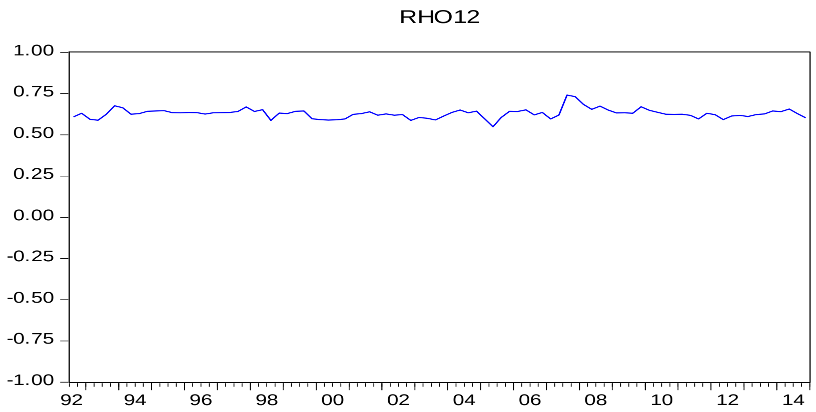


Appendix 6(O) Conditional Correlations – 40% Liquid Assets

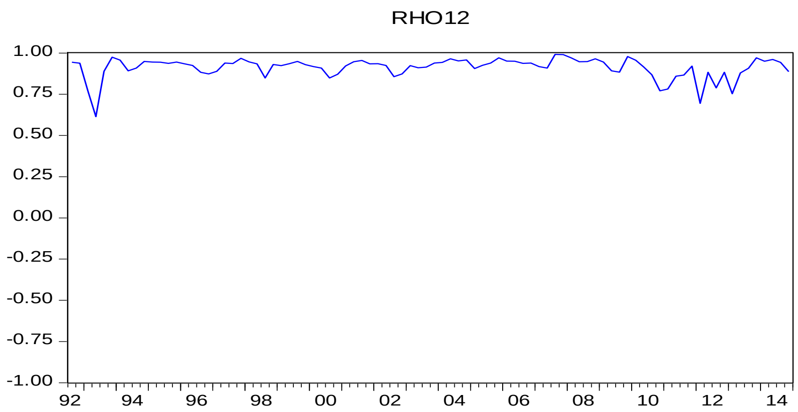
DRE-CASH



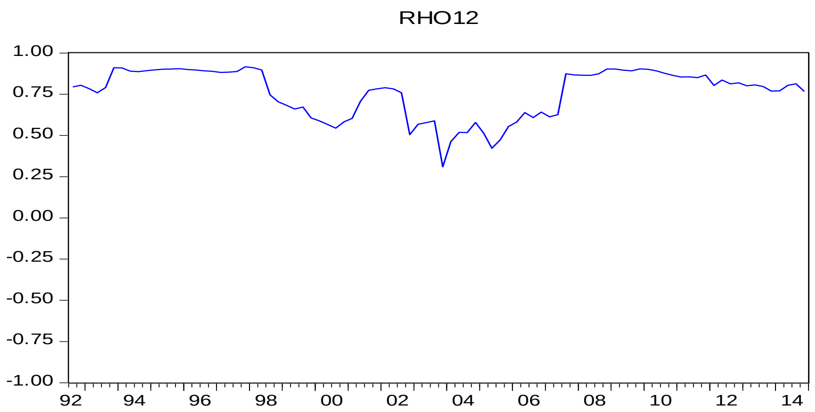
DRE-LRE



DRE-ALL

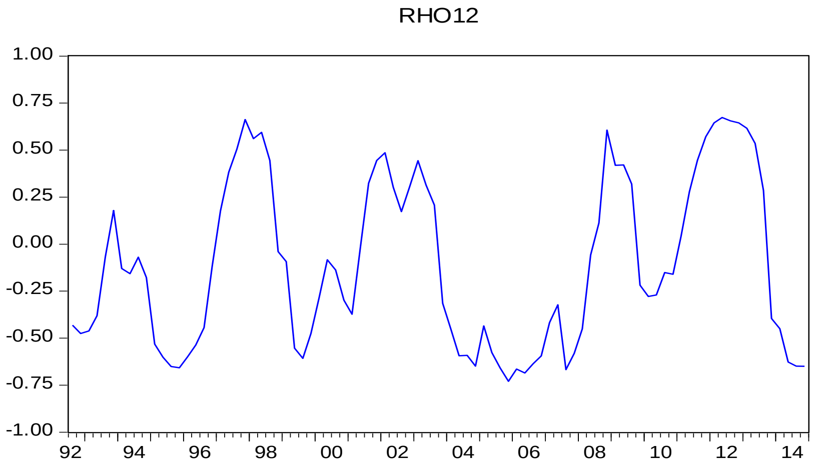


DRE-ALL1

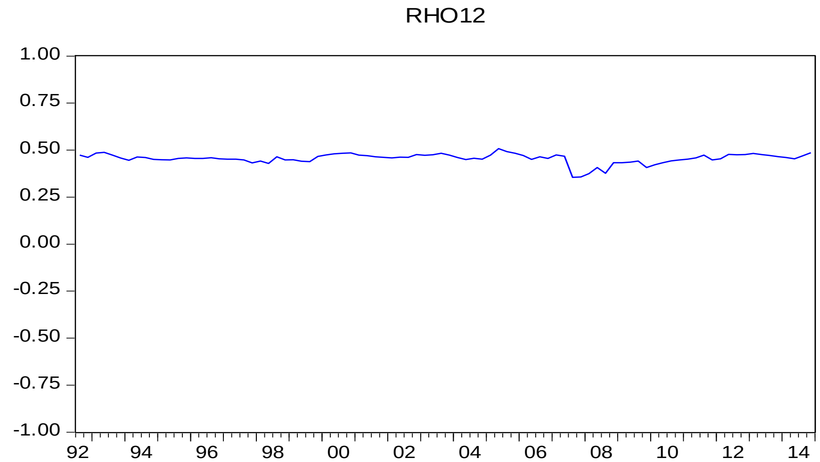


Appendix 6(P) Conditional Correlations – 100% Liquid Assets

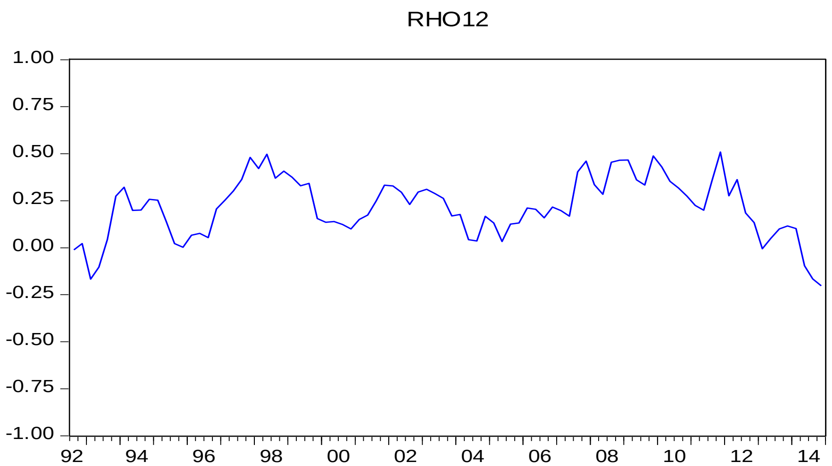
DRE-CASH



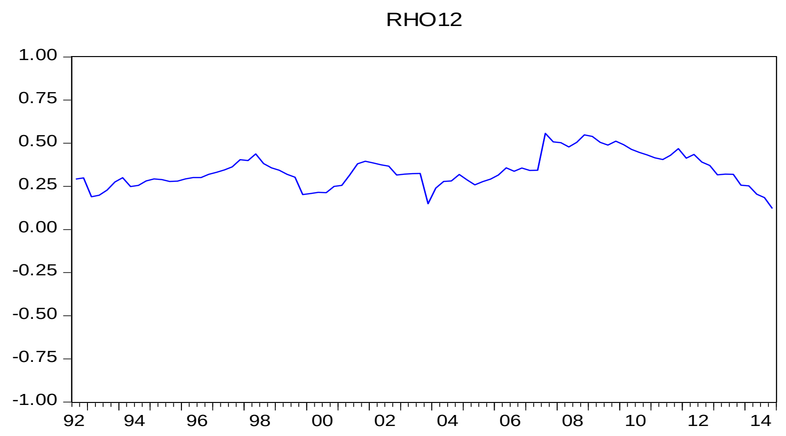
DRE-LRE



DRE-ALL



DRE-ALL1



CHAPTER SEVEN – ASSET SELECTION IN THE PRESENCE OF INFLATION/INTEREST RATE BENCHMARKS FOR DC PENSION FUNDS

7.0 INTRODUCTION

The goal of this study is to provide analysis of the inflation/interest rate-hedging ability of real estate and other assets which pension funds typically invest in, namely, stocks, bonds, commodities, hedge funds and private equity (UBS, 2015). We believe that this subject has become very important in light of the growing importance of DC pension funds most of whose investment objectives are tied to specific inflation and interest rate measures. An understanding of the inflation-hedging ability of various assets along with their return and risk characteristics is thus important for DC investors looking to improve their investment portfolios.

Inflation represents a general increase in the prices of goods and services within an economy. It is one of the leading macroeconomic indicators that causes significant distortions in the overall performance of financial markets. An asset is considered an inflation hedge if it eliminates or at least reduces the uncertainty regarding future real returns (Bodie, 1976).

Inflation-hedging is important not only for private investors who see inflation as a threat to their purchasing power but also for institutional investors such as pension funds and life insurance companies who face payments that are indexed (conditionally or fully) to inflation or wage indexes (Amenc et al. , 2008). Thus Kramer (2017) identified inflation protection is one of the central objectives of strategic asset allocation. Inflation hedging is also consistent with the idea of liability driven investment that has gained prominence within the pension fund industry especially following the 2008 financial crisis.

Although there has been a prolonged period of low inflation, investors with long holding periods need to be mindful of the eroding effects of inflation as well as inflationary shocks (Hoesli et al., 2008). Moreover, low inflation rate environments are often accompanied by low asset returns, making it even more difficult for investors to find inflation-hedging assets (Arnold, 2016).

The inflation and interest rate benchmarks employed in our analysis are those commonly used by DC pension funds for the purposes of performance evaluation and benchmarking. In Chapter 2, we reviewed the Statements of Investment Principles (SIPs) of a number of UK DC pension funds. We found that several DC Master-trust pension funds benchmark their returns that are in line with these rates. For example, NEST, Legal and General and The People's Pension (TPP) link their investment objectives to CPI inflation or RPI inflation. A few other master trust pension funds such as NOW Pension employ risk-free interest rates such as the UK Treasury Bill interest rate, the London Interbank Offering Rate (LIBOR) or Sterling Overnight Index Average (SONIA). In other jurisdictions, governments and regulatory agencies explicitly require DC pension funds to guarantee a minimum rate of return. These minimum return guarantees are often set in line with inflation/interest rate movements. Countries such as Belgium, Czech Republic, Germany and Switzerland have some form of minimum return guarantee in place. Antolin et al. (2012) observed that almost all countries with mandatory DC pension schemes were more likely to impose such requirements given the importance of these funds in retirement income provision. With this in mind, we do not limit the analysis in this chapter to just one inflation rate. We use alternative measures of inflation as well as interest rates.

Amenc et al. (2008) observed that, in order to mitigate inflation risk, investors have often adopted strategies including the holding of index-linked bonds and the use of dedicated over-the counter derivative instruments such as inflation swaps. They found these approaches to be rather costly as they generate modest performance. Furthermore, the capacity of the inflation-indexed bond market has been found to be insufficient relative to the collective demand institutional and private investors. Over-the counter inflation derivative instruments have a significant level of counterparty risk. This finding means that it is important for investors to look to other assets which could potentially be an inflation hedge without requiring a large sacrifice of returns.

Several studies have analysed the inflation hedging ability of assets such as stocks, bonds, real estate and alternative assets such as gold. The goal of these studies is to provide empirically analyse the relationship between inflation and the returns of these assets over time. Assets that are found to have a close relationship with inflation may be used in place, or in addition to, index-linked bonds and inflation swaps. However, Spierdijk and Umar (2013) concluded that the majority of these studies focus on aggregate level data which could result in inaccurate conclusions as the behaviour of an asset on a sector level may be different from the behaviour at an aggregate level. The authors found that the inflation hedging ability of assets within the same asset class varies across industries, maturities, and investment horizon.

In this chapter, we use a number of contemporary approaches to carry out a systematic, sector-level analysis of the short and long-run inflation hedging ability of real estate and a wide range of traditional and alternative assets that pension funds typically hold. We analyse the ability of 47 different asset classes and sectors including real estate, stocks, bonds and alternative assets such as commodities, hedge funds and private equity. For stocks, we investigate the hedging ability of different stock sectors or industries. For bonds, we analyse the hedging ability of different bond maturities. Spierdijk and

Umar (2013) observed that as with different stock sectors, the hedging ability of bonds may differ across different maturities, issuer and risk-rating. We hope that the approach adopted in this study would help to identify assets which DC pension funds should hold in order to hedge against specific measures of inflation and interest rate changes. The analysis in this chapter would uncover assets and sectors that should be considered by DC pension funds seeking to protect the purchasing power of their investment portfolios.

This chapter begins with a discussion of the concept of inflation hedging and how this is relevant to DC pension funds. The mechanics of inflation and interest rate hedging are described and empirical evidence of the inflation and interest rate hedging ability of various assets are presented. We go on to analyse the performance of the various assets relative to the chosen inflation/interest rates. The correlation structure of the various assets relative to the various benchmarks is also analysed. We then use autoregressive distributed lag model of Pesaran et al. (2001) to analyse the long-run inflation-hedging ability of the various assets. An error-correction version of the ARDL model is also used to estimate the long-run coefficients and the speed of adjustment to equilibrium following a shock to inflation and interest rates. The Toda and Yamamoto (1995) approach to testing Granger Causality is also used to examine the short-run relationship and the direction of causality between inflation/interest rates and the returns of the various assets and sectors.

This study covers the period 1991 – 2015. Although we do not explicitly divide the study period into pre- and post- GFC periods, a comparison of the results of this study with studies conducted prior to the 2008 financial crisis may reveal how the relationship between asset returns and inflation been altered following the crisis.

On the whole, we found real estate to be a consistent hedge against four inflation and interest rate measures that are of interest to UK DC pension funds. Like real estate, bonds were also a good hedge against inflation and interest rate changes. However, we did not find inflation-index bonds to possess a short-term hedging ability, although over the long-run, they were found to be a hedge against almost all inflation and interest rates. We found it interesting that index-linked bonds had a stronger relationship with interest rates than inflation rates against which they are benchmarked. Aside real estate and bonds, a number of stock sectors and commodities offered some inflation and interest rate hedge. We find that a lot more assets were a hedge over the long-run but not over the short-run. A policy implication of this result is that, minimum return legislations which require DC pension funds to deliver returns in line with inflation or interest rates may not impact negatively on portfolio diversification unless they have to be delivered upon on a short-term period-by-period basis.

7.1 THEORY OF INFLATION HEDGING

In this section, we discuss the key economic theories that underlie the analysis of inflation/interest rate hedging ability of assets. The Fisher (1930) hypothesis and the Two-Fund Separation Theorem of Tobin (1958) have shaped research on the impact that inflation and interest rates have on the investment and asset allocation decision of individuals and institutional investors. While the Fisher hypothesis forms the basis for expectations that the returns of assets must compensate investors for inflation, the two-fund separation theorem is the intuition behind the use of risk-free interest rates as a benchmark against which investment performance is measured. The work of Fama & Schwert (1977) has also significantly shaped research on the inflation-hedging characteristics of various assets.

7.1.1 THE FISHER HYPOTHESIS

The idea of inflation hedging is believed to date back to Fisher (1930) who hypothesises that the real interest rate equals the nominal interest rate less an anticipated rate of inflation. This means that the ex-ante nominal rate of return contains the market's perception of expected inflation. Fisher (1930) holds that the real and monetary sectors of the economy are largely independent, implying that the expected real rate and expected inflation are unrelated. This is equivalent to saying that the nominal interest rate and the expected inflation move parallel to each other i.e. that there is a one-for-one adjustment in the nominal interest rate to the anticipated rate of inflation. Mathematically:

$$1+R=(1+r)(1+p) \qquad \textbf{7(1)}$$

where:

R= the nominal rate of interest

r = the nominal interest rate

p = inflation rate

The Fisher hypothesis is often formulated by stating that expected real interest rates and expected inflation are statistically uncorrelated. In principle, the Fisher hypothesis can be extended to any asset e.g. stocks, bonds and real estate. In this sense, the hypothesis should be restated to the effect that the nominal asset returns are expected to move one for one with the expected level of inflation.

Although a positive relationship has been observed between interest rates and inflation, several empirical studies have failed to confirm the Fisher hypothesis in its strictest form. A number of studies have attempted to reconcile these deviations. These justifications include the wealth effect (Mundell, 1963; Tobin, 1965) and the tax effect (Darby, 1975; Feldstein, 1976).

Mundell (1963) and Tobin (1965) argue that the nominal rate would tend to rise by less than unity with a change in inflation through the effects of inflation on real rates. An exogenous growth in money supply, they explain, would result in an increase in the nominal rate and velocity of money but a decrease in real interest rate. In other words, with an increase in inflation, people would hold less of money balances but not of other assets. This would drive interest rates down.

Darby (1975) and Feldstein (1976) demonstrated that in the presence of taxes and interest income, nominal rates must increase by more than unity in response to an increase in inflation for a given after-tax real rate of interest. They predicted that the nominal rate would have to increase at a rate of $1/(1\text{-}t)$ where t is the proportional tax rate on interest income. The Darby-Feldstein explanation was further modified by Nielsen (1981) and Gandolfi (1982) who found that although interest rates increased by more than unity in response to a change in inflation rate, the change was not as high as posited by Darby (1975) and Feldstein (1976).

According to the Efficient Capital Market theory of Fama (1970), the amount of information that would be reflected in prices depends on how efficient a market is. Fama (1970) proposed three different forms of efficiency: (i) weak form (ii) semi-strong form and (iii) strong form. Geyser and Lowies (2001) explains that the Fama (1970) hypothesis implies that all information available on the market is immediately reflected in the prices so that any increase in inflation would lead to an increase in the nominal value of financial assets such as stocks and bonds.

7.1.2 FAMA AND SCHWERT FRAMEWORK

Fama & Schwert (1977) adapted the Fisher (1930) framework to test if assets were a hedge against inflation. Within the Fama & Schwert (1977) framework, asset returns are tested against a measure of actual inflation as well as a measure of expected inflation. The only observable data are the actual inflation and nominal asset returns. The expected and unexpected inflation have to be estimated.

The measure of actual inflation used in most studies has been the CPI inflation rate. Studies focused on the UK have however used the RPI inflation rate which until 2013 was the official measure of inflation in the United Kingdom (Limmack and Ward, 1988; Barkham et al., 1997; Chen and Foo, 2006; Hoesli et al., 2008).

T-bills have traditionally been viewed as a reflection of agent's changing perception of future inflation and have been used as a measure of expected inflation in several studies (Fama & Schwert, 1977); Ferris and Makhija, 1987). Andrande and Clare (1994) pointed out that using T-bill returns as a proxy for expected inflation helps to circumvent the problem of generating expected inflation using auxiliary regression models. They however found in their study that T-bill rates were not a good proxy for expected inflation in the UK. Similarly, Ratner (1989) found that T-bill interest rates were a good proxy for expected inflation over the period studied by Fama & Schwert (1977) but not for the period covered by the study of Ferris and Makhija (1987). Consequently, the authors advise that researchers should actually test the hypothesis that T-bill interest rates were a good proxy before proceeding to use them.

Fama and Gibbons (1982) suggested an approach to extract expected inflation rates from T-bill rates. This approach has also been used in several studies to estimate expected inflation. The starting point of this approach is that the risk-free interest rate is the sum of the expected real rate of return and an expected rate of inflation. If the real rate of return is assumed to be constant, then risk-free interest rates such as T-bill interest rates can be appropriate proxy for expected inflation. If real interest rates are not seen as constant but change over time, they can be estimated using univariate time series approaches such as the Box-Jenkins or ARIMA models have (Barkham et al., 1996; Gartzlaff, 1994; Hoesli et al., 2008).

7.1.3 TWO-FUND SEPARATION THEOREM

Tobin (1958) posits that portfolio choice can be separated into two stages. In the first stage, an investor determines the optimal mix of risky assets. Once this mix is determined, the second stage consists of adding a certain amount of risk-free assets to the portfolio of risky assets. The fraction of the investor's capital that is put in the optimal portfolio of risky assets versus the risk-free portfolio is based on his/her risk-aversion. Investors who do not wish to bear any risk at all will put their capital in the risk-free asset.

A risk-free asset is defined as one without any exposure to financial risks. This asset pays a specified unit in a currency at a certain date in the future in every possible state of the world (Hoojman, 2016). The idea of Tobin (1958) is believed to have helped popularise the idea of index-investing. The famous Sharpe ratio of Sharpe (1966) which measures the performance of assets relative to the risk-free rate of return was developed from the Two-Fund Separation Theorem.

Governments are considered creditworthy as they have unlimited taxing authority and can in theory print additional money to meet their outstanding obligations. Demodaran (2010) however contends that in reality, no asset fully satisfies all the characteristics of a risk-free asset as it is almost impossible to eliminate all financial risk. Likewise Hoojman (2016) states that risk-free rates are a theoretical concept and the returns on government securities are proxies or estimators of this return.

Although in practice, the government bonds have been viewed as risk-free assets, some authors have questioned this belief. For example, negative yields have been observed on several Euro-area government bonds (Capital IQ, 2016). This in itself contradicts the fact that humans prefer direct over delayed consumption (Frederick et al., 2002). Fisher (1930) maintains that nominal bond yields must compensate investors for inflation and the time value of money. Additionally, the negligibility of credit risk has also been especially questioned following the recent financial crisis.

Alternative proxies for the risk-free rate include overnight interest swaps such as LIBOR, EONIA, SONIA, as well as repurchase rates. Market implied risk-free rates such as those constructed by Hull et al. (2004) and Blanco et al. (2015) have also been used within the finance literature.

Notwithstanding the difficulty in getting a good risk-free proxy, the concept of risk-free rates has been a key building block for many theories in finance. These include the modern portfolio theory of Markowitz (1952), the two-fund separation theory of Tobin (1958), the Capital Asset Pricing Theorem and the Sharpe Ratio of Sharpe (1964) and the option pricing theorem of Black and Scholes (1973). As discussed earlier, risk-free interest rates such as T-bill rates have often been used as a proxy for expected inflation within the inflation-hedging literature, especially those that work within the Fama & Schwert (1977) framework. The existence of a long-run relationship between asset returns and the risk-free rate is interpreted to mean that the asset is a hedge against expected inflation (Fama & Schwert, 1977).

7.2 LITERATURE REVIEW

7.2.1 INFLATION HEDGING ABILITY OF REAL ESTATE

In this section, we review the empirical studies on the inflation-hedging ability of real estate. We also provide a summary of studies on other markets. Peyton et al. (2008) outlined a number of reasons why real estate can be thought to be an attractive investment: (i) merely being part of the investment universe (ii) a means to diversify portfolios (iii) its ability to generate attractive risk-adjusted returns (iv) its ability to hedge against inflation or deflation (v) a generator of strong cash flows. Similar reasons are provided by Hoesli (1994): (i) real estate's diversification effect owing to the fact that it does not have a perfect correlation with other asset classes (ii) real estate's ability to provide better protection against inflation.

Real estate is believed to be a good hedge against inflation as a general increase in prices is often accompanied by rising rent and an increase in the prices of properties. Landlords can adjust rents to compensate for inflation. Increases in inflation expectations could also motivate households to invest in real estate. Also, an increase in the demand for real estate would consequently put pressure on house prices. An increase in the returns of real estate could also lead to an increase in the number of households that invest in real estate. This could lead to an increase in inflation (Zhou and Clements, 2010). Also, as household income (GDP) increases, inflation increases as well as households increase their demand for goods and services. Since a general increase in the demand of goods means a demand for housing and housing services, real estate returns are expected to increase. This way, the return on real estate would increase with an increase in inflation. Park and Bang (2012) found that GDP may actually dominate CPI in accounting for changes in commercial real estate returns. Miles (1996) however observed that although real estate's income return (rents) can be renegotiated, due to the nature of lease agreements, it is only when returns, it is only when rents are renegotiated that the stream of payments which gives property its value would reflect price rises.

Several studies have gone on to empirically examine the ability of real estate to hedge against inflation and other macroeconomic variables. If true, the inflation hedging ability of real estate would be very desirable especially for pension funds and other institutional investors who need to match real (inflation-adjusted) liabilities (Hoesli et al., 2009). In terms of the assets included in these analysis, we can distinguish between those that analysed real estate in isolation and those that analyse real estate along with other assets. These studies have been summarised in Chapter 3.

Studies which focus exclusively on real estate tend to carry out sector level analysis within the same country These studies have mostly shown that different property types or sectors could have different hedging ability (Hartzell et al., 1987; Limmack and Ward, 1988; Barkham et al., 1996; Barber et al., 1997; Huang and Hudson-Wilson, 2007; Gyourko and Linneman, 1988; Rubens et al, 2001; Zhou and Clements, 2010). For example, Gyourko and Linneman (1988) found that although the overall US real estate market does not provide a hedge against inflation, different property types provide mixed results. Residential real estate were a better hedge than commercial and residential real estate. Rubens et al. (1989) found that residential real estate were a hedge against actual, expected and unexpected inflation.

Other studies have compared the hedging ability of real estate across countries (Stevenson, 2001a; Chen and Foo, 2006; Demary, 2009; Demary and Voigtlander, 2009). A few other estate studies have compared the hedging ability of different real estate investment vehicles within the same country or across countries (Hoesli, 1994; Obereiner and Kurzrock, 2012).

A multi-asset approach has been adopted by a number of studies. Here, the inflation-hedging ability of real estate is analysed along with other assets, mostly stocks and bonds. A few have included alternative assets such as commodity and gold. In fact, one of the earliest studies in this area, Fama & Schwert (1977), was carried out within a multi-asset context. The inflation hedging ability of real estate was analysed along with US Stocks, Bonds and Treasury bills. The study found that US residential real estate offered a hedge against both expected and unexpected inflation, US Bonds offered a partial hedge and Stocks offered a perverse hedge. Other studies such as Newell (1996), Stevenson and Murray (1999), Amenc et al. (2008) and Attie and Roachie (2009) have followed in this trajectory. Alternative assets were analysed along with real estate in the studies of Amenc et al. (2009). Attie and Roachie

(2009) analysed the inflation hedging ability of commodities along with Stocks and Bonds. Gold was analysed in the study of Case et al. (2012).

Another point of departure for studies on the inflation hedging ability of real estate is the data series that is used in the analysis. Most of the early studies within the real estate literature found real estate to be a partial hedge against inflation (e.g. Hoesli et al., 1997; Barber et al., 1997; Quan and Titman, 1999) Studies on the inflation-hedging ability of real estate stocks however found them to behave more like stocks and so were a perverse hedge against inflation. Later studies have however produced mixed results (see Demary and Voigtlander, 2009; Amenc et al., 2009; Simpson et al., 2007). Fama (1981) attributes the findings relative to stocks to the fact that most models do not take into account variables such as real activity, price uncertainty and monetary shocks. It is important to also distinguish between short-run and long-relationships. Over longer horizons, several studies have found stocks to have a positive relationship with inflation as per the Fisher Hypothesis. Hoesli et al. (2008) attributed the mixed result for direct versus listed real estate to difficulties in measuring real estate returns and a lack of high frequency data over long periods. Hoesli et al. (2008) further observed that private market assets were particularly different in their behaviour relative to inflation than publicly traded assets owing to what they described as a 'data composition' effect. Consequently, the authors recommended that a distinction is made of private market assets and public assets given the conceptual and data issues related to each class of assets. Research on private market assets such as real estate entails the use of appraisal-based data. Appraisal-based data is known to be influenced by appraiser behaviour and may also be distorted by appraisal smoothing. On the other hand, the use of securitised real estate returns would imply using data that reflect not only the performance of the underlying real estate assets but also capture factures such as leverage of firms and the behaviour of investment managers. Real estate was generally found to be an inflation hedge when appraisal based series were used (e.g. Hartzell et al., 1987; Limmack and Ward, 1988). When security-based return series were analysed, the results often suggest that real estate is a perverse hedge against inflation (Park et al., 1990; Liu et al., 1997). Hoesli et al. (1997) argue that this may be due to the fact that appraisers typically adjust the value of their estimate by an inflation factor which may account for the positive coefficient often observed between inflation and appraisal-based real estate returns.

Two approaches have dominated the empirical literature on inflation hedging within the context of real estate: the classical OLS technique of Fama & Schwert (1977) and cointegration analysis The classical OLS approach of Fama & Schwert (1977) as well as its variations, is arguably the most used analytical tool for analysing the inflation hedging ability of real estate investments. The approach has however been criticised by more recent authors who argue among other thing that OLS regression analysis is based on the assumption that the underlying data is stationary. If this assumption of stationarity does not hold, the results obtained from such an analysis would be spurious (Granger and Newbold, 1974; Phillips, 1986; Brooks, 2008). Spurious relationships occur when two variables are found to follow a common pattern and the regression process picks up a statistically significant relationship but in actual fact, no causal relationship exists. Tarbet (1996) observed that the results of most of the studies that analysed the inflation hedging ability of real estate using regression analysis displayed signs of mis-specification. The Durbin-Watson statistics for example were often very low.

Recent studies have examined the stationarity of the underlying data and select an appropriate model according to the data characteristics. Several studies have gone on to analyse the inflation-hedging ability of assets using cointegration analysis. The concept of cointegration is based on the belief that in the long run certain variables may be associated although there may be a divergence between them over the short-term. If the two variables are cointegrated, there is an underlying tendency for them to converge towards equilibrium over the long run. Cointegration analysis allows for the relationship between non-stationary time series to be investigated, enabling the detection of any underlying relationships.

Although the cointegration approaches of Engle & Granger (1987) and the Johansen (1988, 1991) have been applied extensively in the real estate literature, these approaches have also been found to have some drawbacks. For example, the two models require all the variables to be integrated of the same order. Again, the Johansen (1988, 1991) approach which is based on maximum likelihood method has been described as an asymptotical efficient estimator. This means that the parameter estimates would be subject to small sample bias when applied to small sample sizes.

The ARDL model of Pesaran et al. (2001) on the other hand has gained popularity and has been used to test the hedging ability of assets in several markets. The model has several advantages over the traditional approaches to cointegration. The model does not require the variables to be integrated of the same order i.e. one could the approach could be used to test for cointegration when the variables being analysed are a combination of I(0) and I(1). It is also argued in a number of studies that this approach provides more robust estimates when the sample size is small (De Vita & Abbott, 2002; Atkins & Coe, 2002; Nam and Lee, 2012; Lotz and Gupta, 2013). Shin and Greenwood-Nimmo (2014) have further proposed a non-linear ARDL model that is capable of simultaneously capturing the asymmetry and nonlinear relationship between different macroeconomic variables.

The use of ARDL model for econometric analysis has also been bolstered by the introduction of a complete module within econometric packages such as EViews and Stata. For example, EViews 9 has a complete suite that enables users to carry out comprehensive ARDL analysis. For example, there is a module that automatically selects the appropriate lag length for each independent variable and the most parsimonious model. It also includes tests for cointegration using bounds test and a provision for directly estimating the error term (co-integrating coefficient) as well as the short and long run coefficients. Several diagnostic tests can also be undertaken to determine the suitability of the selected model.

A growing number of studies have used the approach of Pesaran et al. (2001) to analyse the inflation-hedging ability of real estate especially following the 2008 global financial crisis when interest in the relationship between different assets and macroeconomic variables was renewed (see Anari and Kolari, 2002; Gupta and Ingesi-Loltz, 2011; Zhou and Clements, 2010; Katrakilidis and Tachanas, 2012; Koon and Lee; 2013; Bahmani-Oskooee et al., 2016; Yeap and Leen, 2017). None of these studies have however been based on the United Kingdom.

Anari and Kolari (2002) was one of the earliest studies to employ the use of the ARDL model to real estate. They examined the impact of inflation on homeowner equity by examining the relationship between inflation and housing investments. They used house prices instead of total returns. They believed that even though the total return on housing cannot be accurately measured, house prices fully reflect the total return on housing. They believed that valuable long-run information could be lost when returns or a differenced time series is used in the analysis. Another point of departure for Anari and Kolari (2002) is that they used an inflation measure that excluded housing costs to avoid any potential bias in the estimation of the effects of inflation on house prices. They found that the Fisher coefficients were consistently higher than one, an indication that housing investments are a stable inflation hedge over the long run. Anari and Kolari (2002) obtained a Fisher coefficient of 1.08 for existing houses and 1.26 for new houses. As this is significantly greater than 1 as predicted by Darby's version of the Fisher equation, they concluded that housing investments are a stable inflation hedge over the long run.

Zhou and Clements (2010) used ARDL cointegration technique to test the long-term relationship between real estate prices and different measures of inflation. The inflation measures used were actual inflation is proxied by the Chinese Real Estate Price Index, expected inflation is obtained using ARIMA estimates. Unexpected inflation is the difference between these two. Even at the 10% significance level, Zhou and Clements (2010) could not reject the null hypothesis of no cointegration as the F-statistic obtained fell within the lower and upper bounds. They pointed out however that a limitation of their study is that they was their use of house prices instead of total returns. Granger tests however showed short-term causal relationship from residential real estate to actual inflation. A bi-directional causal relationship was observed between residential real estate and expected inflation. Non-residential real estate granger-caused both actual and expected inflation over the period.

Koon and Lee (2013) used the ARDL model to investigate the long-run and short-run inflation hedging ability of residential real estate in Hong Kong over the period 1980 – 2011. They found that small and medium size residential property in Hong-Kong provide a better hedge over both the short and long term. Stocks only provide a hedge against inflation in the long term but not the short term. Time deposits fail to serve as an inflation hedge in over both the short and long term.

Bahmani-Oskooee et al. (2016) used both the linear ARDL model of Shin and Pesaran (2001) and the nonlinear ARDL (NARDL) model of Shin and Greenwood-Nimmo (2014) to analyse the symmetric and asymmetric effects on inflation on house prices in all 52 states in the United States of America. They found long-run cointegration between house prices and inflation in 30 of the 52 states. The non-linear model revealed more cointegration relationship than the non-linear model. The study also revealed that income and interest rates have asymmetric effects on house prices in almost all states.

Yeap and Lean (2017) decomposed CPI inflation and Energy inflation in Malaysia into positive and negative changes and used the NARDL model of Shin and Greenwood-Nimmo (2014) to analyse the asymmetric and non-linear relationship between house prices and inflation in both the short and long-run. They found that house prices react asymmetrically to both consumer and energy inflation in the short-run but not in the long-run. Only detached houses react symmetrically to consumer and energy inflation in the long-run and short run.

This study differs from these previous studies in a number of ways. First, the cointegration and causality tests we implement both take into account the different levels of integration between the variables. The ARDL approach to cointegration and the Toda-Yamamoto Granger Causality Test are designed to accommodate I(0) and I(1) variables. The Toda-Yamamoto Granger Causality test can also be implemented whether or not the variables are cointegrated.

Also, most of the studies that have used the ARDL framework have been based on the housing market, few have analysed the commercial real estate market. This study is also the first to analyse UK commercial property market using this approach. In addition to commercial real estate, we have analysed a broad range of assets that typify the assets in a DC pension fund's investment portfolio. In all, we analyse 47 assets and sectors.

Another point of departure in our studies is the fact that we have carried out our analysis using alternative measures of inflation and interest rate changes. This way, the results of this studies are relevant to a broad range of DC pension funds in the UK, whether they use an inflation benchmark or an interest rate benchmark. The results of our simulations using interest rate benchmarks, in a sense, are analogous with the results of studies that have analysed the ability of assets to hedge against expected inflation.

7.2.2 INFLATION HEDGING ABILITY OF OTHER ASSETS

Apart from real estate, other assets have been suggested as assets that have the potential to hedge against inflation. The approaches adopted in the studies of these assets has been more diverse than what is observed within the real estate literature.

7.2.2.1 Stocks

The inflation hedging ability of stocks has been extensively studied in the finance and economics literature. The general belief has been that as stocks represent claims to real estate, the Fisher hypothesis should hold for them. Stockholders are expected to be compensated for changes in price levels, on average. Also, Miles (1996) stated that the income return on equities is very likely to increase with inflation as price movements in themselves would mean higher revenues for companies and hence higher dividend pay-outs.

Studies conducted in the early 70s however found that the total returns on stocks were in actual fact negatively correlated with expected inflation, especially over the short-run. In the long-run however, stocks may serve as a good hedge against inflation. Three explanations that have been provided for this negative effect of inflation on stock returns are the proxy hypothesis (Fama, 1981; Kaul, 1987), the money illusion hypothesis (Modigliani and Cohn, 1979) and the information frictions (Barnes et al, 1999). Spierdijk and Umar (2013) analysed the inflation-hedging ability of US stocks, bonds and T-bills at the sector-level between 1983 and 2012. They found that stocks exhibited very little hedging ability prior to the 2008 financial crisis. However, following 2008, several stock sectors began to exhibit statistically significant hedging ability, even over the short-run. In particular, they found that stock sectors and sub-sectors related to oil and gas, utilities, basic materials, industrials and financials possess attractive inflation-hedging abilities especially following the 2007-2008 financial crisis period. They also found that short-term bonds such as T-bills exhibit better hedging ability than long-term bonds. T-bills in particular were found to be a good hedge against inflation. Boudoukh et al. (1993) also analysed the inflation-hedging ability of stocks at the sector level. They analysed the inflation-hedging ability of stocks from different industries between 1953 and 1993. They concluded that stocks in non-cyclical industries offer better protection against inflation.

7.2.2.2 Bonds

Inflation-linked bonds have been viewed by many investors as a natural hedge against inflation as the real interest rates that ILBs pay is fixed at the beginning of the term. The nominal rate that these bonds pay is adjusted periodically by the rate of inflation (Campbell et al.. 2009). Orsolio (2012) however contends that it is a misconception that the primary role of ILBs is to serve as a hedge against inflation. This misconception, the author attributes to a lack of understanding as to how ILBs actually work. They explain that since index-linked bonds are still bonds, the price changes between the time of issue and maturity is subject to the prevailing interest rate. Although price changes may not matter for investors who hold ILBs to maturity, it is important for investors with a target a fixed investment horizon. Amenc et al. (2008) observed that the use of inflation-linked bonds and interest rate swaps represents a costly approach to inflation-hedging given the relatively low returns of these investments. They concluded that a combination of real estate, commodities and index-linked bonds represented a better and cost-saving solution to merely using inflation-linked bonds or interest rate swaps. Park and Bang (2012) observed that although Korean investors had access to inflation-indexed bonds, these assets were not necessarily viewed as an inflation hedge due to the illiquidity of the ILB market.

A few studies have analysed the inflation-indexed ability of bonds. Surprisingly, these studies did not find index-linked bonds to be a good hedge against inflation.

Short-term bonds are expected to adjust rapidly to changes in expected inflation. Consequently, these bonds may not contain an inflation risk premium. This could make them poor hedges against unexpected inflation. Miles (1996) stated that conventional bonds may not be a good hedge against inflation as the capital values and coupon payments are fixed in nominal terms.

Fama & Schwert (1977) note that long-term bonds based on rolling forward short-term bond contracts are less likely to reject the Fisher hypothesis with respect to long-run expected inflation than interest rates based on holding long-term bonds held until maturity. Bekaert and Wang (2010) found that the hedging ability of short-term bonds, specifically T-bills, with respect to expected inflation increases with investment horizon. Hoevenaars et al. (2008) found similar results with respect to total inflation. Bekaert and Wang (2010) found that short-term bonds do not provide protection against unexpected inflation. Regarding long-term bonds, Hoevenaars et al.(2008) found that they offer inflation protection over the long run and not the short-run. Attie and Roachie (2009) and Bekaert and Wang (2010) did not find long-term bonds to be a good hedge against inflation either within the short-run or long-run.

7.2.2.3 Alternatives

A number alternative assets have been analysed with quite a number of them being found to be a good hedge against inflation. In particular, the inflation hedging ability of commodities such as oil and gold have received a lot of attention. Commodities have historically been used as a store of value as they represent real assets. It is believed that any shocks or changes within the economy would be quickly reflected in the prices of commodities. Bird (1984) found commodities offer a hedge against inflation but different commodities behaved differently relative to inflation. Tin, they believed, offered a better hedge against inflation particularly because of its low storage cost. Commodities have also been found to be a hedge against inflation by studies such as Halpern and Warsager (1998); Greer (2000); Gorton and Rouwenhorst (2005) and Worthington and Parlavani (2006). Furlong and Ingenito (1996) however point out that since the early 80s, the hedging ability of most commodities has weakened. Of the different types of commodities, gold has often been singled out as offering a particularly good hedge against inflation (Baur & McDermott, 2010; McCown and Zinnerman, 2006, Dimson et al., 2012). However, a significant number of studies question the ability of gold to hedge against inflation. Mahdavi and Zhou (1997) point to gold's volatile returns especially in the long run. Of the six countries they analysed, Chua & Woodward (1982) found gold to provide an effective hedge against both expected and unexpected inflation only in the USA. Gold was also found by Wang et al. (2011) to behave differently in different market conditions. Generally, gold was a good hedge only when momentum is high.

Apart from commodities, very few alternative assets have received attention within the inflation hedging literature. Parajuli and Chang (2015) used a generalised capital asset pricing model to determine the inflation hedging ability of private equity as opposed to listed stocks. They found that private equity offered superior inflation hedging abilities to stocks.

7.3 METHODOLOGY

We begin our analysis with an assessment of the performance of the various assets relative to the inflation/interest rate measures analysed in this study. We also examine the relationship between asset returns and inflation/interest rate changes over the short run. The static and dynamic conditional correlations between the various assets and the selected inflation and interest rates are examined to give us a sense of the assets that have the closest relationship with inflation and interest rates and how this relationship has evolved over time.

7.3.1 AUTOREGRESSIVE DISTRIBUTED LAG (ARDL) MODEL

We follow a growing body of studies that have employed the ARDL model to determine the inflation long-run inflation/interest rate hedging ability of real estate and alternative assets (Anari & Kolari, 2002; Zhou and Clements, 2010; Inglesi-Lotz and Gupta, 2011; Katrakilidis and Tachanas, 2012; Koon and Lee, 2013; Bahmani-Oskooee et al., 2016; Yeap and Lean, 2017; Fang et al., 2018).

ARDL models are time series models where the dependent variable is a function of its own lags, other variables and their lags. ARDL is convenient for modelling I(0) and I(1) variables together and for the testing of Cointegration relationships. In ARDL, all variables are assumed to be endogenous. Hence, both the regressant and regressors enter the models with lags, and they correct for potential endogeneity of the regressor through appropriate augmentation (Pesaran and Shin, 1999). A more detailed theoretical framework for the ARDL approach along with other models employed in this thesis has been provided in Chapter 4.

Given that y_t is the dependent variable (asset return) and $x_1,\cdots,x_k$ are k explanatory variables (inflation/interest rate), a general $ARDL(p,q_1,\ldots..q_k)$ model is given by:

$$y_t=a_0+a_1t+\sum_{t=1}^{p}\psi_i y_{t-i}+\sum_{j=1}^{k}\sum_{l_j}^{q_j}\beta_{j,l_j}x_{j,t-l_j},+\epsilon_t \qquad \mathbf{7(2)}$$

where:

ϵ_t are the usual innovations

a_0 is the constant term

a_1, ψ_i, β_{j,l_j} are respectively the coefficients associated with a linear trend, lags of the k regressors $x_{j,t}$ for $j=1,\cdots k$.

The first step in the application of ARDL models is an estimation of the intertemporal dynamics. Here, we are interested in the relationship between y_t on both its own lags as well as the contemporaneous and lagged values of the k regressors $x_{j,t}$. Equation 7(2) can be cast into the following representation:

$$y_t=a_0+a_1t+\sum_{i=1}^{p}\psi_i y_{t-i}+\sum_{j=1}^{k}\beta_j(1)x_{j,t}+\sum_{j=1}^{k}\tilde{\beta}_j(L)\Delta x_{j,t}+\epsilon_t \qquad \mathbf{7(3)}$$

where we use the first difference notation, $\Delta=(1\text{-}L)$. Given that equation 3 does not explicitly solve for y_t, it is often considered as a regression for intertemporal dynamics. Within a more practical setting, equation 3 can be restated as:

$$y_t = a_0 + a_1 t + \sum_{i=1}^{p} b_{0,i} y_{t-1} + \sum_{i=1}^{p} b_j x_{j,t} + \sum_{j=1}^{k} \sum_{l_j=1}^{q_j-1} c_{j,l_j} \Delta x_{j,t-l_j} + \epsilon_t \qquad \mathbf{7(4)}$$

The second representation of the ARDL model attempts to derive the long-run relationship between y_t and the k regressors. This representation solves for y_t in terms of $x_{j,t}$. Having estimated the regression equation in model 4, we can use equation 5 to derive the long-run parameters post-estimation. The second representation is formulated thus:

$$y_t = \psi^{-1}(1) \left(a_0^* + a_1 t + \sum_{j=1}^{k} \beta_j (1) x_{j,t} + \sum_{j=1}^{k} \beta_j^* (L) \Delta x_{j,t} + \epsilon_t^* \right) \qquad \mathbf{7(5)}$$

Once we establish the existence of a long-run relationship between the variables, we use the error correction specification of the ARDL model to estimate the magnitude of the long-run relationship and how stable this long-run relationship is. The length of time it takes for the relationship to be restored when there is a shock is also investigated using the error-correction specification of the ARDL model. The speed of adjustment reflects the rate at which the long-run equilibrium relationship is restored if an unexpected event causes the return of a given asset and the inflation/interest rate benchmark to drift apart. In a sense, this shows the ability of the asset to serve as a hedge over the short run.

Equation 6 is the Conditional Error Correction form of the ARDL model in equation (1):

$$\Delta y_t = a_0 + a_1 t - \psi(1) EC_{t-1} + \left(\tilde{\psi}^* (L) \Delta_{x,t-1} \right) + \sum_{j=1}^{k} \beta_j (L) \Delta x_{j,t} + \epsilon_t \qquad \mathbf{7(6)}$$

The error correction term, denoted as EC_{t-1}, represents the Cointegrating relationship when y_t and $x_{1,t}, \cdots, x_{k,t}$ are cointegrated.

Pesaran et al (2001) propose the bound test for cointegration as a test on parameter significance in the Cointegrating relationship of the conditional error correction model. The test is a standard F – or Wald test for the following null and alternative hypotheses:

$H_0 \qquad \psi(1) \cap \{B_j(1)\}_{j=1}^{k} = 0$ *(Variables are not cointegrated)*

$$H_1 \qquad \psi(1) \cap \{B_j(1)\}_{j=1}^{k} \neq 0 \ \textit{(Variables are cointegrated)}$$

The computed test statistic is compared to two asymptotic critical values that correspond to the polar cases of all variables being purely I(0) or purely I(1). This implies that the critical values lie in the lower and upper tails, respectively, of a non-standard mixture distribution involving integral functions of Brownian motions. When the test statistic is below the lower critical value, one fails to reject the null and concludes that cointegration is not possible. If however the test statistic is above the upper critical value, one rejects the null and concludes that cointegration is indeed possible. In either cases, knowledge of the Cointegrating rank is not necessary. However, when the test statistic falls between the lower and upper critical values, it is important to have knowledge of the Cointegrating rank to proceed any further.

Pesaran et al. (2001) offer five alternative interpretations of the Conditional Error Correction model depending on whether deterministic terms integrate into the error correction term. The ARDL model can be formulated with: (i) No constant and trend; (ii) Restricted constant and no trend; (iii) Unrestricted constant and no trend; (iv) Unrestricted constant and restricted trend and (v) Unrestricted constant and unrestricted trend.

7.3.2 GRANGER CAUSALITY TEST – TODA AND YAMAMOTO (1995) APPROACH

One way of thinking about the ability of an asset to hedge against a particular benchmark is to examine the contribution that the benchmark makes in the prediction of the asset's return or vice versa. This predictability can be assessed by employing the principles of Granger causality to examine whether the past values of returns of the asset being examined aids in the prediction of the inflation/interest rate changes or vice versa. This is undertaken using either the restricted or unrestricted versions of the models below:

$$x_t = \sum_{i=1}^{l} a_{1i} x_{t-i} + \sum_{i=1}^{l} \beta_{1i} y_{t-i} + \gamma_1 E_{t-1} + \varepsilon_{1t} \qquad \textbf{7(7)}$$

$$y_t = \sum_{i=1}^{l} a_{2i} y_{t-i} + \sum_{i=1}^{l} \beta_{2i} x_{t-i} + \gamma_2 E_{t-1} + \varepsilon_{2t} \qquad \textbf{7(8)}$$

Where x and y represent asset returns and the inflation/interest rate respectively. The restricted version of each equation only includes the lagged values of respective dependent variable. The third term in both equations is an error correction term, which should be included where there is evidence that the variables are cointegrated (Engle & Granger, 1987).

Wald test is used to test whether all of the lagged values of x and y equation are simultaneously equal to zero in order to find out whether x granger causes y.

If $\sum \beta \neq 0$, x Granger causes y;

If both $\sum a \neq 0$ and $\sum \beta \neq 0$, then there exists a bidirectional causality between x and y.

It is important to understand that granger causality does not imply one variable causes changes in the other. When we say that $x_{1t}, x_{2t}, \ldots, x_{nt}$ Granger-cause y_t, we mean that past values of x are correlated with current values of y. Granger-causality can run in one direction, both directions or there is no Granger-causality at all.

Whiles the Granger representation theorem suggests that for there to be cointegration among two variables, there must be a causal relationship running in at least one direction, some studies have however shown that this is not necessarily the case. For example, Ogaki and Reinhart (1998) provide an example to show that a cointegrated time series does not necessarily have an error correction representation. Gujarati (2003) also indicated that relationship between two variables does not necessarily imply causality.

In this study, we employ the Granger non-causality approach of Toda and Yamamoto (1995) to test the relationship between asset returns and the inflation/interest rates. This approach has the advantage that it can be applied without first testing the cointegration properties of the system. Also, if the order of integration does not exceed the fitted lag length of the model, then the Toda and Yamamoto (1995) approach can be applied whether the series are integrated in levels or first differences (i.e. I(0) AND I(1) (Toda and Yamamoto, 1995; Zapata and Rambaldi; 1997; Caporale and Pittis, 1999).

Following Fang et al. (2018), we specify the following equations to establish the relationship between asset returns and the selected inflation/interest rates:

$$\ln(y_t) = \beta_0^1 + \sum_{i=1}^{K+d\max} \beta_{1i}^1 \ln y_{t-i} + \sum_{i=1}^{K+d\max} \beta_{2i}^1 \ln x_{t-i} + \varepsilon_t \qquad \textbf{7(9)}$$

$$\ln(x_t)=\beta_0^2+\sum_{i=1}^{K+d\max}\beta_{1i}^2\ln x_{t-i}+\sum_{i=1}^{K+d\max}\beta_{2i}^2\ln y_{t-i}+\varepsilon_t \qquad \textbf{7(10)}$$

where *d max =maximum order of integration.*

The coefficient matrices of the last $d\ max$ lagged vectors in the model not used in the estimation as these are regarded as zeros. This way, we can test linear or non-linear restrictions on the first k coefficient matrices using the standard asymptotic theory (Toda and Yamamoto, 1995).

In equations 9 and 10, the hypothesis that asset return is does not Granger-cause inflation/interest rate movements is tested using the following: H_0: β_0^1=0, i=1,2,……K. The hypothesis that inflation/interest rate movements does not Granger-cause asset return changes is also testing as follows: H_0: β_0^2=0, i=1,2,……K.

7.4 RESULTS AND DISCUSSIONS

7.4.1 RELATIVE PERFORMANCE MEASURES

Before proceeding to carry out the econometric analysis, it is useful to analyse some relative performance metrics. This is important for two reasons. The first reason is that many industry practitioners rely on these measures to determine which assets produce the best performance relative to a benchmark. Secondly, these measures act as a complement to the econometric analysis. For example, whiles the econometric models may show that the returns of an asset an inflation move closely together, they do not indicate how this would translate into profit or additional returns for an investor. In this section, we discuss various measures of performance that explicitly link the returns of an asset to the returns of a benchmark. Most investors would want to know how much excess return an asset or investment is able to generate relative to a target position or benchmark. The measure of return which captures this is the excess return and is calculated thus:

$$E(r)=\mathrm{E}[r_{Pt}-r_{bt}] \qquad \textbf{7(11)}$$

One of the key measures of relative performance within the asset management industry is the tracking error. This measures how closely the returns of a portfolio follows (or tracks) the returns of a benchmark portfolio. Within the context of this study, inflation/interest rates serve as the benchmark. We define tracking error as the standard deviation of the difference between the returns of an investment and the returns on a specified benchmark or target position. Mathematically, this can be specified as:

$$TE_P = \sigma(r_{Pt} - r_{bt}) \tag{7(12)}$$

Bringing together the tracking error and excess returns yields the Sharpe ratio. In this chapter, we measure a generalised Sharpe ratio which uses a specific measure of inflation or interest rate as the target return. This way, the Sharpe ratio gives the risk (tracking error) per unit of return earned on the asset or portfolio.

$$\text{Shape ratio} = \frac{E[r_{Pt} - r_{bt}]}{\sigma(r_{Pt} - r_{bt})} \tag{7(13)}$$

The results of the various relative performance measures presented in Appendix 7(B) to 7(E) point to the fact that real estate, bonds and private equity are the best assets that a DC pension fund can hold if it measures its performance against inflation and interest rate changes.

Based on the relative performance measures, we can conclude that real estate, bonds and private equity are the most suitable assets to hold in order to achieve the goal of producing the best performance relative to inflation and interest rate changes.

Although the exact ordering varies, for all the benchmarks analysed, assets with the lowest tracking error were bonds and UK direct real estate. In fact, the assets with the 10 lowest tracking error were consistently bonds and direct real estate sectors. On the other hand, technology stocks and commodities (oil) had the highest tracking error to the inflation/interest rates with tracking errors of 17.44% and 20.86% per quarter respectively.

Index-linked bonds and short-term bonds recorded the lowest average excess returns, along with commodities. These assets recorded average excess returns of less than 1% per quarter. This is consistent with Miles (1996) who found that although commodities generated positive excess returns over the period analysed, the excess returns they produced were far below those of equities. The various real estate sectors delivered only moderate excess returns, with the office sector delivering the highest return of all the real estate sectors (1.51% per quarter). Stocks and private equity sectors took the top spots in terms of average excess returns delivered over the period. Technology stocks recorded an average excess return of 3.93% per quarter whiles US venture capital delivered 3.85% per quarter over the period.

Irrespective of the inflation or interest rate benchmark used, real estate assets, bonds and private equity sectors consistently delivered the highest return per unit of risk (tracking error). The three commodity sectors, aggregate commodities, oil and gold recorded the lowest Sharpe ratios owing to their high tracking error relative to the inflation and interest rates and their not so impressive excess return figures.

Another measure of relative performance is the success ratio. The success ratio captures an asset's ability to produce returns in excess of the inflation/interest rate benchmark on a period-by-period basis. Real estate consistently produced the highest success ratio of the assets analysed with returns in excess of inflation 80% of the time and returns exceeding interest rates over 75% of the time. Again, the poorest success ratio came from commodities which only produced positive excess returns relative to both inflation and interest rates about 50% of the time.

This foregoing discussion does not appear to support the view that commodities are a natural hedge against inflation. Although real estate does not deliver the excess returns, it is clear from the results that its moderate results are commensurate with the low tracking error it produces relative to the various inflation/interest rate benchmarks. This gives it a high Sharpe ratio, compared to other assets. The returns on real estate are also consistently exceeded the quarterly inflation and interest rates.

Table 7(I): Descriptive Statistics – All Assets

Asset	Average return	Standard Deviation	Index growth	Autocorrel, 1	Autocorrel, 2	Autocorrel, 3	Autocorrel, 4
Inflation and Interest Rates							
UK Consumer Price Index	0.57	0.66	172.15	0.03	0.05	0.01	0.40
UK Retail Price Index	0.70	0.67	195.94	-0.06	0.11	-0.34	0.43
UK Treasury Bills (3 months)	1.11	0.70	281.37	0.98	0.95	0.91	0.86
London Interbank Offering Rate	1.15	0.69	293.80	0.98	0.94	0.90	0.85
IPD Property Sectors							
IPD All Property	2.09	3.16	712.85	0.75	0.49	0.25	0.11
Industrial	2.28	2.94	835.76	0.75	0.50	0.28	0.15
Office	2.08	3.38	707.64	0.77	0.54	0.32	0.15
Retail	2.23	3.31	809.29	0.73	0.44	0.20	0.10
Other Real Estate Vehicles							
AREF – All Funds	1.78	3.13	538.38	0.79	0.53	0.31	0.18
AREF – All Balanced Funds	1.79	3.76	546.03	0.78	0.52	0.27	0.16
Hybrid Real Estate	1.95	4.14	600.09	0.64	0.33	0.14	0.05
Bonds							
Index linked bonds - 0-5 Years	1.34	1.28	352.84	0.05	0.30	-0.07	0.10
Index linked bonds - 5+ years	2.07	3.16	682.35	0.12	-0.08	-0.11	-0.02
Bonds – All lives	2.03	3.09	623.89	0.13	-0.18	0.07	0.09
Bonds – 10 + years	2.41	4.49	843.95	0.07	-0.18	0.10	0.02
Bonds – 10 year	2.19	3.68	701.65	0.16	-0.16	0.01	0.01
Bonds – 7 year	2.04	2.91	631.55	0.18	-0.08	0.01	0.05
Bonds – 5 year	1.79	2.39	511.93	0.21	-0.08	0.02	0.08
Bonds – 3 year	1.63	1.62	452.18	0.34	0.13	0.15	0.15
Bonds – 2 year	1.44	1.30	381.07	0.52	0.27	0.28	0.24
Stocks							
Aggregate stocks	2.14	8.09	663.85	-0.01	-0.02	0.00	0.01
Listed real estate	2.64	11.68	563.36	0.16	0.00	-0.05	-0.11
Oil	2.74	9.07	928.93	-0.19	0.03	-0.11	0.07
Basic Materials	2.95	13.07	652.39	0.08	-0.13	-0.13	-0.08
Industrial	3.29	10.86	1278.45	-0.10	0.16	-0.19	0.08
Construction	2.80	10.41	800.44	0.01	0.01	-0.18	0.04
Industrial goods and services	2.91	9.51	985.12	-0.08	0.13	-0.09	0.04
Consumer goods	3.71	10.63	1907.78	-0.11	-0.02	-0.14	-0.03
Health care	2.88	7.17	1125.70	0.03	-0.16	0.14	0.12
Consumer services	2.55	8.75	743.29	-0.02	0.04	-0.03	0.09
Telecom	3.12	12.57	891.55	0.12	0.07	0.07	0.26
Technology	4.50	20.82	1230.61	0.08	0.01	0.17	-0.03
Utilities	3.47	7.11	1946.79	0.10	-0.03	0.27	-0.06
Banks	3.44	13.75	966.71	0.03	-0.09	0.06	-0.05
Insurance	3.07	11.54	932.05	-0.07	0.10	-0.02	0.07
Financial services	3.26	10.34	1210.38	0.15	-0.04	-0.01	-0.18
Alternatives in US$							
Emerging stock market	3.05	13.17	834.48	0.13	-0.10	0.03	-0.13
Developed ex UK stocks	2.46	8.73	670.84	0.07	0.00	-0.01	-0.10
Commodities – all	0.91	11.66	132.40	0.11	-0.03	-0.11	-0.08
Commodities – oil	2.26	17.46	214.87	0.11	-0.05	0.00	-0.02
Commodities – gold	1.35	6.40	295.59	-0.02	0.21	0.07	0.07
Hedge funds	1.72	3.52	483.12	0.25	0.07	0.02	-0.11
US private equity	3.68	5.01	2874.85	0.38	0.28	0.13	0.09
US venture capital	4.42	11.72	3805.54	0.60	0.48	0.33	0.04
Developed ex US private equity	3.56	7.19	2581.47	0.23	0.14	-0.08	0.02
Emerging private equity	1.87	5.38	519.64	0.43	0.21	0.04	-0.02
Alterantives in GB£							
Emerging stock market	2.94	14.22	712.59	0.21	-0.06	-0.03	-0.19
Developed ex UK stocks	2.29	9.67	572.86	0.22	0.04	-0.08	-0.16
Commodities – all	0.78	12.48	113.07	0.15	-0.09	-0.08	-0.02
Commodities – oil	2.18	18.27	183.49	0.15	-0.08	0.00	0.00
Commodities – gold	1.22	8.31	252.42	0.09	-0.01	0.01	0.11
Hedge funds	1.57	6.11	412.56	0.19	-0.04	-0.08	-0.17
US private equity	3.58	7.67	2454.95	0.25	0.05	0.03	-0.01
US venture capital	4.26	12.54	3249.70	0.54	0.35	0.22	-0.02
Developed ex US private equity	3.64	11.00	2204.42	0.16	-0.03	-0.08	-0.05
Emerging private equity	1.81	8.36	443.74	0.28	-0.04	-0.04	-0.15

7.4.2 CORRELATION ANALYSIS

An interesting result from the Pearson (Static) and dynamic correlation coefficients presented in Table 7(II) is the fact that indexed-linked gilts were among the assets with the lowest correlation to inflation. The total returns of inflation-indexed bonds were found to be more highly correlated with interest rates than with inflation rates, against which their interest payments and face value are indexed. Short-term index-linked gilts for example had the highest correlation with T-bill interest rates. The results of the correlation analysis does not collaborate the assertion of Stump (2003) inflation-linked bonds are directly linked to changes in inflation than other types of bonds. Schofield (1996) explains that the low correlation observed between index-linked bond returns and inflation is due to the fact that regression-based analysis do not show the strong association expected between index-linked bonds and inflation owing to the fact that the correlation analysis does ignores the impact of lagged indexation.

As in Amenc et al. (2008), we found that nominal bonds have a negative correlation with changes in inflation but a positive correlation with interet rates. Amenc et al. (2008) explained that bond returns can be decomposed into real yield and expected inflation. In the short run when expected and actual realised inflation deviate from each other, the returns of bonds would have a low or even negative correlation with inflation. In the long run however, they found a long-run cointegrating relationship between inflation and bond returns. This result was attributed to the fact that, in the long-run, expected and actual inflation converge.

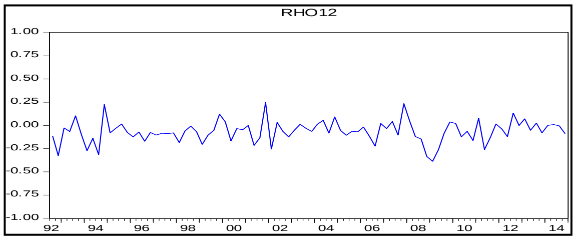
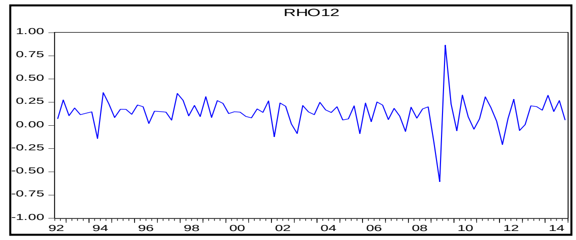
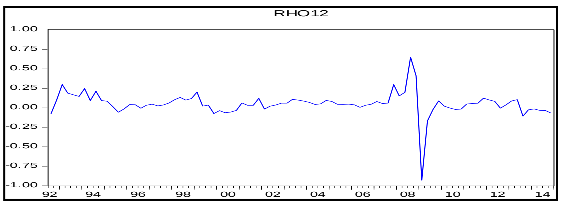
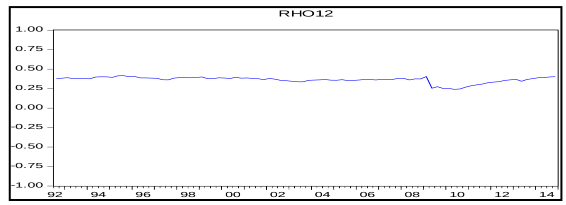
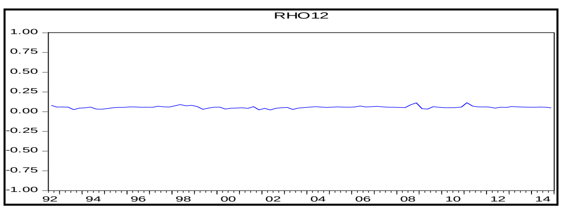
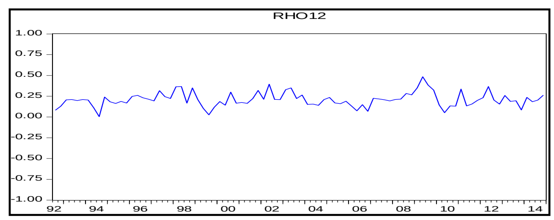
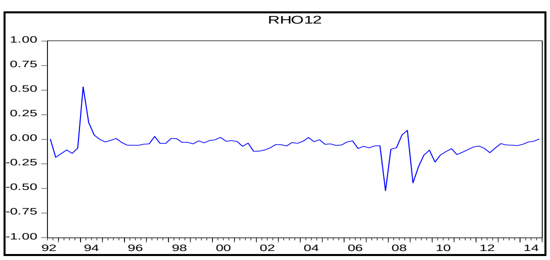
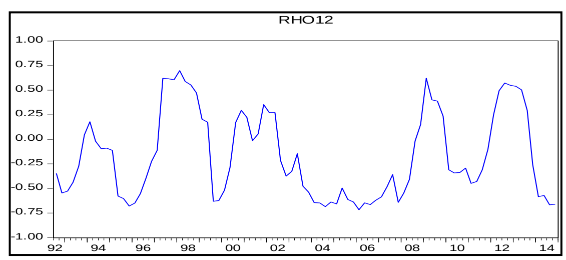
The only benchmark that the various real estate sectors were positively correlated with was the UK RPI. The correlation between real estate and CPI inflation as well as the two interest rates was negative. Miles (1996) found the correlation of UK commercial property to be negative. However, the magnitude (-0.05) of the correlation coefficient was 0.05. They concluded that there low correlation implies that there may actually be no immediate link between nominal returns on commercial real estate and inflation. Tarbet (1996) concluded that static regression was not suitable for real estate given the long rental review periods which impose a nominal rigidity on the market.

UK stocks and commodities were found to be highly correlated with both CPI and RPI inflation based on both static and dynamic conditional correlation estimates. Some stock sectors also had a high correlation with interest rates. Banking sector stocks for example exhibited one of the highest correlations with respect to interest rates. Amenc et al. (2008) linked this to the fact stocks such as utilities and infrastructure stocks typically have revenues that are highly correlated with inflation and so provide returns that tend to be in line with inflation.

Table 7(II): Static and Dynamic Correlations

	CPI		RPI		LIBOR		T-BILL	
Real Estate	**Static Correl.**	**DCC**	**Static Correl.**	**DCC**	**Static Correl.**	**DCC**	**Static Correl.**	**DCC**
IPD All Property	-0.09	-0.06	0.21	0.07	-0.15	-0.14	-0.19	-0.14
IPD Industrial	-0.07	-0.06	0.19	0.05	-0.11	-0.11	-0.14	-0.12
IPD Office	-0.13	-0.13	0.17	0.03	-0.20	-0.04	-0.23	-0.03
IPD Retail	-0.05	-0.02	0.22	0.07	-0.06	-0.14	-0.09	-0.14
Other Real Estate Vehicles								
AREF – All Funds	-0.12	-0.06	0.19	0.05	-0.12	-0.14	-0.16	-0.15
AREF – All Balanced Funds	-0.08	-0.10	0.23	0.07	-0.10	-0.11	-0.14	-0.12
Hybrid Real Estate	-0.06	-0.05	0.18	0.03	-0.11	-0.08	-0.13	-0.06
Stocks								
Aggregate stocks	0.10	0.06	0.29	0.23	0.05	0.14	0.03	0.21
Oil	0.08	0.07	0.04	0.00	0.06	0.14	0.02	0.02
Basic Materials	0.27	0.30	0.31	0.27	0.05	0.12	0.01	0.08
Industrial	0.14	0.11	0.11	0.14	0.01	0.00	0.00	0.10
Construction	0.19	0.16	0.15	0.13	-0.02	-0.11	-0.03	-0.06
Industrial goods and services	0.17	0.13	0.15	0.16	0.03	0.04	0.02	0.15
Consumer goods	0.22	0.09	0.11	0.09	0.05	-0.01	0.04	0.03
Health care	0.08	-0.03	-0.12	-0.12	0.10	0.02	0.12	0.16
Consumer services	0.07	0.03	0.05	0.03	0.02	0.03	0.02	0.12
Telecom	0.01	-0.03	-0.01	0.01	0.07	0.18	0.06	0.17
Technology	-0.04	-0.03	0.08	0.10	0.02	0.16	-0.01	0.23
Utilities	0.03	-0.02	0.02	0.04	0.16	0.10	0.18	0.29
Banks	0.03	-0.03	0.05	-0.02	0.13	0.15	0.15	0.31
Insurance	0.02	-0.05	0.00	-0.02	0.00	0.05	0.01	0.24
Financial services	0.06	0.06	0.15	0.13	-0.02	0.07	-0.04	0.14
Listed real estate	0.04	0.06	0.11	0.07	-0.07	-0.04	-0.07	0.04
Index Linked Bonds								
Index linked bonds - 0-5 Years	0.07	0.06	0.15	0.16	0.34	0.27	0.35	0.37
Index linked bonds - 5+ years	-0.05	-0.04	0.04	0.07	0.01	0.05	0.02	0.22
Bonds								
Bonds – All lives	0.02	-0.06	-0.31	-0.29	0.20	0.10	0.24	0.12
Bonds – 10 + years	-0.06	-0.13	-0.32	-0.32	0.13	0.08	0.15	0.10
Bonds – 10 year	0.01	-0.04	-0.28	-0.20	0.18	0.10	0.21	0.16
Bonds – 7 year	0.06	-0.01	-0.26	-0.20	0.23	0.12	0.28	0.17
Bonds – 5 year	0.06	0.00	-0.26	0.07	0.25	0.13	0.31	0.17
Bonds – 3 year	0.09	-0.01	-0.29	-0.24	0.40	0.23	0.45	0.22
Bonds – 2 year	0.10	-0.05	-0.29	-0.25	0.53	0.29	0.60	0.27
Alternatives in GB£								
Emerging stock market	0.12	0.14	0.22	0.17	0.00	0.06	-0.08	-0.06
Developed ex US stocks	0.09	0.10	0.26	0.18	0.03	0.09	-0.07	0.03
Commodities - all	0.16	0.23	0.50	0.40	0.08	0.14	-0.01	0.05
Commodities - oil	0.06	0.17	0.39	0.35	0.09	0.16	0.01	0.05
Commodities - gold	0.11	0.19	0.24	0.29	-0.10	-0.06	-0.17	-0.16
Hedge funds	0.08	0.08	0.29	0.21	0.22	0.35	-0.01	0.06
US private equity	0.12	0.14	0.27	0.21	0.05	0.17	-0.09	-0.02
US venture capital	0.02	0.09	0.12	0.12	0.13	0.32	0.03	0.14
Developed ex US private equity	0.10	0.15	0.29	0.27	0.06	0.11	-0.06	-0.01
Emerging private equity	0.12	0.16	0.22	0.20	-0.15	-0.01	-0.21	-0.09
Alternatives (IN US$)								
Emerging stock market	0.11	0.13	0.17	0.15	0.00	0.06	-0.04	-0.01
Developed ex UK stocks	0.06	0.04	0.19	0.11	0.03	0.09	0.00	0.05
Commodities – all	0.15	0.18	0.47	0.36	0.08	0.14	0.04	0.11
Commodities – oil	0.05	0.13	0.36	0.32	0.09	0.16	0.04	0.09
Commodities – gold	0.07	0.14	0.17	0.18	-0.10	-0.06	-0.12	-0.19
Hedge funds	0.03	0.04	0.25	0.14	0.22	0.35	0.17	0.30
US private equity	0.10	0.08	0.23	0.14	0.04	0.17	0.00	0.10
US venture capital	-0.01	0.02	0.05	0.01	0.13	0.32	0.09	0.23
Developed ex US private equity	0.10	0.14	0.33	0.30	0.06	0.11	0.00	0.05
Emerging private equity	0.11	0.12	0.19	0.13	-0.15	-0.01	-0.20	-0.06

Figure 7(1) - Dynamic Conditional Correlations – Selected Assets

CPI Inflation Rate	**T-Bill Interest Rate**
Nominal bonds – Aggregate 	**Nominal bonds – Aggregate** 
Index-Linked Bonds (0-5 Years) 	**Index-Linked Bonds (0-5 Years)** 
Aggregate Stocks 	**Aggregate Stocks** 
Real Estate (IPD All Property) 	**Real Estate (IPD All Property)** 

7.4.3 INFLATION/INTEREST RATE HEDGING ABILITY OF ASSETS

In order to carry out the cointegration analysis, we first test for stationarity in the various data series using the Augmented Dickey Fuller (ADF) test and the Phillips Perron unit root test. The results were presented earlier in Chapter 4 (Table 4(IV)). As in Zhou and Clements (2010), the results were mixed. Although most of the asset returns were found to be I(1), a few assets such as the IPD office sector, utilities stocks, technology stocks, index-linked bonds and aggregate bonds were found to be I(0). LIBOR interest rates were not found to be stationary by the ADF test, even after first differencing, however the Phillips Perron approach did. As explained in the methodology section, the ARDL model of Pesaran et al. (2001) is able to handle a mix of I(0) and I(1) variables within the same equation. Hence, we proceed to use this approach in the estimation of the long-run relationship between inflation/interest rates and asset returns.

Following Anari & Kolari, (2002) and Zhou and Clements (2010), we use the bounds test to examine the long-run cointegration relationship between inflation/interest rates and the returns of real estate, alternative and traditional asset classes and sectors. If the computed F-statistic is higher than the upper bound critical value, we reject the null hypothesis of no cointegration and accept the alternative hypothesis. Once we conclude that there is a long-run cointegration relationship between an asset's return and the inflation/interest rate, we proceed to use an error-correction specification of the ARDL model to determine the long-run coefficient and the error-correction coefficient. The long-run coefficient shows the relationship between the variables when there is no short-run shock. In other words, it is the relationship from which the variables deviate but always return to. To determine whether there is a stable long-run relationship between an asset's return and the inflation/interest rate, it is important for the error-correction coefficient to be negative and significant. The error-correction coefficient shows how quickly the equilibrium relationship between the returns of an asset and inflation/interest rate is restored if a shock causes the returns of the asset and the inflation/interest rate to drift apart.

We use the Block Exogeneity Wald Test (Granger Causality Test) to analyse the short-run relationship between inflation/interest rates and the asset returns. Granger Causality Tests are used to determine whether a change in inflation/interest rates induces a change in the return of a particular asset or vice versa. If there is a unidirectional or bidirectional causality, we can conclude that there is a short-run relationship between inflation and the asset being analysed (Chu and Sing, 2004; Zhou and Clements, 2010). In carrying out the causality test, we use the approach of Toda and Yamamoto (1995). Like the ARDL model, the Toda and Yamamoto (1995) approach can be used irrespective of the order of integration of the variables and whether or not the variables are cointegrated.

In the following sections, we present the results of both the ARDL analysis and the Toda and Yamamoto Granger Causality Tests. We put the assets into four groups – real estate, alternatives, stocks and bonds.

7.4.3.1 Real Estate

The results show that UK direct real estate is a good hedge against all the inflation and interest rates. Apart from the office sub-sector which was found to not be cointegrated with CPI inflation, almost all the other sectors significantly cointegrated with the four inflation and interest rates. This result means that irrespective of the inflation/interest rate benchmark that is of interest to a DC pension fund, including direct real estate in its portfolio would result in a better portfolio. As in this study, Wurtzebach et al. (1991) found the UK office real estate sector to be a poor hedge against inflation, especially when vacancy rates were taken into account.

The long-run coefficients confirm the fact that UK real estate provides a complete hedge against inflation and interest rate changes as the coefficients are all above 1. The long-run coefficient for the IPD industrial real estate sector relative to RPI inflation was 2.50, the highest of the real estate sectors and in fact for all the assets analysed in this study. The result implies that, on average, the industrial real estate sector returns increased by 2.5% for any 1% increase in RPI inflation. The results of Park and Bang (2012) were even higher. The long-run elasticity of the CBRE office returns was estimated at 6.261, meaning that for every 1% change in inflation, office real estate prices increased by 6.26%.

We however found that the speed of adjustment of direct real estate returns to equilibrium following interest rate and inflationary shocks was however among the lowest of the various asset classes analysed. This is also quite consistent with the results of many other studies that analysed real estate. Park and Bang (2012) estimated that the error-correction coefficient for inflation and commercial real estate in was -0.016 compared to for equities that was -0.292. Similarly, Barber and White (1995) observed that it takes time for real estate to react to inflationary shocks. Even after three years, less than 40% of the erosion in real values caused by inflation had been recaptured.

An issue of concern for econometric analysts when dealing with private market assets is that of appraisal smoothing and its impact on the results obtained when the returns of these assets are used along with publicly traded assets. Appraisal smoothing, as discussed earlier, does not only affect the volatility of private market assets but impacts on the turning points – i.e. the ability of asset returns to respond to changes in market fundamentals (Devaney and Diaz, 2011). Using the unsmoothed direct real estate series obtained from the J. Fisher et al., 2003) model, we did not see any significant change in the results of the Bounds test. We however observe a modest increase in the speed of adjustment to equilibrium. For example, before unsmoothing, the speed of adjustment of the retail real estate sector to CPI inflation was 0.62% per quarter but increased to 2.25% per quarter when the series was unsmoothed. Similarly, the retail real estate sector's speed of adjustment following a shock to T-bill interest rates increased from 0.37% per quarter to 5.96% per quarter. These figures still fell below what was obtained for publicly traded assets such as stocks and bonds. This points to the fact that private market assets adjust more slowly to changes in market fundamentals. Tarbet (1996) explains that due to the long rental review periods, even if inflation is properly forecast, the real estate market could still not quickly react to inflationary shocks. Tarbet (1996) explains that due to the long rental review periods, even if inflation is properly forecast, the real estate market could still not quickly react to inflationary shocks.

The error correction coefficients in Hoesli et al. (2008) were found to be negative and significant in all the models analysed. However, they found that the adjustment to inflation shocks occurs gradually, though the error correction process rather than through direct, in-period changes to returns. For the analysis using UK data, the magnitude of the coefficients ranted from -0.15 in the stocks and REIT model. However, the coefficient for private real estate was only -0.04. When the unsmoothed series was used in the analysis, Hoesli et al. (2008) found that the error-correction coefficient was higher, indicating a faster adjustment to long-run equilibrium position. Similarly, the error-correction coefficient was higher when the MIT transaction based real estate series was used for the US analysis than when the NCREIF series was used.

Another issue worth exploring is whether the vehicle used to access the direct real estate market has an impact on the inflation or interest rate protection received by an investor. Table 7(III) contains the results obtained when we analysed the returns of 4 different direct real estate vehicles and the selected inflation and interest rate benchmarks. The 4 vehicles are the IPD All Property Portfolio, the AREF/IPD All Unlisted Funds Index, the AREF/IPD Balanced Unlisted Funds Index and a Hybrid real estate fund with a 70:30 allocation to direct real estate and listed real estate respectively. The results show that all four vehicles possess the ability to hedge against the selected inflation and interest rate benchmarks. The noticeable difference is the speed of adjustment following any disequilibrium. The speed of adjustment was consistently higher for the hybrid real estate series irrespective of the benchmark being hedged against. This may also be as a result of the fact that the hybrid real estate series contains some exposure to publicly traded asset (listed real estate) and so may be responding faster to changes in market fundamentals.

Table 7(III) Autoregressive Distributive Lag Model - Direct Real Estate

	Bounds Test				Long-Run Coefficient				Error-Correction Coefficient			
	CPI	**RPI**	**LIBOR**	**TBILL**	**CPI**	**RPI**	**LIBOR**	**TBILL**	**CPI**	**RPI**	**LIBOR**	**TBILL**
IPD Property Sectors												
IPD All Property	3.30*	14.18***	7.62***	10.03***	1.45***	2.15**	1.17***	1.17***	-0.0062**	-0.0005***	-0.0324***	-0.0035***
Industrial	5.66**	13.12***	5.29**	5.99**	1.84***	2.5	1.21***	1.20***	-0.0050***	-0.0004***	-0.0201***	-0.0240***
Office	2.49	10.71***	7.98***	9.50***	-	2.02**	1.15***	1.15***	-	-0.0005***	-0.0357***	-0.0037***
Retail	4.35**	13.84***	6.43***	9.06***	1.38***	1.84***	1.20***	1.20***	-0.0062*	-0.0008***	-0.0304***	-0.0037***
Other Real Estate Vehicles												
AREF – All Funds	9.94***	14.68***	3.51*	4.13**	1.63***	2.01**	1.12***	1.12***	-0.0105***	-0.0072**	-0.0257***	-0.0283***
AREF – All Balanced Funds	8.48***	14.15***	3.87*	4.32**	1.56***	1.99**	1.11***	1.19***	-0.0091***	-0.0059**	-0.0247***	0.0261***
Hybrid Real Estate	7.97***	8.45***	6.89***	3.29*	1.53***	1.60***	1.14***	1.16***	-0.0195***	-0.0146***	-0.0598***	-0.0407***
Unsmoothed IPD Property Sectors												
IPD All Property	4.57**	11.04***	6.42***	7.94***	1.48***	2.02**	1.17***	1.18***	-0.0157***	-0.0137***	-0.0691***	-0.0718***
Industrial	6.09***	10.94***	4.83**	4.35**	1.72***	2.37	1.22***	1.21***	-0.0141***	-0.0098***	-0.0442***	-0.0493***
Office	3.31*	8.83***	6.68***	7.23***	1.43***	2.00*	1.15***	1.16***	-0.0118***	-0.0133***	-0.0801***	-0.0767***
Retail	3.78*	9.78***	3.74*	5.72***	1.34***	1.90**	1.12***	1.13***	-0.0225***	-0.0138***	-0.0474***	-0.0596***

Table 7(IV) Block Exogeneity Wald Test (Granger Causality Test) – Real Estate

	Dependent variable: Asset Return (Chi-Square)				Dependent variable: Inflation/Interest rate (Chi-Square)			
	CPI	**RPI**	**LIBOR**	**TBILL**	**CPI**	**RPI**	**LIBOR**	**TBILL**
IPD Property Sectors								
IPD All Property	5.29*	26.95***	10.52**	6.65*	2.13	35.13***	9.90**	24.52***
IPD Industrial	11.38***	31.41***	24.11***	7.36*	2.87	14.60***	10.97	30.87***
IPD Office	3.87	19.80***	4.99	6.16	1.73	24.32***	8.61**	15.28***
IPD Retail	4.89*	28.50***	13.59***	7.20*	1.92	38.73***	6.29*	30.06***
Other Real Estate Vehicles								
AREF – All Funds	2.93	13.12**	5.84	13.11**	2.17	47.43***	45.57***	47.43***
AREF – All Balanced Funds	2.69	13.69***	7.57*	6.90*	1.33	47.43***	32.07***	34.98***
Hybrid Real Estate	13.89***	13.99***	8.58**	10.52**	0.91	18.29***	15.68***	14.94***
Unsmoothed IPD Property Sectors								
IPD All Property	6.08**	25.37***	11.20**	7.91**	0.75	33.57***	4.85	24.09***
IPD Industrial	20.15***	26.54***	22.55***	7.35*	7.81*	28.51***	7.83**	32.72***
IPD Office	5.00*	20.01***	9.19**	9.75**	0.68	21.95***	4.74	13.97***
IPD Retail	3.87	22.02***	13.93***	4.37	2.63	29.73***	7.32**	33.12***

The results of the Toda Yamamoto Granger Causality test show that real estate is a good hedge against inflation and interest rates over the short-run as causality is observed in at least one direction between inflation/interest rate changes and real estate returns. The test revealed a bi-directional causal relationship between real estate returns and inflation/interest rate movements with an exception being CPI inflation which is Granger-caused by real estate return changes but not the other way round. Our results confirm that of Chu and Sing (2004) who found short-term granger causality between real estate prices and inflation. On the other hand, Zhou and Clements (2010) found no dynamic short-run causal relationship between real estate prices and various measures of inflation in China. They however had mixed results when they analysed residential and non-residential real estate sectors separately.

7.4.3.2 Alternatives

Amenc et al. (2008) found alternative assets to be a good hedge against inflation. However, we found very few of the to be cointegrated with inflation, a noticeable exception being US private equity and hedge funds was a hedge against both measures of inflation. Quite a number of alternative assets were however found to be able to hedge against both interest rates. 7 out of the 10 alternative assets a hedge against at least one interest rate measure and 6 were a hedge against both.

Regarding the long-run relationship between the various alternative assets and the two interest rates, we found that most produced a coefficient greater than 1, implying that they were a complete hedge against inflation. Commodities however produced a long-run coefficient of 0.92 and 0.95 relative to LIBOR and T-bill interest rates respectively. This implies that they were only a partial hedge against inflation.

The error-correction coefficients were remarkably high for many alternative assets. Commodities for example recorded an error correction coefficient of 0.1537 relative to LIBOR and 0.1671 relative to T-bills, suggesting that about 77% and 86% respectively of a disequilibrium is corrected per annum.

As discussed in the data chapter, the issue of return smoothing does not pertain only to real estate. Hedge funds and other private market alternatives have also been reported to suffer from significant autocorrelation in return patterns (Fund and Hsieh, 2000; Eling, 2006; Getmansky et al., 2004). Consequently, we used the technique of J. Fisher et al., 2003) to unsmooth the returns of all private market alternative assets namely hedge funds and private equity. Like real estate, unsmoothing of the returns of the private market alternative assets had a noticeable impact on the speed of adjustment for most alternative assets that are not publicly traded. The results of the Bounds test however did not change significantly.

Another challenge in a UK DC fund holding alternative assets is that they are exposed to foreign exchange risk. Converting the returns of an asset from one currency to another may distort the time-series features of the asset and possibly its ability to hedge against inflation and interest rates. We found that converting the rates from US$ to UK pound sterling led to some of the assets losing their inflation/interest rate hedging ability.

Unlike the results of the long-run ARDL estimates, we found that several of the alternative assets had a short-run causal relationship with UK inflation/interest rates. This result holds whether the returns were in US dollars or converted into pound sterling.

Table 7(V) Autoregressive Distributive Lag Model – Alternative Assets

	Bounds Test				Long-run coefficient				Error correction coefficient			
	CPI	RPI	LIBOR	TBILL	CPI	RPI	LIBOR	TBILL	CPI	RPI	LIBOR	TBILL
Alternatives in US$												
Emerging stock market	1.91	4.99**	2.05	2.65	-	1.60***	-	-	-	-0.0329***	-	-
Developed ex UK stocks	1.95	3.31*	6.76***	4.52**	-	1.32***	1.13***	1.14***	-	-0.0389***	-0.1400***	-0.1098***
Commodities – all	2.83	1.71	3.95*	4.04*	-	-	0.92***	0.95***	-	-	-0.1537***	-0.1671***
Commodities – oil	2.13	1.04	2.02	2.37	-	-	-	-	-	-	-	-
Commodities – gold	1.52	1.19	2.76	2.94	-	-	-	-	-	-	-	-
Hedge funds	8.38***	6.81***	7.90***	8.40***	1.24***	1.22***	1.08***	1.09***	-0.030***	-0.0389***	-0.1134***	-0.1232***
US private equity	5.91**	6.72***	7.07***	6.23***	1.96***	1.94***	1.45***	1.44***	-0.0083***	-0.0008***	-0.0375***	-0.0379***
US venture capital	2.92	3.04	3.52*	4.44**	-	-	1.46***	1.48***	-	-	-0.0345***	-0.0372***
Developed ex US private equity	1.95	0.96	3.17	4.25**	-	-	-	1.53***	-	-	-	-0.0290***
Emerging private equity	1.98	2.95	3.53*	3.75*	-	-	1.23***	1.15***	-	-	-0.0018***	-0.0269***
Alternatives in GB£												
Emerging stock market	1.98	6.28***	2.62	3.41*	-	1.68***		1.20***	-	-0.0313***	-	-0.0867***
Developed ex UK stocks	2.4	7.20***	6.47***	5.79**	-	1.41***	1.11***	1.12***	-	-0.0448***	-0.1358***	-0.1213***
Commodities – all	2.12	1.37	3.15	2.85	-	-	-	-	-	-	-	-
Commodities – oil	0.24	0.94	2.02	1.97	-	-	-	-	-	-	-	-
Commodities – gold	1.98	0.9	4.63**	4.82**	-	-	1.07***	1.07***	-	-	-0.0511***	-0.0530***
Hedge funds	3.54*	4.34**	8.63***	3.34*	1.18***	1.18***	1.06***	1.07***	-0.0456***	-0.0484***	-0.1169***	-0.0944***
US private equity	2.35	3.76*	8.69***	5.71**	-	1.83***	1.45***	1.42***	-	-0.0119***	-0.0487***	-0.0487***
US venture capital	2.04	3.86*	2.77	3.25	-	1.71***	-	-	-	-0.0211***	-	-
Developed ex US private equity	2.33	1.81	3.13	4.02*	-	-	-	1.44***	-	-	-	-0.0490***
Emerging private equity	0.26	2.08	2.71	4.01*	-	-	-	1.06***	-	-	-	-0.0576***
Unsmoothed Private Market Alternatives												
Hedge funds	2.96	3.59*	6.82***	4.60*	-	1.27***	1.10***	1.11***	-	-0.0464***	-0.1573***	-0.1237***
US private equity	2.62	1.8	4.92**	3.25	-	-	0.90***	-	-	-	-0.1988***	-
US venture capital	2.44	1.09	3.52*	1.9	-	-	1.47***	-	-	-	-0.0345***	-
Developed ex US private equity	0.36	1.17	2.78	2.97	-	-	-	-	-	-	-	-
Emerging private equity	8.74***	10.54***	6.81***	4.52*	1.17***	1.17***	1.00***	1.02***	-0.0542***	-0.0569**	-0.2387***	-0.1642***

Table 7(VI) Block Exogeneity Wald Test (Granger Causality Test) – Alternative Assets

	Dependent variable: Asset Return (Chi-Square)				Dependent variable: Inflation/Interest rate (Chi-Square)			
	CPI	**RPI**	**LIBOR**	**TBILL**	**CPI**	**RPI**	**LIBOR**	**TBILL**
Alternative Assets (In US$)								
Emerging stock market	0.34	12.82**	8.42**	11.28**	0.78	18.67***	3.57	8.91*
Developed ex UK stocks	0.44	10.50**	7.45*	3.96	0.40	16.07***	7.45*	3.96
Commodities – all	3.78	1.96	16.43***	1.67	3.77	0.61	1.43	3.55
Commodities – oil	23.96***	23.16***	15.56***	3.17	6.43	18.27***	1.01	1.64
Commodities – gold	4.03	0.02	1.69	4.03	14.67***	1.39	0.73	1.37
Hedge funds	0.1	8.69*	6.26*	0.88	0.11	14.90***	4.82	18.33***
US private equity	6.87**	16.56***	7.89**	4.90	0.97	18.72***	6.74*	15.84***
US venture capital	1.64	4.51	1.93	3.08	1.71	2.88	2.19	5.29
Developed ex US private equity	0.34	8.34*	1.10	3.52	1.45	36.62***	6.41*	34.85***
Emerging private equity	3.01	7.11	5.44	7.09*	3.72	26.41***	15.04***	12.81***
Alternatives in GB£								
Emerging stock market	0.00	12.41**	8.80**	11.96***	0.01	38.38***	4.72	18.74***
Developed ex UK stocks	0.16	15.02***	7.00*	5.46	0.01	34.77***	9.34**	24.96***
Commodities – all	28.84***	13.62***	10.42**	0.81	4.64	14.75***	0.70	9.17**
Commodities – oil	29.96***	22.63***	11.27**	2.92	6.62	18.72***	0.52	5.08
Commodities – gold	0.96	6.46	6.47*	8.24**	0.75	16.96***	1.04	11.36***
Hedge funds	0.07	11.76***	0.42	2.88	1.58	19.98***	6.88**	56.42***
US private equity	2.90	20.88***	6.16**	7.74*	1.18	34.37***	14.35***	48.67***
US venture capital	1.69	12.55**	9.06**	6.21	1.01	8.18*	6.69*	21.30***
Developed ex US private equity	1.03	9.52**	3.68	3.98	0.40	38.86***	8.36**	44.66***
Emerging private equity	2.70	11.37**	6.34*	7.93**	0.59	46.47***	15.72***	33.08***
Unsmoothed Private Market Alternatives								
Hedge funds	0.09	8.39**	6.25*	0.87	0.11	9.01**	4.82	18.83***
US private equity	7.17**	16.55***	6.82*	4.90	0.90	19.59***	7.98**	15.84***
US venture capital	1.26	4.21	9.88**	3.08	1.13	3.23	1.72	5.29
Developed ex US private equity	0.56	8.20*	3.23	3.52	1.46	38.71***	6.51*	34.85***
Emerging private equity	5.65*	7.53	6.69	7.09*	1.81	28.65***	14.13	12.81***

7.4.3.3 Bonds

Like real estate, almost all the bond sectors were a hedge against inflation and interest rate movements. In a few cases where bonds failed to hedge against interest rates, these were long-term bonds with maturity exceeding 7 years. This suggests that short-term bonds are more likely to keep up with inflation and interest rate changes than long-term bonds.

The long-run coefficients for the various bond sectors always exceeded 1 – implying nominal bonds were a complete hedge against inflation and interest rate changes. Interestingly, we find that the long-run coefficients increased with the maturity of the bonds. For example, a 10% change in CPI inflation results in a 12.5% change in the return of 2 year bonds, 12.7% change in the return of 3 year bonds and so on, up to a 14.3% change in the return of bonds with maturity greater than 10 years. This result also provides evidence of an upward sloping yield curve.

The speed of adjustment to equilibrium also follows a noticeable trend. The speed of adjustment is were found to be higher for shorter maturity bonds than for longer maturity ones providing further proof that shorter-maturity bonds had a more stable long-run relationship with inflation and interest rate changes.

Inflation indexed bonds have long been viewed as a natural hedge against inflation. However, as noted in our earlier discussions, the inflation-hedging ability of these bonds has been questioned by some authors. The results of the correlation analysis undertaken earlier also appear to cast doubt on the inflation-hedging ability of index-linked bonds. However, as noted by Schofield (1996), correlation analysis may not be able to pick up the relationship between inflation and index-linked bonds due to the fact that correlation analysis only works with contemporaneous relationships.

In order to investigate the hedging ability of inflation-indexed bonds, analyse the relationship between inflation/interest rates and the total returns from index-linked bonds. We include index-linked bonds with maturity less than 5 years and those with maturity over 5 years. The results show that the total returns of both index linked bonds are a good hedge against inflation and interest rate movements over the long-run as both bonds were cointegrated with all 4 inflation/interest rate benchmarks.

The long-run coefficients are also greater than one, demonstrating that index-linked bonds are a complete hedge against inflation/interest rates over the long run. As with nominal bonds, we find that the long-run coefficient is higher for longer-maturity index-linked bonds than shorter-maturity ones. For example, a 10% change in CPI inflation would result in about 12.10% change in the total returns of 0-5 year inflation-indexed bonds and a 16.10% change in the returns of inflation-indexed bonds with maturity greater than 5 years. A 10% change in T-bill interest rate would result in a 10.4% change in the returns of 0-5 year index-linked bonds and a 14.4% change in the returns of 5+ year index-linked bonds.

Interestingly, we did not find a causal relationship between index-linked bond total returns and any of the inflation/interest rates analysed. This implies that inflation-indexed bonds may not be a good hedge against inflation/interest rate changes over the short run, contrary to the belief that these bonds are a natural hedge against inflation in particular.

Nominal bonds on the other hand were found to be a good hedge against inflation/interest rate changes over the short-run as several of these bonds had a short-run causal relationship with at least one inflation and interest rate. Inflation/interest rate changes often lead (Granger-cause) bond returns in the short-run. In a number of cases too, we observed a bi-directional causality which implies that bond return changes could also be used to predict future inflation/interest rate changes.

Table 7(VII) Autoregressive Distributive Lag Model – Stocks and Bonds

	Bounds Test				Long-run coefficient				Error-correction coefficient			
	CPI	**RPI**	**LIBOR**	**TBILL**	**CPI**	**RPI**	**LIBOR**	**TBILL**	**CPI**	**RPI**	**LIBOR**	**TBILL**
Stocks												
Aggregate stocks	4.27**	2.16	4.08*	4.03*	1.22***	-	1.08***	1.09***	-0.0429**	-	-0.1186***	-0.1132***
Listed real estate	3.47*	2.85	6.39***	3.39*	1.28***	-	1.12***	1.12***	-0.0653**	-	-0.1340***	-0.1036**
Oil	6.35***	6.39***	4.80**	4.44**	1.46***	1.41***	1.25***	1.26***	-0.0248**	-0.0271**	-0.1013***	-0.0952***
Basic Materials	1.51	1.76	2.08	3.84*	-	-	-	1.21***	-	-	-	-0.1196***
Industrial	4.12**	4.34**	3.31*	3.93*	1.36***	1.32***	1.23***	1.24***	-0.0288*	-0.0366*	-0.0964**	-0.1022***
Construction	1.75	3.44*	3.72*	3.06	-	1.71**	1.20***	-	-	-0.0193***	-0.0842***	-
Industrial goods and services	5.09**	5.40**	4.84**	4.81**	1.30***	1.27***	1.17***	1.18***	-0.0389	-0.0484**	-0.0785**	-0.0817**
Consumer goods	5.37**	5.64**	5.60**	3.27	1.46***	1.41***	1.28***	-	-0.0323	-0.0312**	-0.0889**	-
Health care	8.70***	8.45***	8.59***	2.62	1.39***	1.39***	1.22***	-	-0.0330**	-0.0366*	-0.0682**	-
Consumer services	6.56***	6.80***	5.51**	5.61**	1.25***	1.23***	1.13***	1.14***	-0.0754***	-0.0836***	-0.0971**	-0.0997**
Telecom	3.10	3.44*	3.01	3.00	-	1.25***	-	-	-	-0.0660**	-	-
Technology	3.20	3.13	3.01	3.01	-	-	-	-	-	-	-	-
Utilities	3.58*	3.74*	3.94*	2.87	1.59***	1.52***	1.34***	-	-0.0171**	-0.0183**	-0.0490*	-
Banks	7.65***	5.30**	4.55**	3.88*	1.59***	1.43***	1.31***	1.25***	-0.0917***	-0.0585***	-0.0622**	-0.0839***
Insurance	3.81*	3.97*	3.58*	3.54*	1.28***	1.26***	1.16***	1.16***	-0.0609**	-0.0645**	-0.0739**	-0.0712*
Financial services	3.00	2.17	7.04***	7.00***	-	-	1.26***	1.26***	-	-	-0.1183***	-0.1217***
Index Linked Bonds												
Index linked bonds - 0-5 Years	8.00***	9.05***	15.01***	14.66***	1.21***	1.19***	1.03***	1.04***	-0.0159***	-0.0159***	-0.0662***	-0.0618***
Index linked bonds - 5+ years	5.87**	19.70***	19.41***	19.37***	1.65***	1.62**	1.39**	1.44**	-0.0083***	-0.0069***	-0.0111***	-0.0099***
Nominal Bonds												
Bonds – All lives	6.45***	11.54***	3.56*	4.14**	1.33***	1.33***	1.14***	1.14***	-0.0230***	-0.0285***	-0.0900***	-0.0813***
Bonds – 10 + year	5.62**	7.28***	3.45*	3.71*	1.43***	1.39***	1.17***	1.19***	-0.0226***	-0.0276***	-0.0975***	-0.0859***
Bonds – 10 years	4.43**	4.94**	2.78	3.30*	1.37***	1.34***	-	1.16***	-0.0191***	-0.0236***	-	-0.0915**
Bonds – 7 year	5.02**	6.96***	3.12	3.71*	1.36***	1.32***	-	1.14***	-0.0170***	-0.0242***	-	-0.0918***
Bonds – 5 year	5.89**	6.72***	3.56*	4.13**	1.29***	1.26***	1.10***	1.11***	-0.0187***	-0.0245***	-0.1121***	-0.1020***
Bonds – 3 year	9.30***	12.77***	5.60**	7.24***	1.27***	1.25***	1.08***	1.08***	-0.0147***	-0.0267***	-0.1479***	-0.1349***
Bonds – 2 year	9.14***	10.26***	5.80**	7.21***	1.25***	1.21***	1.05***	1.06***	-0.0230***	-0.0231***	-0.2062***	-0.1702***

Table 7(VIII) Block Exogeneity Wald Test (Granger Causality Test) – Stocks and Bonds

	Dependent variable: Asset Return (Chi-Square)				Dependent variable: Inflation/Interest rate (Chi-Square)			
	CPI	**RPI**	**LIBOR**	**TBILL**	**CPI**	**RPI**	**LIBOR**	**TBILL**
Stocks								
Aggregate stocks	0.20	1.65	4.82	1.87	1.01	0.01	5.17	3.28
Listed real estate	0.50	10.04	6.16	8.53**	0.05	9.63	19.10**	11.68***
Oil	0.06	4.15	0.43	3.12	0.32	8.96*	8.18**	12.89**
Basic Materials	0.20	8.30*	4.43	5.43	1.32	17.40***	1.31	12.17***
Industrial	0.02	3.43	3.43	2.42	0.09	5.20	1.87	2.66
Construction	0.94	7.62	1.84	2.31	3.30*	17.35***	12.05**	9.83**
Industrial goods and services	0.01	2.44	3.81	1.24	0.13	4.53	1.49	2.70
Consumer goods	0.01	0.34	2.27	2.46	0.03	0.71	3.75	4.20
Health care	0.36	1.15	5.67	5.37	0.38	0.27	1.70	2.00
Consumer services	1.75	5.42	2.54	0.17	0.35	7.40	5.60	7.39*
Telecom	1.08	5.69	3.81	1.57	1.52	3.86	2.83	3.68
Technology	0.74	3.40	3.29	0.83	5.35	1.48	0.71	1.56
Utilities	0.03	8.69*	4.49	9.13*	1.16	4.37	3.08	2.53
Banks	0.58	0.42	5.23	5.02	0.04	1.38	10.46**	7.05*
Insurance	0.58	0.52	2.1	2.84	0.61	3.14	4.39	4.24
Financial services	0.51	4.13	3.98	5.94	0.17	7.80*	5.99	7.35*
Index Linked Bonds								
Index linked bonds - 0-5 Years	0.62	1.84	5.74	0.76	0.09	6.92	0.81	2.35
Index linked bonds - 5+ years	0.07	7.15	0.24	1.03	0.26	6.21	1.75	4.26
Nominal Bonds								
Bonds – All lives	12.27***	13.82***	15.65***	1.59	4.44	9.64**	0.59	2.17
Bonds – 10 + years	9.40***	12.87**	11.34**	1.94	1.60	9.16*	0.39	0.77
Bonds – 10 year	15.85***	18.18***	14.11***	1.69	3.83	8.84*	14.11***	2.77
Bonds – 7 year	18.14***	18.10***	15.53***	2.00	5.87	9.38*	15.53***	5.34
Bonds – 5 year	20.78***	22.80***	20.57***	3.02	6.32*	10.82**	1.23	6.91*
Bonds – 3 year	17.61***	22.32***	29.25***	6.46*	6.24	7.15	1.09	6.46*
Bonds – 2 year	15.12***	16.16***	38.26***	9.53**	5.25	7.06	2.17	9.53**

7.4.3.4 Stocks

Overall, the results show that several stock sectors were a good hedge against inflation and interest rate changes over the long-run. At least 10 of the 16 stock sectors were cointegrated with each of the benchmarks analysed. The aggregate stock portfolio analysed was found to be an effective hedge against all but one of the benchmarks. 6 of the 16 stock sectors analysed were found to be a hedge against all four inflation and interest rate benchmarks. Three additional stock sectors, consumer goods, health care and utilities, were a found to be a hedge against inflation but not interest rates.

All the stock sectors were found to be cointegrated with the inflation/interest rate benchmarks had a significant long-term coefficient. The coefficients were all greater than unity, implying that they were a complete hedge against inflation and interest rate changes. The highest coefficient was recorded by utility and banking sector stocks. For every ten percent change in inflation or interest rate, the returns of both utility stocks and bank stocks increased by 15.9%. Aggregate stocks recorded the lowest long-run coefficient of 1.08, an almost one-to-one movement relative to inflation and interest rate changes.

Compared to the private market assets such as real estate, stocks exhibited a high speed of adjustment following a shock to inflation or interest rates. Interestingly, we found the speed of adjustment following an interest rate shock to be consistently higher than the speed of adjustment to inflation rate shocks. This may be an indication that stock returns are more sensitive to interest rate changes than inflation

From Table 7(VIII), we can see that only very few stocks had a short-run causal relationship with the various inflation/interest rates. In the few instances where a causal relationship was detected, we found that it went from asset returns to the inflation/interest rates i.e. stock returns granger-cause inflation/interest rate movements. Remarkably, construction sector stock returns were found to lead (granger-cause) all 4 inflation and interest rates. Three stock sectors were also found to be a good hedge against interest rate movements as they granger-cause both LIBOR and T-bill interest rates. These are the listed real estate, oil and banking sector stocks. Campbell and Shiller (1988) however found that inflation leads stock returns.

Listed real estate had the highest speed of adjustment to equilibrium with as much as 63% of any disequilibrium being corrected within 4 quarters (one year).

7.5 CONCLUSION

In this Chapter we employed cointegration and causality techniques that take into account the degree of integration of the variables to clarify the relationship between real estate returns and selected inflation and interest rates. The autoregressive distributed lag model (Pesaran & Shin, 1998; Pesaran et al., 1999) and the Toda & Yamamoto (1995) approach to testing granger causality are used along with dynamic conditional correlations and relative performance metrics to determine the assets that should be included in the portfolio of DC pension funds that seek to provide returns in line with specific inflation and interest rates. One of the short-comings of traditional cointegration tests is that they require the all the variables to be integrated of the same order (Engle & Granger, 1987; Johansen, 1988 and Johansen & Juselius, 1990). The ARDL model can be used to test the long-run cointegration relationship whether the variables are I(0) or I(1). Given that this study is located within the context of DC pension funds, we also analyse the inflation/interest rate hedging ability of stocks, bonds and alternative assets that institutional investors such as pension funds typically invest in (UBS, 2015).

This study offers a systematic analysing the inflation and interest rate hedging ability of a broad range of assets that institutional investors typically invest in. We carry out a sector-level analysis of a broad range of assets. We analyse the ability of 47 different asset classes and sectors including real estate, stocks, bonds and alternative assets such as commodities, hedge funds and private equity. For stocks, we investigate the hedging ability of different stock sectors or industries. For bonds, we analyse the hedging ability of different bond maturities. Spierdijk and Umar (2013) observed that as with different stock sectors, the hedging ability of bonds may differ across different maturities, issuer and risk-rating.

This study is situated in within the context of UK Master-trust DC pension funds. Many of these funds benchmark their performance against inflation and/or interest rate benchmarks of their choosing. Examples of these benchmarks include CPI Inflation, RPI inflation, T-bill interest rates, SONIA interest rate etc. International evidence shows that some pension funds also benchmark against economic variables such as GDP and wage growth rates. The results of the study are also relevant to institutional investors such as life insurance companies and investment firms whose obligations are tied to inflation and interest rate movements.

A study of the ability of real estate and other alternative assets to hedge against inflation and interest rate movements is also very timely in view of the current call for UK DC Pension funds to become more diversified. Given that most of these funds have explicit investment objectives tied to domestic inflation and interest rates, the question is whether they should limit their portfolios to UK assets such as stocks, inflation-indexed bonds and nominal bonds or is it appropriate for them to incorporate real estate, international stocks and bonds as well as alternative investments such as commodities, private equity and hedge funds? This study contributes to this discussion.

This study contributes to the real estate literature by combining multiple approaches to clarify the relationship between asset return and selected inflation/interest rates. The study also presents new evidence on the dynamic relationship between asset returns and inflation/interest rates. Few studies have touched on this issue following the recent financial crisis. - This study covers the period 1991 – 2015. This period spans the period of the 2007-2008 financial crisis. The results of this study can be compared to those carried out prior to the crisis to see if the relationship between inflation and asset returns has been affected by the crisis.

Unlike previous studies that analyse real estate along with the traditional asset classes of stocks and bonds, we also examine the inflation hedging ability of alternative assets such as hedge fund, commodities and private equity. This would show us whether these assets offer a hedge against UK inflation and interest rates especially since most of these alternatives are denominated in US$ and not primarily traded in the United Kingdom. This aspect of our study also shows whether it is worth diversifying internationally when local inflation and interest rates are being hedged against.

The results show that real estate is a hedge against all the inflation and interest rates analysed. All the four real estate sectors – retail, office, industrial and the aggregate property – were found to be a hedge against the different inflation and interest rates over both the short-run and long-run. Long-run results show that real estate was a complete hedge as they all produced long-run coefficients greater than 1.0, satisfying the definition of a complete hedge per the Darby (1975) version of the Fisher (1930) hypothesis. Short-run Toda & Yamamoto (1995) Granger causality tests also show that all real estate sectors are able to offer a short-term inflation hedge. We further find that the inflation-hedging ability of real estate is retained even when different real estate investment vehicles such as the AREF balanced fund, the AREF All Funds or blended/hybrid real estate vehicles are used. We investigated the issue of appraisal smoothing in the results obtained. We observe that the main result that changes is the error-correction coefficient which increased remarkably. Hoesli et al. (2017) believes that such a result merely confirms the fact that private asset market assets take a long time to respond to changes in economic fundamentals.

Index-linked bonds have been viewed by many investors as a natural hedge against inflation (Orsolio, 2012; Kramer, 2017). The results of our analysis revealed that inflation-indexed bonds are not a good hedge over the short-term, although they are cointegrated with inflation in the long-run. The dynamic conditional correlation and the Granger causality test results point to the fact that inflation-indexed bonds are not a good short term hedge. The DCC estimates actually suggest that inflation-indexed bonds are be more strongly correlated with interest rates than inflation. This is consistent with the position of Orsilio (2012) that inflation-indexed bonds are still bonds and their total returns are subject to interest rate changes. Some authors such as Schofield (1996) maintain that the weak results obtained is as a result of the lagged indexation phenomenon. Nominal bonds on the other hand were found to be a good hedge over the short and long run. The long-term coefficients show that longer maturity bonds adjust their returns by a higher percentage for any change in inflation than shorter-maturity ones pointing to an upward slopping yield curve.

Further, we find that several stock sectors were a hedge against inflation over the long run but not over the short-run. Ironically, alternative assets which are mostly not denominated in GBP or primarily traded in the UK were a better short-term hedge. However, few alternative assets were found to be a hedge over the long-run. Results obtained when we used unsmoothed series in place of the original series for private market alternative assets were similar to what we obtained for real estate. The error-correction coefficient increased compared to what was obtained for the original series.

APPENDICES

Appendix 7(A) List of Variables

ASSET	ABBREVIATION
IPD Real Estate	
IPD All Property	UKRE_IPD
IPD Industrial	UKRE_IPDIND
IPD Office	UKRE_IPDOFF
IPD Retail	UKRE_IPDRET
Other Real Estate Vehicles	
AREF – All Funds	AREF_ALL
AREF – All Balanced Funds	AREF_LRE
Hybrid Real Estate	AREF_BAL
Stocks	
Aggregate stocks	UKS_ALL
Oil	UKS_OIL
Basic Materials	UKS_BMAT
Industrial	UKS_IND
Construction	UKS_CONST
Industrial goods and services	UKS_INDGDSV
Consumer goods	UKS_CGDS
Health care	UKS_HCARE
Consumer services	UKS_CSVS
Telecom	UKS_TEL
Technology	UKS_TEC
Utilities	UKS_UTIL
Banks	UKS_BANK
Insurance	UKS_INS
Financial services	UKS_FSV
Listed real estate	UKS_REALEST
Index Linked Bonds	
Index linked bonds - 0-5 Years	UKILB_0_5
Index linked bonds - 5+ years	UKILB__5
Bonds	
Bonds – All lives	UKB_ALL
Bonds – 10 + years	UKB_10_
Bonds – 10 year	UKB_10Y
Bonds – 7 year	UKB_7Y
Bonds – 5 year	UKB_5Y
Bonds – 3 year	UKB_3Y
Bonds – 2 year	UKB_2Y
Alternatives (IN US$)	
Emerging stock market (in US$)	EM_SM
Developed ex UK stocks (in US$)	DEV_SMEXUK
Commodities – all (in US$)	COMM_ALL
Commodities – oil (in US$)	COMM_OIL
Commodities – gold (in US$)	COMM_GOLD
Hedge funds (in US$)	HFRI
US private equity (in US$)	US_PE
US venture capital (in US$)	US_VC
Developed ex US private equity (in US$)	DEXUS_PE
Emerging private equity (in US$)	EM_PE
Alternatives (in GB£)	
Emerging stock market (in GB£)	EM_SM_GBP
Developed ex UK stocks (in in GB£)	DEV_SMEXUK_GBP
Commodities – all (in in GB£))	COMM_ALL_GBP
Commodities – oil (in in GB£))	COMM_OIL_GBP
Commodities – gold (in in GB£))	COMM_GOLD_GBP
Hedge funds (in in GB£))	HFRI_GBP
US private equity (in in GB£))	US_PE_GBP
US venture capital (in in GB£))	US_VC_GBP
Developed ex US private equity (in in GB£))	DEXUS_PE_GBP
Emerging private equity (in in GB£))	EM_PE_GBP
Inflation/Interest Rates	
UK Consumer Price Index	UK_CPI
UK Retail Price Index	UK_RPI
London Inter-Bank Offering Rate	LIBOR
UK Treasury Bills - 3 Months	T_BILL

Appendix 7(B) Relative Performance Metrics (Consumer Price Index)

	Excess returns	Tracking error	Sharpe Ratio	Success ratio	Static Correl.	DCC
Real Estate						
IPD All Property	1.52	3.28	0.46	0.8	-0.09	-0.06
IPD Industrial	1.7	3.06	0.56	0.8	-0.07	-0.06
IPD Office	1.51	3.53	0.43	0.8	-0.13	-0.13
IPD Retail	1.66	3.4	0.49	0.82	-0.05	-0.02
Other Real Estate Vehicles						
AREF – All Funds	1.21	3.28	0.37	0.80	-0.12	-0.06
AREF – All Balanced Funds	1.22	3.87	0.31	0.81	-0.08	-0.10
Hybrid Real Estate	1.38	4.22	0.33	0.71	-0.06	-0.05
Stocks						
Aggregate stocks	1.56	8.05	0.19	0.66	0.1	0.06
Oil	2.17	9.04	0.24	0.62	0.08	0.07
Basic Materials	2.38	12.91	0.18	0.61	0.27	0.3
Industrial	2.71	10.79	0.25	0.65	0.14	0.11
Construction	2.23	10.3	0.22	0.6	0.19	0.16
Industrial goods and services	2.33	9.43	0.25	0.66	0.17	0.13
Consumer goods	3.14	10.51	0.3	0.62	0.22	0.09
Health care	2.31	7.15	0.32	0.63	0.08	-0.03
Consumer services	1.98	8.73	0.23	0.64	0.07	0.03
Telecom	2.55	12.59	0.2	0.63	0.01	-0.03
Technology	3.93	20.86	0.19	0.63	-0.04	-0.03
Utilities	2.89	7.12	0.41	0.71	0.03	-0.02
Banks	2.87	13.75	0.21	0.6	0.03	-0.03
Insurance	2.5	11.55	0.22	0.66	0.02	-0.05
Financial services	2.69	10.32	0.26	0.65	0.06	0.06
Listed real estate	2.07	11.68	0.18	0.66	0.04	0.06
Index Linked Bonds						
Index linked bonds - 0-5 Years	0.77	1.39	0.55	0.74	0.07	0.06
Index linked bonds - 5+ years	1.5	3.26	0.46	0.69	-0.05	-0.04
Bonds						
Bonds – All lives	1.45	3.15	0.46	0.66	0.02	-0.06
Bonds – 10 + years	1.84	4.58	0.4	0.64	-0.06	-0.13
Bonds – 10 year	1.61	3.73	0.43	0.64	0.01	-0.04
Bonds – 7 year	1.47	2.95	0.5	0.69	0.06	-0.01
Bonds – 5 year	1.22	2.44	0.5	0.71	0.06	0
Bonds – 3 year	1.06	1.69	0.62	0.72	0.09	-0.01
Bonds – 2 year	0.87	1.4	0.62	0.75	0.1	-0.05
Alternatives in GB£						
Emerging stock market	2.37	14.16	0.17	0.59	0.12	0.14
Developed ex US stocks	1.72	9.63	0.18	0.62	0.09	0.10
Commodities - all	0.21	12.39	0.02	0.56	0.16	0.23
Commodities - oil	1.60	18.24	0.09	0.61	0.06	0.17
Commodities - gold	0.65	8.27	0.08	0.52	0.11	0.19
Hedge funds	1.00	6.09	0.16	0.64	0.08	0.08
US private equity	3.00	7.62	0.39	0.69	0.12	0.14
US venture capital	3.69	12.54	0.29	0.63	0.02	0.09
Developed ex US private equity	3.07	10.95	0.28	0.65	0.10	0.15
Emerging private equity	1.23	8.31	0.15	0.56	0.12	0.16
Alternatives (IN US$)						
Emerging stock market	2.48	13.11	0.19	0.60	0.11	0.13
Developed ex UK stocks	1.89	8.72	0.22	0.67	0.06	0.04
Commodities – all	0.34	11.58	0.03	0.56	0.15	0.18
Commodities – oil	1.69	17.44	0.1	0.58	0.05	0.13
Commodities – gold	0.78	6.39	0.12	0.55	0.07	0.14
Hedge funds	1.15	3.56	0.32	0.68	0.03	0.04
US private equity	3.1	4.99	0.62	0.79	0.1	0.08
US venture capital	3.85	11.75	0.33	0.69	-0.01	0.02
Developed ex US private equity	2.99	7.16	0.42	0.70	0.10	0.14
Emerging private equity	1.29	5.35	0.24	0.60	0.11	0.12

Appendix 7(C) Relative Performance Metrics (Retail Price Index)

	Excess returns	Tracking error	Sharpe Ratio	Success ratio	Static Correl.	DCC
Real Estate						
IPD All Property	1.39	3.09	0.45	0.80	0.21	0.07
IPD Industrial	1.57	2.89	0.54	0.80	0.19	0.05
IPD Office	1.38	3.33	0.41	0.78	0.17	0.03
IPD Retail	1.53	3.22	0.47	0.80	0.22	0.07
Other Real Estate Vehicles						
AREF – All Funds	1.08	3.08	0.35	0.80	0.19	0.05
AREF – All Balanced Funds	1.09	3.67	0.30	0.80	0.23	0.07
Hybrid Real Estate	1.25	4.07	0.31	0.71	0.18	0.03
Stocks						
Aggregate stocks	1.43	7.92	0.18	0.66	0.29	0.23
Oil	2.04	9.06	0.22	0.63	0.04	0.00
Basic Materials	2.25	12.88	0.17	0.61	0.31	0.27
Industrial	2.58	10.80	0.24	0.65	0.11	0.14
Construction	2.10	10.33	0.20	0.59	0.15	0.13
Industrial goods and services	2.20	9.43	0.23	0.66	0.15	0.16
Consumer goods	3.01	10.58	0.28	0.63	0.11	0.09
Health care	2.18	7.29	0.30	0.63	-0.12	-0.12
Consumer services	1.85	8.74	0.21	0.65	0.05	0.03
Telecom	2.41	12.60	0.19	0.62	-0.01	0.01
Technology	3.80	20.78	0.18	0.60	0.08	0.10
Utilities	2.76	7.13	0.39	0.69	0.02	0.04
Banks	2.74	13.74	0.20	0.59	0.05	-0.02
Insurance	2.36	11.56	0.20	0.66	0.00	-0.02
Financial services	2.56	10.26	0.25	0.65	0.15	0.13
Listed real estate	1.93	11.63	0.17	0.66	0.11	0.07
Index Linked Bonds						
Index linked bonds - 0-5 Years	0.63	1.35	0.47	0.69	0.15	0.16
Index linked bonds - 5+ years	1.37	3.20	0.43	0.67	0.04	0.07
Bonds						
Bonds – All lives	1.32	3.36	0.39	0.62	-0.31	-0.29
Bonds – 10 + years	1.71	4.75	0.36	0.59	-0.32	-0.32
Bonds – 10 year	1.48	3.93	0.38	0.64	-0.28	-0.20
Bonds – 7 year	1.33	3.15	0.42	0.66	-0.26	-0.20
Bonds – 5 year	1.08	2.65	0.41	0.65	-0.26	0.07
Bonds – 3 year	0.93	1.92	0.48	0.64	-0.29	-0.24
Bonds – 2 year	0.74	1.63	0.45	0.64	-0.29	-0.25
Alternatives (IN GB£)						
Emerging stock market	2.24	14.09	0.16	0.58	0.22	0.17
Developed ex UK stocks	1.59	9.51	0.17	0.61	0.26	0.18
Commodities - all	0.08	12.15	0.01	0.55	0.50	0.40
Commodities - oil	1.47	18.02	0.08	0.61	0.39	0.35
Commodities - gold	0.51	8.17	0.06	0.49	0.24	0.29
Hedge funds	0.87	5.95	0.15	0.63	0.29	0.21
US private equity	2.87	7.52	0.38	0.68	0.27	0.21
US venture capital	3.56	12.48	0.29	0.63	0.12	0.12
Developed ex US private equity	2.94	10.82	0.27	0.65	0.29	0.27
Emerging private equity	1.10	8.23	0.13	0.57	0.22	0.20
Alternatives (IN US$)						
Emerging stock market	2.34	13.07	0.18	0.57	0.17	0.15
Developed ex UK stocks	1.76	8.63	0.20	0.66	0.19	0.11
Commodities – all	0.21	11.36	0.02	0.54	0.47	0.36
Commodities – oil	1.56	17.23	0.09	0.58	0.36	0.32
Commodities – gold	0.65	6.32	0.10	0.55	0.17	0.18
Hedge funds	1.01	3.42	0.30	0.63	0.25	0.14
US private equity	2.97	4.91	0.61	0.78	0.23	0.14
US venture capital	3.72	11.71	0.32	0.68	0.05	0.01
Developed ex US private equity	2.86	7.00	0.41	0.70	0.33	0.30
Emerging private equity	1.16	5.30	0.22	0.61	0.19	0.13

Appendix 7(D) Relative Performance Metrics (LIBOR)

	Excess returns	Tracking error	Sharpe Ratio	Success ratio	Static Correl.	DCC
Real Estate						
IPD All Property	0.94	3.33	0.28	0.79	-0.15	-0.14
IPD Industrial	1.13	3.09	0.36	0.77	-0.11	-0.11
IPD Office	0.93	3.58	0.26	0.72	-0.20	-0.04
IPD Retail	1.08	3.42	0.32	0.74	-0.06	-0.14
Other Real Estate Vehicles						
AREF – All Funds	0.63	3.28	0.19	0.72	-0.12	-0.14
AREF – All Balanced Funds	0.64	3.89	0.16	0.74	-0.10	-0.11
Hybrid Real Estate	0.80	4.27	0.19	0.66	-0.11	-0.08
Stocks						
Aggregate stocks	0.99	8.08	0.12	0.65	0.05	0.14
Oil	1.59	9.05	0.18	0.59	0.06	0.14
Basic Materials	1.80	13.06	0.14	0.59	0.05	0.12
Industrial	2.14	10.87	0.20	0.63	0.01	0.00
Construction	1.65	10.45	0.16	0.58	-0.02	-0.11
Industrial goods and services	1.76	9.52	0.18	0.63	0.03	0.04
Consumer goods	2.56	10.62	0.24	0.60	0.05	-0.01
Health care	1.73	7.14	0.24	0.63	0.10	0.02
Consumer services	1.40	8.76	0.16	0.62	0.02	0.03
Telecom	1.97	12.54	0.16	0.60	0.07	0.18
Technology	3.35	20.82	0.16	0.60	0.02	0.16
Utilities	2.32	7.03	0.33	0.65	0.16	0.10
Banks	2.29	13.68	0.17	0.59	0.13	0.15
Insurance	1.92	11.56	0.17	0.62	0.00	0.05
Financial services	2.11	10.37	0.20	0.63	-0.02	0.07
Listed real estate	1.49	11.75	0.13	0.64	-0.07	-0.04
Index Linked Bonds						
Index linked bonds - 0-5 Years	0.19	1.23	0.15	0.55	0.34	0.27
Index linked bonds - 5+ years	0.92	3.23	0.29	0.64	0.01	0.05
Bonds						
Bonds – All lives	0.88	3.03	0.29	0.61	0.20	0.10
Bonds – 10 + years	1.26	4.46	0.28	0.57	0.13	0.08
Bonds – 10 year	1.04	3.62	0.29	0.63	0.18	0.10
Bonds – 7 year	0.89	2.83	0.31	0.62	0.23	0.12
Bonds – 5 year	0.64	2.31	0.28	0.61	0.25	0.13
Bonds – 3 year	0.48	1.49	0.32	0.59	0.40	0.23
Bonds – 2 year	0.29	1.10	0.27	0.58	0.53	0.29
Alternatives (IN GB£)						
Emerging stock market	1.90	13.19	0.14	0.57	0.00	0.06
Developed ex UK stocks	1.31	8.75	0.15	0.61	0.03	0.09
Commodities - all	-0.24	11.63	-0.02	0.54	0.08	0.14
Commodities - oil	1.11	17.42	0.06	0.57	0.09	0.16
Commodities - gold	0.20	6.50	0.03	0.50	-0.10	-0.06
Hedge funds	0.57	3.43	0.17	0.62	0.22	0.35
US private equity	2.53	5.03	0.50	0.72	0.05	0.17
US venture capital	3.27	11.65	0.28	0.72	0.13	0.32
Developed ex US private equity	2.41	7.18	0.34	0.67	0.06	0.11
Emerging private equity	0.72	5.53	0.13	0.57	-0.15	-0.01
Alternatives (IN US$)						
Emerging stock market (in US$)	1.90	13.19	0.14	0.57	0.00	0.06
Developed ex UK stocks (in US$)	1.31	8.74	0.15	0.61	0.03	0.09
Commodities – all (in US$)	-0.24	11.63	-0.02	0.54	0.08	0.14
Commodities – oil (in US$)	1.11	17.41	0.06	0.57	0.09	0.16
Commodities – gold (in US$)	0.20	6.50	0.03	0.49	-0.10	-0.06
Hedge funds (in US$)	0.57	3.43	0.17	0.62	0.22	0.35
US private equity (in US$)	2.53	5.03	0.50	0.72	0.04	0.17
US venture capital (in US$)	3.27	11.65	0.28	0.72	0.13	0.32
Developed ex US private equity (in US$)	2.41	7.18	0.34	0.67	0.06	0.11
Emerging private equity (in US$)	0.72	5.53	0.13	0.57	-0.15	-0.01

Appendix 7(E) Relative Performance Metrics (Treasury Bills)

	Excess returns	Tracking error	Sharpe Ratio	Success ratio	Static Correl.	DCC
Real Estate						
IPD All Property	0.99	3.36	0.29	0.77	-0.19	-0.14
IPD Industrial	1.17	3.12	0.38	0.77	-0.14	-0.12
IPD Office	0.98	3.61	0.27	0.73	-0.23	-0.03
IPD Retail	1.12	3.44	0.33	0.73	-0.09	-0.14
Other Real Estate Vehicles						
AREF – All Funds	0.67	3.31	0.20	0.72	-0.16	-0.15
AREF – All Balanced Funds	0.68	3.92	0.17	0.75	-0.14	-0.12
Hybrid Real Estate	0.84	4.29	0.20	0.67	-0.13	-0.06
Stocks						
Aggregate stocks	1.03	8.09	0.13	0.65	0.03	0.21
Oil	1.63	9.08	0.18	0.59	0.02	0.02
Basic Materials	1.85	13.09	0.14	0.59	0.01	0.08
Industrial	2.18	10.88	0.20	0.63	0.00	0.10
Construction	1.69	10.45	0.16	0.58	-0.03	-0.06
Industrial goods and services	1.80	9.53	0.19	0.64	0.02	0.15
Consumer goods	2.60	10.63	0.24	0.61	0.04	0.03
Health care	1.77	7.12	0.25	0.63	0.12	0.16
Consumer services	1.44	8.76	0.16	0.62	0.02	0.12
Telecom	2.01	12.55	0.16	0.60	0.06	0.17
Technology	3.39	20.84	0.16	0.60	-0.01	0.23
Utilities	2.36	7.02	0.34	0.65	0.18	0.29
Banks	2.34	13.67	0.17	0.60	0.15	0.31
Insurance	1.96	11.55	0.17	0.63	0.01	0.24
Financial services	2.16	10.39	0.21	0.64	-0.04	0.14
Listed real estate	1.53	11.75	0.13	0.63	-0.07	0.04
Index Linked Bonds						
Index linked bonds - 0-5 Years	0.23	1.22	0.19	0.58	0.35	0.37
Index linked bonds - 5+ years	0.96	3.22	0.30	0.64	0.02	0.22
Bonds						
Bonds – All lives	0.92	3.01	0.31	0.61	0.24	0.12
Bonds – 10 + years	1.30	4.44	0.29	0.57	0.15	0.10
Bonds – 10 year	1.08	3.60	0.30	0.63	0.21	0.16
Bonds – 7 year	0.93	2.80	0.33	0.63	0.28	0.17
Bonds – 5 year	0.68	2.27	0.30	0.62	0.31	0.17
Bonds – 3 year	0.52	1.44	0.36	0.61	0.45	0.22
Bonds – 2 year	0.34	1.04	0.32	0.59	0.60	0.27
Alternatives (IN GB£)						
Emerging stock market	1.83	14.29	0.13	0.59	-0.08	-0.06
Developed ex UK stocks	1.19	9.74	0.12	0.59	-0.07	0.03
Commodities - all	-0.33	12.51	-0.03	0.56	-0.01	0.05
Commodities - oil	1.07	18.28	0.06	0.60	0.01	0.05
Commodities - gold	0.11	8.46	0.01	0.47	-0.17	-0.16
Hedge funds	0.47	6.16	0.08	0.62	-0.01	0.06
US private equity	2.47	7.77	0.32	0.69	-0.09	-0.02
US venture capital	3.16	12.54	0.25	0.62	0.03	0.14
Developed ex US private equity	2.54	11.06	0.23	0.62	-0.06	-0.01
Emerging private equity	0.70	8.53	0.08	0.54	-0.21	-0.09
Alternatives (IN US$)						
Emerging stock market (in US$)	1.94	13.21	0.15	0.58	-0.04	-0.01
Developed ex UK stocks (in US$)	1.36	8.76	0.15	0.63	0.00	0.05
Commodities – all (in US$)	-0.20	11.66	-0.02	0.54	0.04	0.11
Commodities – oil (in US$)	1.16	17.44	0.07	0.55	0.04	0.09
Commodities – gold (in US$)	0.24	6.52	0.04	0.51	-0.12	-0.19
Hedge funds (in US$)	0.61	3.47	0.18	0.62	0.17	0.30
US private equity (in US$)	2.57	5.06	0.51	0.72	0.00	0.10
US venture capital (in US$)	3.32	11.68	0.28	0.73	0.09	0.23
Developed ex US private equity (in US$)	2.45	7.23	0.34	0.67	0.00	0.05
Emerging private equity (in US$)	0.76	5.56	0.14	0.57	-0.20	-0.06

Appendix 7(F) Relative Performance Metrics – Unsmoothed Private Market Asset Return Series

	Consumer Price Index						Retail Price Index					
Unsmoothed IPD Sectors	**Excess return**	**Tracking error**	**Sharpe ratio**	**Success ratio**	**Static Correl**	**DCC**	**Excess return**	**Tracking error**	**Sharpe ratio**	**Success ratio**	**Static Correl**	**DCC**
IPD All Property	1.62	5.34	0.30	0.76	0.01	0.05	1.49	5.27	0.28	0.73	0.12	0.11
IPD Industrial	1.77	5.06	0.35	0.73	0.02	0.06	1.64	5.01	0.33	0.72	0.09	0.10
IPD Office	1.65	5.63	0.29	0.76	-0.04	-0.04	1.52	5.53	0.27	0.74	0.10	0.10
IPD Retail	1.30	5.00	0.26	0.71	0.00	0.00	1.17	4.95	0.24	0.69	0.09	0.08
Unsmoothed Private Market Alternatives												
Hedge funds	0.16	11.57	0.01	0.55	0.17	0.20	0.03	11.36	0.00	0.54	0.47	0.37
US private equity	1.24	17.51	0.07	0.59	0.07	0.16	1.10	17.30	0.06	0.58	0.38	0.34
US venture capital	0.81	6.38	0.13	0.55	0.07	0.14	0.68	6.31	0.11	0.55	0.17	0.19
Developed ex US private equity	0.69	3.45	0.20	0.63	0.03	0.02	0.56	3.35	0.17	0.60	0.18	0.09
Emerging private equity	1.73	4.61	0.38	0.73	0.13	0.13	1.60	4.59	0.35	0.72	0.16	0.13

	LIBOR Interest Rate						T-bill Interest Rate					
Unsmoothed IPD Sectors	**Excess return**	**Tracking error**	**Sharpe ratio**	**Success ratio**	**Static Correl**	**DCC**	**Excess return**	**Tracking error**	**Sharpe ratio**	**Success ratio**	**Static Correl**	**DCC**
IPD All Property	1.04	5.43	0.19	0.68	-0.13	-0.14	1.09	5.45	0.20	0.69	-0.15	-0.12
IPD Industrial	1.19	5.16	0.23	0.73	-0.12	-0.09	1.24	5.18	0.24	0.72	-0.15	-0.08
IPD Office	1.07	5.71	0.19	0.70	-0.15	-0.09	1.12	5.72	0.20	0.70	-0.17	-0.04
IPD Retail	0.73	5.09	0.14	0.65	-0.12	-0.12	0.77	5.12	0.15	0.66	-0.16	-0.14
Unsmoothed Private Market Alternatives												
Hedge funds	-0.42	11.64	-0.04	0.51	0.06	0.14	-0.38	11.67	-0.03	0.51	0.02	0.10
US private equity	0.66	17.52	0.04	0.57	0.06	0.17	0.70	17.55	0.04	0.57	0.01	0.08
US venture capital	0.23	6.50	0.04	0.51	-0.10	-0.06	0.28	6.52	0.04	0.49	-0.12	-0.19
Developed ex US private equity	0.11	3.37	0.03	0.59	0.15	0.29	0.16	3.41	0.05	0.59	0.10	0.23
Emerging private equity	1.15	4.69	0.25	0.63	0.01	0.13	1.19	4.71	0.25	0.63	-0.02	0.02

Appendix 7(G) Diagnostic Test Results - Consumer Price Index

	Serial correlation LM Test		Heteroskedasticity		Ramsey Reset test	
	F-statistic	Prob.	F-statistics	Prob.	F-statistic	Prob.
Real Estate						
IPD All Property	0.4160	0.6611	2.4485	0.0160	0.0027	0.9586
Industrial	0.0319	0.9686	3.2439	0.0020	0.0384	0.8450
Office	0.1906	0.8268	2.0565	0.0495	0.0016	0.9679
Retail	0.1978	0.8209	2.6997	0.0084	0.0003	0.9859
Other Real Estate Vehicles						
AREF – All Funds	2.2167	0.1155	3.3432	0.0016	0.0010	0.9750
AREF – All Balanced Funds	0.6669	0.5162	2.7322	0.0061	0.3535	0.5538
Hybrid Real Estate	0.4229	0.6566	1.7910	0.0904	0.4700	0.4949
Stocks						
Aggregate stocks	0.0133	0.9868	0.4967	0.6101	3.6857	0.0580
Listed real estate	0.1363	0.8728	0.4621	0.7094	0.0737	0.7866
Oil	0.6493	0.5249	1.5353	0.2107	11.8316	0.0009
Basic Materials	0.4447	0.6425	3.5893	0.0032	0.4068	0.5253
Industrial	1.2681	0.2865	1.1184	0.3529	0.0927	0.7614
Construction	0.4137	0.6625	0.3957	0.8506	0.0003	0.9863
Industrial goods and services	1.4139	0.2485	0.0782	0.9249	0.3828	0.5376
Consumer goods	0.1145	0.8919	1.2220	0.2993	0.8162	0.3687
Health care	0.9829	0.3782	1.9896	0.1210	0.0201	0.8876
Consumer services	1.0762	0.3455	0.8791	0.5139	0.1229	0.7268
Telecom	0.2215	0.8018	0.9280	0.5183	0.0733	0.7873
Technology	1.5782	0.2130	2.6797	0.0057	0.1815	0.6713
Ultilities	0.0985	0.9063	1.0990	0.3733	3.6541	0.0598
Banks	0.5385	0.5855	0.2944	0.7457	1.5853	0.2112
Insurance	1.0869	0.3416	0.0103	0.9898	0.0147	0.9039
Financial services	0.1061	0.8994	1.5654	0.2032	2.1941	0.1420
Index-Linked Bonds						
Index-Linked Bonds (0-5)	0.2756	0.7598	1.4749	0.1963	0.0116	0.9146
Index-Linked Bonds (5+)	0.1178	0.8890	1.6015	0.1563	0.8160	0.3689
Bonds						
Bonds – All lives	0.1515	0.8597	0.8418	0.5558	2.0406	0.0444
10+ year bonds	0.2153	0.8068	0.6628	0.7028	4.0385	0.0476
10 year bonds	0.3898	0.6784	0.4981	0.8335	4.9992	0.0280
7 year bonds	0.2089	0.8119	0.8402	0.5423	4.0637	0.0469
5 year bonds	0.4060	0.6676	0.8406	0.5420	2.4882	0.1184
3 year bonds	0.5207	0.5960	0.6916	0.6570	0.0092	0.9240
2 year bonds	0.7664	0.4678	1.0539	0.3966	0.1790	0.6733
Alternatives in GB£						
Hedge funds	1.5353	0.2213	5.1808	0.0001	0.0990	0.7538
US private equity	2.2149	0.1153	4.1455	0.0020	0.0990	0.7538
US venture capital	0.1745	0.8402	2.0395	0.0807	4.8367	0.0305
Developed ex US private equity	2.7135	0.0720	3.2375	0.0064	1.7942	0.1839
Emerging private equity	0.8035	0.4516	1.5754	0.1167	0.1264	0.7231
Emerging stock market	1.6291	0.2026	2.1921	0.0308	0.0096	0.9223
Developed ex US stocks	0.7825	0.4605	7.6682	0.0000	0.2985	0.5862
Commodities – all	0.8639	0.4253	6.8123	0.0000	0.7046	0.4830
Commodities - oil	0.0262	0.9741	2.3033	0.0337	0.2425	0.6237
Commodities - gold	2.3498	0.1025	0.7605	0.6980	4.6107	0.0350
Alternatives in US$						
Hedge funds	0.1804	0.8352	1.1896	0.3194	0.0374	0.8472
US private equity	0.6467	0.5264	2.0604	0.0567	2.1020	0.1508
US venture capital	0.4238	0.6560	3.8928	0.0018	8.8221	0.0039
Developed ex US private equity	2.4879	0.2882	0.8718	0.5972	1.8981	0.1726
Emerging private equity	0.4183	0.6595	1.1373	0.3467	0.1468	0.7025
Emerging stock market	0.3335	0.7173	1.0246	0.3856	0.0241	0.8769
Developed ex US stocks	0.0037	0.9963	3.4356	0.0043	0.7143	0.4004
Commodities – all	0.4816	0.6195	5.1360	0.0001	0.8054	0.4229
Commodities - oil	0.1426	0.8673	1.8909	0.0809	0.4399	0.5090
Commodities - gold	0.1063	0.8993	0.8755	0.5164	3.0843	0.0826

Appendix 7(H) Diagnostic Test Results – Retail Price Index

	Serial correlation LM Test		Heteroskedasticity		Ramsey Reset test	
	F-statistic	**Prob.**	**F-statistics**	**Prob.**	**F-statistic**	**Prob.**
Real Estate						
IPD All Property	1.1254	0.3294	3.3515	0.0033	0.1797	0.6727
Industrial	0.4701	0.6266	3.5095	0.0024	1.0287	0.3134
Office	1.3648	0.2611	2.5847	0.0182	0.3012	0.5846
Retail	0.0484	0.9528	3.9328	0.0001	0.0189	0.8909
Other Real Estate Vehicles						
AREF – All Funds	0.4166	0.6607	2.7142	0.0137	0.3600	0.5816
AREF – All Balanced Funds	0.2719	0.7626	2.8632	0.0073	0.4821	0.4894
Hybrid Real Estate	0.4940	0.6120	0.8783	0.5272	0.1085	0.7427
Stocks						
Aggregate stocks	0.1446	0.8655	0.1403	0.9356	2.7661	0.0997
Listed real estate	0.2501	0.7793	1.8913	0.0809	0.0143	0.9053
Oil	0.1728	0.8416	0.9271	0.4797	10.7036	0.0015
Basic Materials	0.1449	0.8653	1.4446	0.1907	0.6528	0.4215
Industrial	1.0625	0.3500	1.0759	0.3733	0.0220	0.8825
Construction	0.9477	0.3917	0.7718	0.5726	0.0006	0.9800
Industrial goods and services	1.4551	0.2388	0.0418	0.9591	0.7916	0.3759
Consumer goods	0.0540	0.9474	1.1813	0.3115	2.8760	0.0933
Health care	0.6688	0.5151	1.8875	0.0815	1.2476	0.2672
Consumer services	0.2579	0.7733	0.3506	0.7052	0.0058	0.9392
Telecom	0.0683	0.9340	1.4986	0.1884	0.0614	0.8048
Technology	1.8474	0.1644	4.5423	0.0001	0.1195	0.7305
Ultilities	0.2199	0.8031	1.5247	0.1457	1.7171	0.1938
Banks	0.5531	0.5771	0.2196	0.8032	1.4569	0.2305
Insurance	1.1655	0.3164	0.0179	0.9822	0.0006	0.9801
Financial services	0.2885	0.7501	1.7410	0.1479	2.1731	0.1440
Index-Linked Bonds						
Index-Linked Bonds (0-5)	0.2438	0.7842	1.3126	0.2662	0.0637	0.9493
Index-Linked Bonds (5+)	0.0129	0.9872	1.9066	0.0887	4.8078	0.0310
Nominal Bonds						
Bonds – All lives	0.5558	0.5757	0.4442	0.8164	2.2264	0.0286
10+ year bonds	0.4259	0.6546	0.6419	0.6683	2.4592	0.1205
10 year bonds	0.0600	0.9418	0.5530	0.7664	3.6989	0.0578
7 year bonds	0.0011	0.9989	0.6459	0.6932	3.4904	0.0651
5 year bonds	0.0878	0.9160	1.0956	0.3715	2.1143	0.1496
3 year bonds	0.6404	0.5296	0.8570	0.5299	0.0208	0.8857
2 year bonds	0.0771	0.9258	1.6667	0.1388	0.4295	0.5140
Alternatives in GB£						
Hedge funds	0.7429	0.4792	2.5717	0.0096	0.0540	0.8169
US private equity	0.2514	0.7783	2.4924	0.0368	1.8615	0.1759
US venture capital	0.4559	0.6355	2.9731	0.0056	11.3223	0.0012
Developed ex US private equity	1.1848	0.3107	3.6401	0.0048	0.8580	0.3568
Emerging private equity	1.1269	0.3287	1.3059	0.2687	0.0490	0.8253
Emerging stock market	2.0341	0.1378	1.5245	0.1394	0.0348	0.8525
Developed ex US stocks	0.1058	0.8997	2.8790	0.0095	0.3974	0.5301
Commodities - all	0.6366	0.5316	3.5440	0.0058	0.5997	0.4408
Commodities - oil	1.1688	0.3157	0.8240	0.5544	0.0517	0.8207
Commodities - gold	0.1133	0.8930	0.3984	0.7545	2.2193	0.1398
Alternatives in US$						
Hedge funds	0.9429	0.3937	0.8971	0.5127	0.1403	0.7089
US private equity	1.2155	0.3018	1.5123	0.1740	6.5840	0.0121
US venture capital	0.4102	0.6648	4.1250	0.0011	8.3114	0.0050
Developed ex US private equity	0.0999	0.9050	1.5675	0.1091	1.9661	0.1651
Emerging private equity	1.1269	0.3287	1.3059	0.2687	0.0490	0.8253
Emerging stock market	0.4388	0.6464	0.9006	0.5438	0.0509	0.8221
Developed ex US stocks	0.2881	0.7504	0.9583	0.4479	0.2727	0.6028
Commodities - all	1.3006	0.2776	3.2507	0.0154	0.0967	0.7565
Commodities - oil	1.3667	0.2605	1.4036	0.2224	0.0136	0.9073
Commodities - gold	1.9658	0.1460	0.7750	0.5109	3.8680	0.0523

Appendix 7(I) Diagnostic Test Results - LIBOR Rate

	Serial correlation LM Test		Heteroskedasticity		Ramsey Reset test	
	F-statistic	Prob.	F-statistics	Prob.	F-statistic	Prob.
Real Estate						
IPD All Property	0.4200	0.6585	3.2858	0.0013	0.0006	0.9801
Industrial	1.8226	0.1685	3.5707	0.0006	0.0818	0.7756
Office	0.0110	0.9890	1.4067	0.2212	0.3202	0.5729
Retail	0.0325	0.9681	2.1029	0.0296	1.1503	0.2868
Other Real Estate Vehicles						
AREF – All Funds	0.6472	0.5261	3.3847	0.0048	5.0677	0.0269
AREF – All Balanced Funds	0.9500	0.3912	2.6512	0.0077	0.4521	0.5033
Hybrid Real Estate	2.2319	0.1144	0.9223	0.5344	0.2933	0.5897
Stocks						
Aggregate stocks	0.0332	0.9673	0.4746	0.7943	0.2629	0.7932
Listed real estate	1.1759	0.3143	0.7259	0.7420	3.5921	0.0620
Oil	0.1583	0.8539	0.6142	0.6535	1.3034	0.2566
Basic Materials	0.3662	0.6945	1.9158	0.0873	6.7314	0.0112
Industrial	1.4599	0.2378	0.3051	0.8739	1.2956	0.2581
Construction	0.3317	0.7186	0.0453	0.9558	1.2352	0.2693
Industrial goods and services	0.9600	0.3869	0.1183	0.9757	1.2265	0.2711
Consumer goods	0.5499	0.5790	1.3418	0.2607	5.0267	0.0274
Health care	0.8891	0.4149	1.1095	0.3636	0.0031	0.9559
Consumer services	0.1980	0.8207	0.0935	0.9634	0.5706	0.4520
Telecom	0.0824	0.9209	1.1848	0.3222	0.0647	0.7999
Technology	1.8522	0.1636	4.5130	0.0001	0.1584	0.6917
Ultilities	1.2124	0.3028	2.0941	0.0391	2.4093	0.1245
Banks	0.5505	0.5786	1.0738	0.3459	1.3933	0.2409
Insurance	1.2147	0.3016	0.7393	0.4802	0.1766	0.6753
Financial services	1.3783	0.2577	0.9061	0.5058	0.1475	0.7019
Index-Linked Bonds						
Index-Linked Bonds (0-5)	0.1378	0.8715	1.4085	0.2292	2.9251	0.0044
Index-Linked Bonds (5+)	0.1826	0.8335	1.4101	0.2286	7.6419	0.0070
Bonds						
All lives	1.0078	0.3695	0.5586	0.8087	0.9064	0.3674
10+ year bonds	0.1971	0.8216	0.9814	0.4705	0.0281	0.8672
10 year bonds	0.1534	0.8580	0.9047	0.5400	0.3525	0.5544
7 year bonds	1.1282	0.3286	0.9846	0.4480	0.2669	0.6068
5 year bonds	0.8493	0.4315	1.1526	0.3379	1.1906	0.2784
3 year bonds	0.2421	0.7856	0.6077	0.7480	0.0386	0.8448
2 year bonds	0.6781	0.5104	0.8133	0.5788	1.2274	0.2711
Alternatives in GB£						
Hedge funds	0.8983	0.4112	0.8983	0.4112	0.5618	0.4556
US private equity	0.4121	0.6636	1.5282	0.1784	0.0298	0.8634
US venture capital	0.3855	0.6813	2.5386	0.0201	10.3429	0.0018
Developed ex US private equity	0.4172	0.6602	1.9616	0.1071	3.6485	0.0593
Emerging private equity	0.1387	0.8707	1.7528	0.1076	0.7033	0.4041
Emerging stock market	0.8832	0.4173	1.6921	0.1219	0.9897	0.3227
Developed ex US stocks	0.5838	0.5600	0.7836	0.5851	0.6518	0.4217
Commodities – all	0.2858	0.7521	2.6862	0.0194	3.7012	0.0577
Commodities - oil	0.1992	0.8198	0.4475	0.9049	0.5528	0.4594
Commodities - gold	0.1344	0.8745	0.4032	0.8750	2.4739	0.1195
Alternatives in US$						
Hedge funds	0.2544	0.7760	0.8450	0.5215	2.3108	0.1321
US private equity	0.8743	0.4209	1.7886	0.1107	0.1681	0.6828
US venture capital	0.6270	0.5367	3.9483	0.0016	5.9536	0.0168
Developed ex US private equity	0.8024	0.4521	1.8019	0.0680	1.4397	0.2339
Emerging private equity	1.8886	0.1574	2.6886	0.0261	0.1976	0.6578
Emerging stock market	1.4208	0.2474	1.4407	0.2001	1.8217	0.1808
Developed ex US stocks	0.2238	0.8000	1.3341	0.2573	1.2063	0.2751
Commodities – all	1.2837	0.2825	2.6300	0.0169	1.3908	0.1680
Commodities - oil	1.2199	0.3007	0.5142	0.8603	0.5812	0.4481
Commodities - gold	1.9120	0.1537	1.4961	0.2293	3.4829	0.0652

Appendix 7(J) Diagnostic Test Results – T-Bill Rate

	Serial correlation LM Test		Heteroskedasticity		Ramsey Reset test	
	F-statistic	Prob.	F-statistics	Prob.	F-statistic	Prob.
Real Estate						
IPD All Property	0.3540	0.7030	2.4067	0.0179	1.4278	0.2357
Industrial	1.2056	0.3050	2.7055	0.0083	1.7887	0.1849
Office	0.0139	0.9862	0.9314	0.4495	0.0039	0.9505
Retail	0.3165	0.7296	2.0429	0.0447	3.8949	0.0519
Other Real Estate Vehicles						
AREF – All Funds	0.6472	0.5261	3.3847	0.0048	5.0677	0.0269
AREF – All Balanced Funds	0.2580	0.7733	5.9635	0.0000	2.4518	0.1215
Hybrid Real Estate	0.1699	0.8440	0.9468	0.4899	0.0069	0.9339
Stocks						
Aggregate stocks	0.0090	0.9958	0.4654	0.7609	0.3047	0.7613
Listed real estate	2.1945	0.1178	2.1437	0.0475	0.9064	0.3438
Oil	0.1704	0.8436	1.0538	0.3728	2.6961	0.1041
Basic Materials	0.2029	0.8167	2.8461	0.0198	1.3630	0.2462
Industrial	1.4404	0.2424	0.5528	0.6975	1.1983	0.2766
Construction	0.3210	0.7263	0.0495	0.9517	1.4205	0.2364
Industrial goods and services	0.9012	0.4098	0.3985	0.8093	1.1630	0.2837
Consumer goods	0.2916	0.7478	2.1203	0.1030	8.6908	0.0041
Health care	1.1337	0.3266	1.5130	0.1939	0.3219	0.5719
Consumer services	0.1877	0.8292	0.1228	0.9465	0.6114	0.4363
Telecom	0.0860	0.9177	1.1793	0.3251	0.0651	0.7992
Technology	1.8556	0.1631	4.5309	0.0001	0.1732	0.6784
Ultilities	0.7009	0.4991	2.7657	0.0092	3.8718	0.0524
Banks	0.6561	0.5215	3.2611	0.0062	1.2793	0.2612
Insurance	1.2052	0.3044	0.7699	0.4660	0.1803	0.6721
Financial services	0.2961	0.7444	1.9579	0.0927	0.0702	0.7917
Index-Linked Bonds						
Index-Linked Bonds (0-5)	0.1826	0.8335	1.4101	0.2286	2.7644	0.0070
Index-Linked Bonds (5+)	1.0240	0.3633	11.13	0.0000	1.4771	0.1431
Nominal Bonds						
Bonds – all lives	0.6167	0.5421	0.6669	0.6994	0.8273	0.4104
10+ year bonds	0.7118	0.4936	1.2954	0.2732	1.0790	0.3018
10 year bonds	1.6318	0.2017	1.3247	0.2550	1.7137	0.1940
7 year bonds	0.5038	0.6061	0.7751	0.5916	1.8131	0.1817
5 year bonds	0.3535	0.7033	0.7366	0.6216	2.8959	0.0925
3 year bonds	0.0870	0.9167	0.5421	0.7748	0.8892	0.3484
2 year bonds	0.2896	0.7493	0.6636	0.6792	0.2381	0.6268
Alternatives in GB£						
Hedge funds	0.5585	0.5741	1.9505	0.0940	0.1778	0.6743
US private equity	0.0176	0.9825	4.2794	0.0032	0.4273	0.5150
US venture capital	0.3044	0.7384	1.6025	0.1282	13.2915	0.0005
Developed ex US private equity	1.2134	0.3020	4.3621	0.0064	2.5055	0.1170
Emerging private equity	0.2138	0.8079	4.9816	0.0011	0.1189	0.7310
Emerging stock market	1.4746	0.2347	1.6603	0.1404	0.5331	0.4673
Developed ex US stocks	0.5344	0.5880	2.2811	0.0431	0.0678	0.7953
Commodities – all	0.4892	0.6148	3.5033	0.0062	0.1997	0.6561
Commodities - oil	0.6600	0.5196	0.1941	0.9910	0.0425	0.8371
Commodities - gold	0.3026	0.7397	1.3328	0.2579	5.4707	0.0216
Alternatives in US$						
Hedge funds	0.1908	0.8266	0.1908	0.8266	2.6120	0.1098
US private equity	0.5650	0.5705	1.9630	0.0920	0.0501	0.8234
US venture capital	0.6360	0.5320	3.9529	0.0016	5.8975	0.0173
Developed ex US private equity	1.7455	0.1815	1.5891	0.1185	1.6686	0.2003
Emerging private equity	0.2138	0.8079	4.9816	0.0011	0.3732	0.5429
Emerging stock market	0.3247	0.7237	0.9773	0.4533	0.1189	0.7310
Developed ex US stocks	0.2867	0.7514	1.7458	0.1469	0.6873	0.4093
Commodities – all	2.5277	0.0856	6.2080	0.0002	0.9064	0.3672
Commodities - oil	1.2199	0.3007	0.5142	0.8603	0.4088	0.5244
Commodities - gold	1.8842	0.1578	1.4913	0.2304	3.4000	0.0684

CHAPTER EIGHT – AN EXAMINATION OF THE ROLE OF REAL ESTATE IN THE INFLATION AND INTEREST RATE HEDGING PORTFOLIOS OF DC PENSION FUNDS

8.0 INTRODUCTION

This chapter revisits the role of real estate within the portfolio of institutional investors, such as DC pension funds, whose main concern is the preservation of the capital value of their investments as well as those who require a minimum required rate of return on their investment. In particular, this chapter seeks to understand the role that real estate plays within the resulting portfolios by analysing the performance implication of including or excluding direct real estate in such portfolios. The results of this study are also relevant to institutional investors such as investment funds and life insurance companies that have minimum return promises tied to given inflation and interest rate benchmarks.

Monetary policies put in place in the US and Europe following the recent global financial crisis (2007 - 2008) could pave the way for rising inflation. In particular, a low interest rate environment has resulted in a continuous rise in money supply. An injection of liquidity to stimulate the economies of many developed countries could also push up price levels (Koniarski and Sebastian, 2015). These policies have also created a bond market with very low returns, leading investors to explore other asset classes to improve their yields and gain inflation protection (Shepard, 2015).

A rising inflation level is of great concern for institutional investors such as pension funds whose liabilities are linked to price and wage inflation. Individual investors are also concerned about rising inflation as it affects their real capital. The debate over which assets possess the ability to protect investors against a fall in their capital has been revived especially following the increase in dominance of DC pension funds. Many DC funds in the United Kingdom have their performance objectives stated in line with specified inflation and interest rates.

In this chapter, we examine the ability of real estate to provide protection against inflation within a portfolio context. Many of the studies that have analysed the inflation-hedging ability of real estate have mostly focused on the interdependcies between asset returns and inflation (Campbell and Viciera, 2005; Hoevenas et al., 2008; Jurek and Viciera, 2011). However, Koniarski and Sebastian (2015) pointed out that these approaches could lead to conclusions about inflation-hedging abilities that can be misleading. For example, an asset could move in conjunction with an inflation or interest rates but then the rate of inflation or interest rate could always be higher than the returns of that asset. If this is the case, that asset is actually a bad hedge despite the close interdependence.

Although several studies have analysed the benefits of adding real state to a multi-asset portfolio, very few of these studies have considered real estate's role in portfolios constructed to hedge against of inflation and interest rate changes. In general, very few quantitative studies exist to address the question of of how the average investor should structure his portfolios in the presence of inflation and interest rate changes. Bruno & Chincarini (2011) cite three possible reasons for the lack of quantitative studies in this area. Firstly, maximising real returns effectively means maximising nominal returns. Given that many studies have already examined the issue of maximising nominal returns, it is felt that the carrying out studies that focus on maximising real returns was not worth pursuing separately. Secondly, very little theoretical work has focused on which asset classes and in what proportion would be good hedges or would provide positive real returns. Thirdly, it could be difficult to find a model that provides a good hedge in both high and low inflationary environments.

A few studies have explored the optimal composition of inflation hedging portfolios (e.g. Bruno & Chincarini, 2010; Bruno & Chincarini, 2011; Twomey et. al, 2011; Downing et al., 2012; Briere and Signori, 2012; Crawford et al., 2013; Koniarski and Sebastian, 2015, Ogunc and Ogunc, 2016). Of these studies, Koniarski and Sebastian (2005) is the only one that focuses on the role of real estate within inflation hedging portfolios.

In this chapter, we construct different portfolios designed to help preserve the purchasing power of DC members' contributions. The role of real estate within the resulting portfolios is of particular interest. We initially assume a DC investor who seeks to hedge against a given inflation and interest rate. Thus, the objective is to minimise the risk of achieving a negative real rate of return. We then consider a more ambitious investor who wishes to maximise risk-adjusted returns. The risk-adjusted returns used is a modified version of the Sharpe ratio of Sharpe (1966) and the Sortino ratio of Sortino and Van Der Meer (1991). The Sharpe ratio is usually calculated relative to the risk-free rate of return. But we use both an inflation rate and interest rate. The Sortino ratio is just like the Sharpe ratio but only considers the risk of achieving negative real returns. We run a separate optimisation that excludes direct real estate in order to determine the role that real estate plays in the various portfolios. In our study, we use four different optimisation models that measure risk relative to a chosen benchmark – tracking error and semi-variance of tracking error. While acknowledging that other downside risk measures such as Value-at-Risk and Conditional Value-at-Risk are useful, we do not use them in this thesis because of their drawbacks when used within a portfolio context. These drawbacks are highlighted in our literature review.

Two different inflation and interest rate benchmarks are chosen to reflect the range of benchmarks used by UK DC pension investors. Inflation rate benchmarks reflect the preferences of those funds/investors who desire to protect the real value of their capital over time. The interest rate benchmarks on the other hand reflect the preferences of those investors who wish to earn a minimum of a risk-free rate over time. This study is relevant within environments such as the UK where DC pension funds have stated inflation and interest rates against which they benchmark their performance.

We find that adding real estate to inflation-hedging portfolios leads to a reduction in tracking-error for all the portfolios. This means that for the similar returns, a portfolio containing some real estate allocations would have a lower tracking error compared to another portfolio that does not have any real estate. Interestingly, the portfolios that include real estate also recorded higher returns, especially for the tracking error portfolios. In terms of allocations, we find that tracking error portfolios and Sharpe ratio portfolios were heavily invested in bonds. However, when the measure of risk is changed to account only for downside risk, the bonds receive a much lower allocation. The portfolios based on tracking error were also found to be diversified i.e. a lot more assets gain allocations. Although in a few cases, an 80-20 stock-bond portfolio generated cumulative returns that were higher than the returns of our inflation-hedging portfolios, the tracking error and the standard deviation and tracking error of the 80-20 portfolios far exceeded those of our inflation-hedging portfolios.

8.1 LITERATURE REVIEW

8.1.1 INFLATION HEDGING PORTFOLIOS

Boasen et al. (2011) observed that institutional investors such as life insurance companies and pension funds are most concerned with minimising downside deviation whiles maintaining a certain level of returns. This is because most of the policies of these life insurance companies and defined contribution funds contain a certain element of return guarantee/promise.

In the chapter 1, we discussed the issue of return guarantees as it relates to defined contribution pension funds and how this makes it imperative for them to invest in assets that enable them to deliver on these guarantees, sometimes on a periodic basis. Bodie (2003) notes that transaction costs, agency costs, and cognitive limitations provide important theoretical justifications for financial intermediaries to supply user-friendly, guaranteed retail investment products that have only a small number of well-understood options. A guarantee of a minimum rate of return could then be a good substitute for what they described as "a course in statistics". Altmann (2001) also argues that one means of improving the investment options available to DC plan members in the U.K, may be to introduce measures based on U.S,-style 'safe harbour' guidelines under ERISA, These guidelines, as discussed in Papke (2004) specify that the sponsor must provide sufficiently varied investment alternatives to allow the participant an opportunity to materially affect the potential returns on assets and account risk; allow the participant to choose from at least three investments, each of which must be diversified and each with different risk/return characteristics (employer's securities may not be one of the three); allow the participant to change investments with a frequency that is appropriate for the expected market volatility of the investment; and provide sufficient information for the participant to make investment decisions.

An analysis of the Statement of Investment Principles of UK Master Trust pension funds that have been established to help companies meet their responsibilities under Auto-Enrolment have specific inflation and interest rate measures that they aim to benchmark their performance against. These rates can also be considered as the promised return to contributors who join the scheme. Invariably, members of these funds would expect to earn returns that broadly follow the DC scheme's chosen performance benchmark. For example, the UK National Employment Savings Trust (NEST) has three different investment objectives all tied to the UK CPI inflation. The foundation stage, covering the first five years aims to keep pace with inflation, after charges. The growth phase promises a return of 3% above inflation while the consolidation phase keeps pace with inflation whiles minimising volatility. NOW Pensions hedges the returns of the various funds against the SONIA rate. The people's pension trustees expect the returns on the default fund to exceed CPI inflation and the wage growth rate over the long run. Legal and general promises real rates of return net of fees. The fund uses both the CPI and RPI to design its annuity contracts when members retire.

The challenge for DC pension schemes that have obligations tied to specific inflation and interest rate benchmarks is to construct portfolios that would generate returns in line with changes in the benchmark. This portfolio would determine a combination of assets that would generate sufficient returns while at the same time protect investors against inflation rate changes, especially on the downside (Bruno & Chincarini, 2011).

Ogunc and Ogunc (2016) examined the role that Treasury Inflation Protected Securities (TIPS) play within multi-asset portfolios. They implemented three different investment objectives. The first objective was to maximise real returns. The second minimises risk whiles the third objective maximises risk-adjusted returns. They found that portfolios containing TIPs improved the efficiency of portfolios during both the pre and post-crisis periods.

Briere and Signori (2012) investigate the optimal asset allocation for investors who seek to hedge against inflation in both volatile and stable macroeconomic environments. The found that in volatile economic environments, stocks, cash, inflation-indexed bonds and precious metals play an important role in investment portfolios. In a stable environment however, pro-cyclical stock sectors, nominal bonds and cash play a significant role within investment portfolios.

Bruno & Chincarini (2011) examined the possibility of hedging against inflation within investment portfolios that contain a full set of assets available to a US investor. They used both tracking-error and semi-variance optimisation to determine the best allocation for investors who wish to hedge against inflation. For investors who wish to minimise downside deviation, the best allocation often did not include stocks. The portfolios were made up of treasury bonds, gold, some oil and emerging market equities. The portfolios were found to perform well out-of-sample with the average returns being positive and close to the target real returns. The tracking errors were also relatively low. The authors suggest using rolling window analysis to determine how the allocations change over time.

Within the specific context of inflation-hedging, Koniarski and Sebastian (2015) used a downside risk approach instead of the mean-variance approach of Markowitz (1952) to determine the optimal allocations within the inflation-hedging portfolios. They used Lower Partial Moments to measure the risk of asset's returns falling below the inflation rate. They explained that Lower Partial Moments are useful for studying optimal inflation-protection over different horizons as they can account for the downside deviation of assets and asymmetric return distributions. They compared the results of their correlation analysis to results of the LPM analysis and concluded that assets exhibiting a high correlation with inflation do not necessarily produce low LPMs. They found that real estate had the most attractive inflation-hedging property over the medium and long-term. Cash is only a good hedge against inflation only over the short-term. Similarly, bonds outperform stocks in terms of their inflation-hedging ability over the medium term but not over the long-term.

8.1.2 BENCHMARK RELATIVE RETURN AND RISK MEASURES

Although the mean-variance optimisation model of Markowitz (1952) remains the most standard and widely used portfolio optimisation tool in the investment industry today (Boasson et al., 2011), many researchers have questioned the measurement of risk in terms of variance of expected portfolio returns. One of the main arguments against using variance as a measure of risk the fact that it is based on an assumption that investors weight the probability of negative returns equally against the probability of positive returns (Fishburn, 1977; Tse et al., 1993; Swisher and Kasten, 2005). Boassen et al (2011) found that for most investment managers, the challenge following the recent global financial crisis is the selection of optimal portfolios that would enable them minimise downside risk while improving the upside return of their investments. Many of these managers have turned consequently turned to use of alternative measures of risk – particularly those that help them minimise downside risk whiles at the same time improve the upside potential of their investments. Another problem with using the variance is its assumption of normality of asset return distributions. Another drawback of the variance is that it measures dispersion around the mean and so cannot be customised for individual investors. In other words, it ignores investor's risk aversion. Several studies have found that investment returns are not normally distributed (Fama and Roll, 1968; Jansen and De Vries, 1991).

8.1.2.1 Target Returns

Benchmark relative risk measures take into consideration returns relative to a certain threshold. The threshold captures the investor's perspective of risk. For example, an investor concerned with capital preservation would set a threshold of zero so that the probability of losing their initial investment would be viewed as risky. An investor with a 10% required return would consider any return below this rate to be risky. Often, institutional investors use a certain peer performance benchmark to measure their downside risk (Boason et al., 2011). By far, the most common benchmarks used by investment managers are a risk-free rate of return and the inflation rate (see Sivitanides, 1998; Sing and Ong, 2000, Cheng, 2001; Cheng and Wolverton, 2001; Kroencke and Schincler, 2010, Koniarski and Sebastian, 2015).

Vilkancas (2014) found that although target rate of return is often selected by investors based on their risk preferences, in practice, this rate is often set equal to a risk-free rate, an expected rate of return or zero. Similarly, an OECD (2012) survey found that most countries have a minimum return benchmark for DC pension funds often set the expected return equal to the average return on this benchmark.

Sivitaides (1998) constructed three different efficient frontiers using the mean-semideviation framework. The first efficient frontier uses a target return of 0%, indicating the risk borne by an investor who defines risk as any loss of initial principal. The second efficient frontier is constructed using a target return set equal to the risk-free rate. The study used the return on the 5-year Treasury security rate. The third target return is the weighted average rate of return for all four NCREIF property types. This reflects the risk preferences of institutional investors who use the NCREIF property index as their performance benchmark.

Sing and Ong (2000) used a three target returns to determine the effect of target returns on portfolio allocation and performance. They used target rate of returns of 0%, 1% and 2%. Koniarski and

Sebastian (2015) consider an investor who seeks to purely hedge against inflation, thus, they set target rate of return to inflation rate i.e. real rate of return of 0. Afterward, they consider an ambitious investor who wishes to obtain real rates of return ranging from 1% to 3%. Crawford used the percentage change in inflation over non-overlapping periods as the target rate of return.

Cheng (2001) used four possible target returns in their analysis of downside risk portfolios. They used 0% to represent the preference of an investor who is concerned with maintaining their capital. The second target return was the average return on the one-year Treasury bill rate. This is used to represent the preferences of an investor who requires at least the risk-free rate of return on their investment. The third and fourth target returns were set 8% and 12% respectively.

Similarly, Kroencke and Schindler (2010) used four different target return rates in their analysis. First, they used a target return of zero to capture the situation where at least the nominal preservation of capital is considered the investment goal. They also used the average return on an equally weighted portfolio as the target return rate. The third benchmark they used is the risk-free rate of return, specifically the 3-month US Treasury Bill rate. Finally, they use the US inflation rate, measured by the US consumer price index. They noted that the four thresholds that they use are just a selection from a wide range of feasible reference points that investors may use.

In this thesis, I have used as target returns selected inflation and risk-free interest rates. Instead of imposing arbitrary target returns higher aimed at obtaining returns that are higher than the inflation or risk-free rates, I have employed the use of two risk-adjusted measures, namely, the Sharpe and Sortino ratios. I believe this would result in more optimal portfolios than simply setting absolute target returns. The problem with setting absolute return targets is that tend to be too high or too low and so may need to be changed regularly. The OECD survey on pension regulations has shown that countries such as Switzerland which used to have absolute minimum return requirements have moved to the use of relative benchmarks. Both the Sortino ratio and Sharpe ratio have been found to give be consistent with the utility or preference functions of investors. Platinga and Groot (2002) studied the link between performance measures and utility functions. They compared the rankings obtained based on 6 different measures of risk-adjusted returns and three different preference functions. The risk-adjusted return measures they examined were the Sharpe ratio, the Sortino ratio, Sharpe's alpha, Foust Index and Upside Potential ratios. The preference functions are the quadratic utility function, power utility function and the prospect theory value function. They found that the Sharpe ratio, Sharpe's alpha and expected return correspond with the preferences of investors with a low level of risk aversion whereas the Sortino ratio, Fause Index and Upside potential correspond with the preferences of investors with intermediate to high risk aversion. Similarly, Cerny (2003) found that the Sharpe ratio has a close relationship with investors' quadratic utility function.

8.1.2.2 Semi-Variance

Semivariance as a special case of downside risk measurement has received a lot of support of all the various measures of downside risk. Ballestero (2005) defines semi-variance as the weighted sum of squared deviations from a certain threshold, considering only those returns that fall below this threshold. Markowitz (1959, 1970) contended that since investors are often more concerned with downside risk than overall volatility, using semi-variance as a measure of risk rather than variance leads to better portfolios. Markowitz (1970) showed that the mean-variance and mean-semivariance models can produce the same results when the returns are normally distributed. However, when this is not the case, the semivariance model produces better optimal solutions.

Roy (1952) was one of the first to discuss the idea of downside risk as it relates to portfolio selection. He uses the concept of 'safety-first' where an investor measures the probability of his investment value falling short of a given disaster level. In particular, he posits that investors will prefer the safety of their principal first anytime they are faced with uncertainty. Markowitz (1959) presented the semivariance as an alternative to the variance which could lead to the construction of better portfolios but did not apply it in his study due to the computational complexity of implementing downside risk models at the time. Markowitz (1970) found that if returns were normally distributed, both the variance and semivariance would produce the same allocation. However, if returns are not normally distributed, the semivariance is more likely to produce a better solution.

Hogan and Warren (1972) proved the convexity and differentiability of mean-semivariance models. Their analysis showed the theoretical and computational viability of downside risk models. Fishburn (1977) used a utility function to model downside risk based on investors' risk-aversion level and target returns. Bawa (1978) generalised the model of Fishburn (1977) to an nth order 'safety-first' rule. Tse et al. (1993) applied the safety-first idea of Fishburn (1977) in a dynamic structure. Since the early 1990's, the actual application of downside risk measures to the portfolio optimisation problems. Sortino and Meer (1991) proposed a downside deviation and a reward-to-downside variability ratio (Sortino ratio) as tools that could be applied in the selection of optimal portfolios. Balzer (1994) discussed the issue of skewness in asset return data and issues relating to the application of downside variance. Merriken (1994) proved that semivariance could be applied to different hedging policies. Other studies that have used semi-variance in the context of portfolio allocation include Nawrocki (1999), Kroencke and Schindler (2010), Boasson et al. (2011) and Cumova and Nawrocki (2011).

Boasson et al. (2011) found the use of semivariance for the measurement of risk to be consistent with the intuitive perception of risk of investors who aim to measure the downside risk of their investment. Optimisation using this approach is most suitable for institutional investors such as pension funds and life insurance companies who aim to minimise downside risk. Boassen et al. (2011) compared and tested the differences between the minimum semivariance approach to portfolio allocation and the traditional mean-variance approach. They found that the mean semivariance approach produced portfolios that were quite different from the mean-variance approach. The mean semivariance approach produced returns that at least helps maintain and even improve the expected returns of a portfolio.

The use of semi-variance for the construction of real estate portfolios has been undertaken by studies such as Sivitanides (1998), Sing and Ong (2000), Cheng and Wolverton (2001). In comparing mean-variance and downside risk, Sivitanides (1998) and Sing and Ong (2000) analysed which of the two models produced less risky portfolios given a certain expected return. Cheng and Wolverton (2001) commented that the approach adopted by, Sivitanides (1998) and Sing and Ong (2000) were flawed as both approaches use different risk measures. Whiles the mean-variance approach focuses on the variance, downside risk portfolios use the semi-variance. Consequently, each approach would be inferior when judged from the perspective of the other. Cheng (2001) believes a common dimension that could be used to determine which approach is produced better portfolios is the expected return and terminal wealth of the terminal portfolios. Cheng (2001) used bootstrap simulations to compare the performance and return distribution of the traditional mean-variance analysis and downside risk approach to construct portfolios that included direct real estate. They found that the allocations suggested for direct real estate by the downside optimisation model was closer to allocations observed in practice for institutional investors such as pension funds. Furthermore, they found that the return distribution of the downside portfolio tended to be negatively skewed with a smaller left tail. The median of semi-variance portfolios were also found to be higher than those obtained within mean-variance portfolios. They concluded that downside risk models lead to better portfolios than mean-variance portfolios. Cheng (2001)'s approach was based on Nawrocki (1991) who compared the performance of mean-variance portfolios and downside risk portfolios using common stock data.

8.1.2.3 Value at Risk

Another measure of downside risk that has received significant attention within the finance literature especially following the recent financial crisis is the value-at-risk (VAR) measure and its counterpart, the conditional value-at-risk (CVAR). Value at risk (VaR) is a measure of risk which provides an estimate of the amount of loss that could be expected over a given time horizon with a given level of confidence. VaR therefore reflects the potential downside risk that an investment faces in nominal terms (Jorion, 2006). VaR's appeal lies in the fact that it is easy to understand and is widely used by regulators especially within the banking industry. The results that are produced by VaR models are easily understood by staff from all areas of an organisation (Bohdalova, 2007).

Although intuitively appealing, VaR models have some theoretical and practical limitations that most asset allocators and portfolio managers believe limit their usefulness in the construction of investment portfolios (Arztner et al., 1999; Szego, 2004; Zhang and Rachev, 2004; Sereda et al., 2010). Sereda et al. (2010) found that most institutional investors use VaR only when required by regulators or when they wish to present a measure of risk that is simple for clients to interpret.

Unlike risk measures such as variance and semi-variance, there is no standard approach for calculating VaR. Several VaR models and implementation techniques have been applied in the estimation of risk. These models have been found to produce varied estimates of risk for similar or even the same portfolio (Bohdalova, 2007; Guldimann, 1995; Dowd et al, 2004).

Value at risk as a measure of risk has been found to not be coherent due to its violation of the sub-additivity property required of good risk measures. Combining several assets in a portfolio could result in a combined VaR level that is higher than the sum of individual asset VaRs. This means that the value at risk model inherently discourages diversification. (Arztner et al., 1999; Danielson et al., 2005).

VaR has been shown to be ill-behaved as a function of portfolio positions and tends to exhibit multiple local extrema. This tends to be a major handicap when VaR models are used to determine the optimal mix of assets to be included in an investment portfolio (McKay and Keefer, 1996; Mauser and Rosen, 1999). Longin (2005) suggests using VaR primarily when one is interested in extreme events.

Value-at-risk is also an incomplete measure of risk as it cannot give any information regarding the amount of losses that would be incurred once the VaR limit is exceeded. In other words, VaR ignores extreme events that fall below the specified quantile. This limitation of VaR is remedied by CVaR models which measure the extent of losses that would be incurred beyond the VaR limit. It also captures the probability of those losses occurring. However, Boassen et al. (2011) note that within an optimisation framework, the use of CVaR requires an assumption regarding the return distribution or a large amount of return observations that fall below the target return. This naturally presents a problem when using real world data, unless simulation techniques are used. For a sample of 100 return observations, a 99% CVaR would be based on only 1 observation only. The analysis in this thesis is based on historical data. Consequently, the use of CVaR would be problematic. The sample size would be reduced even further when we carry out the rolling window analysis that is subsequently use for our out-of-sample analysis. Both VaR and CVaR require an investor to specify a probability level and cumulative losses (Weiner, 1998). The investor also has to specify an investment horizon, mostly a short-term one, ranging from 1 to 10 days. This makes VaR and CVaR models unsuitable for long-term investors. Campbell et al (2001) show that the longer the time period, the less efficient and precise is the VAR frontier. Alexander and Batista (2002) found that mean-VaR optimisations do not improve upon the optimisation in MVA models. On the contrary, mean-VaR models resulted in more volatile portfolios. In applying VaR models to a portfolio context, the objective function is often to maximise expected returns given a VaR or CVaR. The goal is to directly control the asymmetric distribution of residual errors, and for constraining one of its tail means to not exceed some pre-specified value.

Although a few studies have applied VaR and CVaR in the construction of investment portfolios, within the specific context of inflation hedging, no study has to our knowledge applied value at risk models. By far the most popular investment objective when it comes to constructing inflation-hedging portfolios is the minimisation tracking error minimisation and/or the semi-variance of tracking error (Consequently, while we acknowledge the intuitive appeal of VaR models, they are not selected for the analysis in this chapter.

8.1.3 BENCHMARK RELATIVE RISK-ADJUSTED RETURNS

Modern Portfolio Theory started with the seminal work of Professor Harry Markowitz of the University of Chicago in 1952. Markowitz was the first to quantify risk and also provide a framework that demonstrated that diversification could work to reduce risk and also enhance investors' returns. The work of Markowitz has underpinned by financial economics, probability and statistical theory. Markowitz's work, published in the Journal of Finance in 1952, demonstrated how investors can combine assets efficiently into diversified portfolio by correctly accounting for the risk and returns of the asset as well as the correlation between the individual assets (Lettau et al., 2002). The mean-variance optimisation model of Markowitz (1952) still remains the most standard and widely used portfolio optimisation tool in the investment industry today (Boasson et al., 2011).

The Sharpe ratio was first introduced by Sharpe (1966) as a measure for comparing mutual fund performance. The measure was originally christened the 'reward-to-variability' ratio. The Sharpe ratio is based on the idea that investors should be compensated with additional returns for investing in assets other than Treasury securities. The additional return that an investor earns over and above the risk-free rate is known as the excess return (Feibel, 2003). Although the return on there is a general consensus among investment professionals and academics that the return on government securities ought to be used, there is no consensus as to whether long-term or short-term government security rates. Whiles academic studies favour short-term Treasury bill rates, most practitioners prefer using short term rates as they are less volatile and are consistent with the goal of estimating long-term required rate of return (Hirt and Block, 2004; Cornell et al, 1997). The Sharpe ratio shows whether higher returns from an investment are enough to compensate the investor for the level of additional risk taken or whether decreases in volatility is enough to make up for decreases in portfolio returns (Schnesweis et al., 2010). The Sharpe ratio has been described by several authors as the best gauge of how successfully an investment manager balances the goal of return maximization and minimizing the volatility in their portfolios. For their contribution to investment management industry, Harry Markowitz, William Sharpe and Merton Miller were jointly awarded the Nobel Prize in 1990.

Although the Sharpe ratio is the most commonly used measure of risk-adjusted return, it has undergone several refinements over the past fifty years. McLeod and Vuuren (2004) believes that the several refinements that the Sharpe ratio has undergone in itself is proof of how significant this ratio is.

Perhaps the most widely known modification to the Sharpe ratio is the Sortino ratio (Fiebel, 2003). The Sortino ratio is a modification of the Sharpe ratio which uses downside risk as its denominator and a target rate of return in place of the hurdle (risk-free) rate. This measure is credited to Dr. Frank Sortino and his colleagues at the Pension Research Institute of the San Francisco State University. The expanded risk/return paradigm developed at the Pension Research Institute has come to be known as Post-Modern Portfolio Theory. The methods provide a framework that considers investors preferences for upside volatility over downside risk. Downside risk is defined in terms of target semi-variance or semi-deviation. Post-modern portfolio theory suggests that all moments of return distribution (mean, standard deviation, skewness and kurtosis) have to be taken into account in the construction of investment portfolios. Although the idea of downside risk measurement was popularised by Sortino and Van de Meer 1991, Roy (1952) was the first to discuss the idea. Roy (1952) used the concept of 'safety-first' where an investors measure the probability of his investment value falling short of a given disaster level. Roy (1952) posits that investors will prefer the safety of their principal first anytime they are faced with uncertainty.

8.2 OPTIMISATION APPROACH

In order to model the preferences of an investor interested in seeking protection from inflation, we use an extension of Markowitz (1952) mean-variance model with an objective function related to inflation and inflation rate changes. Per Bruno & Chincarini (2011), the model maximises real return subject to minimising the nominal deviation from the inflation or interest rate benchmark:

$$\min\left[V\left(r_{P,t,t+k}-\pi_{t,t+k}\right)\right] \qquad \textbf{8(1)}$$

s.t. $r_{P,t,t+k}-\pi_{t,t+k}=\tilde{\mu}_P$

where:

$r_{P,t,t+k}$ is the return on the portfolio from time t to $t+k$

$\pi_{t,t+k}$ is the inflation or interest rate being hedged against from time t to $t+k$

Since the objective is to select a group of assets for the investor that achieves this goal, the problem can be re-written as:

$$\min\left[V\left(\sum_{i=1}^{N} w_{i,t}r_{i,t,t+k}-\pi_{t,t+k}\right)\right] \qquad \textbf{8(2)}$$

$$\text{s.t}\ \left(\sum_{i=1}^{N} w_{i,t}r_{i,t,t+k}-\pi_{t,t+k}\right)=\tilde{\mu}_P \qquad \textbf{8(3)}$$

The above can be written in matrix notation as:

$$\min_{w} w'\Sigma w-2w'\gamma \qquad \textbf{8(4)}$$

s.t. $w'\mu=\tilde{\mu}_P+\pi_{t,t+k}$

Where γ is an N-dimensional vector of the covariances between individual asset returns and the liability benchmark returns over the horizon from t to t+k, Σ is the variance-covariance matrix of returns of the asset classes and the returns of the liability benchmarks and w represents the weights of the portfolio of asset classes.

$$\gamma=\begin{bmatrix} C\left(r_1,\pi_{t,t+k}\right) \\ \vdots \\ C\left(r_N,\pi_{t,t+k}\right) \end{bmatrix} \qquad \textbf{8(5)}$$

Constraints are added to prohibit short selling of asset classes by setting asset weights equal to or greater than zero (0) and also that the portfolio weights sum to one.

Bruno & Chincarini (2011) again suggest an alternative model to more accurately specify an investor's optimisation problem in terms of minimising downside risk, rather than variance:

$$\min_{w_i} \frac{1}{T} \sum_{j=1}^{T} \left[\min \left(\sum_{i=1}^{N} w_{i,t}\, r_{i,t,t+k} - \pi_{t,t+k},\ 0 \right)^2 \right] \quad \mathbf{8(6)}$$

s.t. $\left(\sum_{i=1}^{N} w_{i,t} r_{i,t,t+k} - \pi_{t,t+k}\right) = \tilde{\mu}_p$

We do not only limit our optimisations to DC funds who only desire to preserve their capital but also those who aim to achieve returns in excess the inflation and interest rate benchmarks they have adopted. One of the ways of accounting for the need to earn a premium in excess of inflation is to increase the target return beyond the inflation rate as done in Koniarski and Sebastian (2015). Another approach is to maximise risk-adjusted returns. Risk-adjusted measures are motivated by the belief that investors are risk-averse and would consequently want to be compensated for every unit of risk they are exposed to (Platinga and Groot, 2002). Consequently, we use two of the most important measures of risk-adjusted performance measures – the Sharpe ratio and Sortino ratios. The Sortino ratio is similar to the Sharpe ratio but uses the downside semivariance thereby penalizing only returns that fall below a certain user-specified rate.

In this study, we also explore two measures of risk-adjusted returns – a generalised Sharpe ratio and Sortino ratios. As indicated by Arzac and Bawa (1977) deriving a measure such as the Sharpe ratio gives portfolio managers a tool which they can use to evaluate the efficiency of several candidate portfolios. Amenc et al. (2010) hold that the maximization of risk-adjusted returns is fully consistent with financial theory. The CFA Institute's Global Investment Performance Standards (2012) requires that firms present at least one composite-level measure of performance. Among the measures proposed are the beta coefficient, tracking error, modified duration, information ratio, Sharpe ratio, Treynor ratio, value at risk (VaR), volatility and credit ratings.

The Sortino ratio and Sharpe ratio which we employ in this study have been found to be consistent with the utility or preference functions of investors. For example, Platinga and Groot (2002) studied the link between performance measures and utility functions. They compared the rankings obtained based on 6 different measures of risk-adjusted returns and three different preference functions. The risk-adjusted return measures they examined were the Sharpe ratio, the Sortino ratio, Sharpe's alpha, Foust Index and Upside Potential ratios. The preference functions are the quadratic utility function, power utility function and the prospect theory value function. They found that the Sharpe ratio, Sharpe's alpha and expected return correspond with the preferences of investors with a low level of risk aversion whereas the Sortino ratio, Fause Index and Upside potential correspond with the preferences of investors with intermediate to high risk aversion. Similarly, Cerny (2003) showed that the Sharpe ratio is closely related to an investor's quadratic function. Ogunc and Ogunc (2016) explored the objective of maximising the Sharpe ratio in determining the role of Treasury inflation protected securities (TIPS) within portfolios constructed to offer inflation protection.

In this study, we use a generalised form of the Sharpe ratio where the risk-free rate is replaced with the selected inflation and interest rate benchmarks:

$$\text{Shape ratio}=\frac{E\left[r_{P,t,t+k}-\pi_{t,t+k}\right]}{\sigma\left[r_{P,t,t+k}-\pi_{t,t+k}\right]} \qquad \mathbf{8(7)}$$

where σ_p is the portfolio standard deviation.

Similarly, a generalised Sortino ratio is used. The target return is replaced with the returns on the selected inflation and interest rate benchmarks:

$$\text{Sortino Ratio}=\frac{E\left[r_{P,t,t+k}-\pi_{t,t+k}\right]}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(r_{P,t,t+k}-\pi_{t,t+k}\right)^{2}f(t)}} \qquad \mathbf{8(8)}$$

$f(t)=1$ if return < target return

$f(t)=0$ if return $\geq$ target return

In-sample portfolios are estimated from the first quarter of 1991 to the first quarter of 2015 for which we have data available for all the 32 variables. The out of sample portfolios are estimated from the beginning of 1991 plus five additional years. This estimate is used to construct portfolios for the next quarter. The window is then expanded forward by a quarter and a new portfolio re-estimated. This process is repeated until the first quarter of 2015. Quarterly rebalancing is possible as almost all the asset sectors included are liquid, except for real estate. However, the use of a hybrid real estate for example makes it easier for DC pension funds to rebalance their real estate holdings more frequently without significant costs. A quarterly rebalancing period is also consistent with the practice among pension funds (Blake et al., 2009; Ibbotson and Kaplan, 2000; Bams et al., 2016; De Jong and Driessen, 2013).

In this study, we convert the returns of all the non-UK asset returns into GB£ terms. Moss & Farrelly (2015) found that unhedged GBP-based performance matrices for various assets that they examined in their study were closely related. Also, currency risk was found to be neutral over the sample period.

Risk and return improved slightly for a UK investor whose when returns were estimated in GBP rather than US$ terms.

8.3 RESULTS

The analysis in this chapter is in three parts. We first determine the optimal mix of assets within the various inflation and interest rate hedging portfolios. The risk and return metrics of the various portfolios are also analysed. The second part investigates whether direct real estate can improve the inflation hedging ability of portfolios designed to act as a hedge against the selected inflation and interest rate benchmarks. To demonstrate the role of real estate within these inflation and interest rate hedging portfolios, we run the analysis with and without direct real estate. In the third part, we determine whether the specific real estate investment vehicle used affects the allocation to direct real estate within the various inflation and interest rate hedging portfolios and the subsequent performance of these portfolios. We run the simulations using three real estate return series – the AREF IPD unlisted funds index, the IPD UK direct real estate index and a hybrid real estate index. As mentioned earlier, the AREF IPD unlisted fund index represents the returns that accrue to investors net of fees. The hybrid real estate index is constructed by blending the AREF IPD real estate fund series and a listed real estate index in the ratio 80:20. This is similar to the approach used by Legal and General, the largest DC pension fund in the UK. This approach is also used by empirical studies such as NAREIT (2011), Farrelly and Moss (2014) and Lee (2014). The effective exposure to real estate then is the sum of both listed and unlisted real estate allocations. Consequently, where a mix of direct and listed real estate is used, we drop listed real estate from the asset universe. As an additional robustness check, we also run the analysis using an unsmoothed IPD UK direct real estate series. One of the issues raised about the use of appraisal based real estate indices is whether a smoothing bias exists and how to deal with this bias. Researchers are divided as to whether such as bias exists and also whether there is an appropriate way to deal with this bias (Cheng, 2001).

8.3.1 DESCRIPTIVE STATISTICS

Table 8(I) presents the summary statistics for the assets included in this study as well as the selected inflation and interest rate benchmarks. Technology stocks have the highest mean return of 4.5% per quarter whiles gold has the lowest average return of 1.22% per quarter. These two rates therefore represent the range of achievable portfolio returns. Commensurate with the high returns technology stocks provide, they also had the highest standard deviation along with oil. Short-term bonds recorded the lowest volatility of all the selected assets. For the 1990 – 2006 sample period however, venture capital recorded the highest expected return, followed by bank stocks. Technology stocks still had the highest standard deviation of 24.45% for the 1990 – 2006 sample period while gold still recorded the lowest average return of 1.09%.

Within the context of inflation hedging or index tracking in general, the preferred measure of risk is the tracking error relative to a selected benchmark. Short-term bonds exhibit the smallest tracking error relative to all the selected inflation and interest rates. Technology stocks, which recorded the highest expected return also had the highest tracking error relative to each inflation and interest rate benchmark. Another measure of the interdependence between asset returns and the returns on a selected benchmark is the correlation coefficient between the two series. Short-term bonds had the highest correlation relative to both interest rates. Oil had the highest correlation with RPI inflation while stocks (basic materials in particular) were the most highly correlated with CPI inflation.

The skewness of the return distribution of the various return series is also of interest in this chapter. A skewness value of less than -1 or greater than 1 shows that there is significant asymmetric distribution. Positive skewness implies that the distribution is skewed to the right with a small right tail. This is representative of higher downside risk. A negative value for skewness is indicative of a left skew with a small left tail and is representative of lower downside risk. As can be seen in Appendix 7(A) almost all the stock and bond sectors are symmetrically distributed. Of the four real estate return series, the unsmoothed IPD series and listed real estate series are found to be symmetrically distributed. The IPD all property portfolio returns and AREF unlisted fund series as well as the blended real estate series exhibited a negative skew. This implies that real estate assets would generally exhibit lower downside risk. The only stock series that exhibited a positive skew is technology stock. This implies that technology stocks exhibit higher downside risk. Of the various alternative assets, we found that hedge fund and US venture capital were skewed in opposite directions. Whiles hedge fund series were negatively skewed, venture capital exhibited significant positive skewness.

Table 8(I): Descriptive Statistics (1990 – 2015)

	MEAN	STD. DEV	TRACKING ERROR				CORRELATION			
			CPI	RPI	LIBOR	TBILL	CPI	RPI	LIBOR	TBILL
Real Estate										
AREF Real Estate Funds	1.78	3.13	3.28	3.08	3.28	3.31	-0.12	0.19	-0.12	-0.16
Blended/Hybrid real estate	1.95	4.16	4.22	4.07	4.27	4.29	-0.06	0.18	-0.11	-0.13
IPD All Property	2.09	3.17	3.28	3.09	3.33	3.36	-0.09	0.21	-0.15	-0.19
Unsmoothed IPD All Property	2.19	5.33	5.34	5.27	5.43	5.45	0.01	0.12	-0.13	-0.15
Listed real estate	2.64	11.68	11.68	11.63	11.75	11.75	0.04	0.11	-0.07	-0.07
Stocks:										
Oil and gas	2.74	9.07	9.04	9.06	9.05	9.08	0.08	0.04	0.06	0.02
Basic materials	2.95	13.07	12.91	12.88	13.06	13.09	0.27	0.31	0.05	0.01
Industrials	3.29	10.86	10.79	10.80	10.87	10.88	0.14	0.11	0.01	0.00
Construction	2.8	10.41	10.30	10.33	10.45	10.45	0.19	0.15	-0.02	-0.03
Industrial goods and services	2.91	9.51	9.43	9.43	9.52	9.53	0.17	0.15	0.03	0.02
Consumer goods	3.71	10.63	10.51	10.58	10.62	10.63	0.22	0.11	0.05	0.04
Health care	2.88	7.17	7.15	7.29	7.14	7.12	0.08	-0.12	0.10	0.12
Consumer services	2.55	8.75	8.73	8.74	8.76	8.76	0.07	0.05	0.02	0.02
Telecommunications	3.12	12.57	12.59	12.60	12.54	12.55	0.01	-0.01	0.07	0.06
Technology	4.5	20.82	20.86	20.78	20.82	20.84	-0.04	0.08	0.02	-0.01
Utilities	3.47	7.11	7.12	7.13	7.03	7.02	0.03	0.02	0.16	0.18
Banks	3.44	13.75	13.75	13.74	13.68	13.67	0.03	0.05	0.13	0.15
Insurance	3.07	11.54	11.55	11.56	11.56	11.55	0.02	0.00	0.00	0.01
Financial Services	3.26	10.34	10.32	10.26	10.37	10.39	0.06	0.15	-0.02	-0.04
Bonds:										
10+ year bonds	2.41	4.49	4.58	4.75	4.46	4.44	-0.06	-0.32	0.13	0.15
10 year bonds	2.19	3.68	3.73	3.93	3.62	3.60	0.01	-0.28	0.18	0.21
7 year bonds	2.04	2.91	2.95	3.15	2.83	2.80	0.06	-0.26	0.23	0.28
5 year bonds	1.79	2.39	2.44	2.65	2.31	2.27	0.06	-0.26	0.25	0.31
3 year bonds	1.63	1.62	1.69	1.92	1.49	1.44	0.09	-0.29	0.40	0.45
2 year bonds	1.44	1.3	1.40	1.63	1.10	1.04	0.10	-0.29	0.53	0.60
Alternatives:										
Emerging market stocks	2.94	14.22	14.16	14.09	14.26	14.29	0.12	0.22	-0.03	-0.08
Developed market stocks	2.29	9.67	9.63	9.51	9.70	9.74	0.09	0.26	-0.02	-0.07
Commodities - Oil	2.18	18.27	18.24	18.02	18.24	18.28	0.06	0.39	0.07	0.01
Commodities - Gold	1.22	8.31	8.27	8.17	8.42	8.46	0.11	0.24	-0.12	-0.17
Hedge fund	1.57	6.11	6.09	5.95	6.10	6.16	0.08	0.29	0.07	-0.01
US private equity	3.58	7.67	7.62	7.52	7.72	7.77	0.12	0.27	-0.02	-0.09
US venture capital	4.26	12.54	12.54	12.48	12.50	12.54	0.02	0.12	0.09	0.03
Developed ex-US private equity	3.64	11	10.95	10.82	11.01	11.06	0.10	0.29	0.01	-0.06
Emerging market private equity	1.81	8.36	8.31	8.23	8.49	8.53	0.12	0.22	-0.14	-0.21

Note: Tracking error = Tracking error between asset and inflation/interest rate measure; CPI = UK Consumer Price Index; RPI = UK Retail Price index; LIBOR = LIBOR interest rate; TBILL = 3-month Treasury bill interest rate

8.3.2 IN-SAMPLE PORTFOLIO COMPOSITION

We estimated two sets of in-sample portfolios. The first in-sample portfolio weights were estimated using data from the first quarter of 1991 to the first quarter of 2015 and the second using data from 1991 to 2006. This is done to isolate the effect of the last financial crisis (2007-2008) on the optimal composition of inflation and interest rate hedging portfolios.

It is clear that the investment objective has a far greater impact on the allocation to the various assets than the specific inflation or interest rate benchmark being hedged against. The differences in allocation between the two interest rates – T-bill and LIBOR rates was found to be very small compared to the differences in allocation within the two inflation hedging portfolios. The time period analysed also had a significant impact on the suggested allocation to the various assets. In other words, the most significant influences on the allocation to various assets were the investment objective, time frame analysed and the type of benchmark (inflation or interest rate). The actual inflation or interest rate i.e. CPI vs RPI or T-bill vs LIBOR were not found to be significant in determining the portfolio composition.

We found that Real estate received significant allocations within all the portfolios prior to 2006. However, when the analysis period was extended to 2015, the allocation to real estate fell sharply. This happens irrespective of the model used and is in contrast to what we observed for bond allocations. For example, the average allocation to direct real estate within mean-tracking error portfolios ranged from 16 to 28%. Once the analysis period was extended to cover the entire 1990 – 2015 sample period, real estate allocations fell to a range of 10 to 18%.

A comparison of the allocations for the two sample periods (1991-2006 and 1991 – 2015) reveals that bonds have become more prominent in the various inflation/interest rate hedging portfolios. For example, bonds received an allocation ranging from 22% to 24% in Sortino ratio portfolios prior to 2006, this however jumped to between 71% and 72% when the entire 1990 – 2015 sample period was analysed. Bonds were found to dominate portfolios that use tracking error as the risk measure but not those that use semi-deviation of tracking error.

The analysis also shows that stocks tend to receive higher allocations when downside risk measures are used. For example, stocks received very little allocations within mean-tracking error and Sharpe ratio portfolios. Stocks however received significant allocation within semi-variance and Sortino ratio portfolios. The Sortino ratio portfolios suggest an allocation of 19 to 20% for the 1990 – 2006 sample period and 13 – 14% for the entire sample period.

Likewise alternative assets only received significant allocations within downside risk portfolios and not within tracking error portfolios. The mean tracking error model for example suggested an allocation of 3% to 5% to alternative assets irrespective of the time period analysed. The highest allocation for alternative assets was within the Sortino maximising portfolio which suggested an allocation of 23% to 24% for the 1990 – 2006 sample period.

8.3.3 OUT-OF-SAMPLE PORTFOLIO COMPOSITION

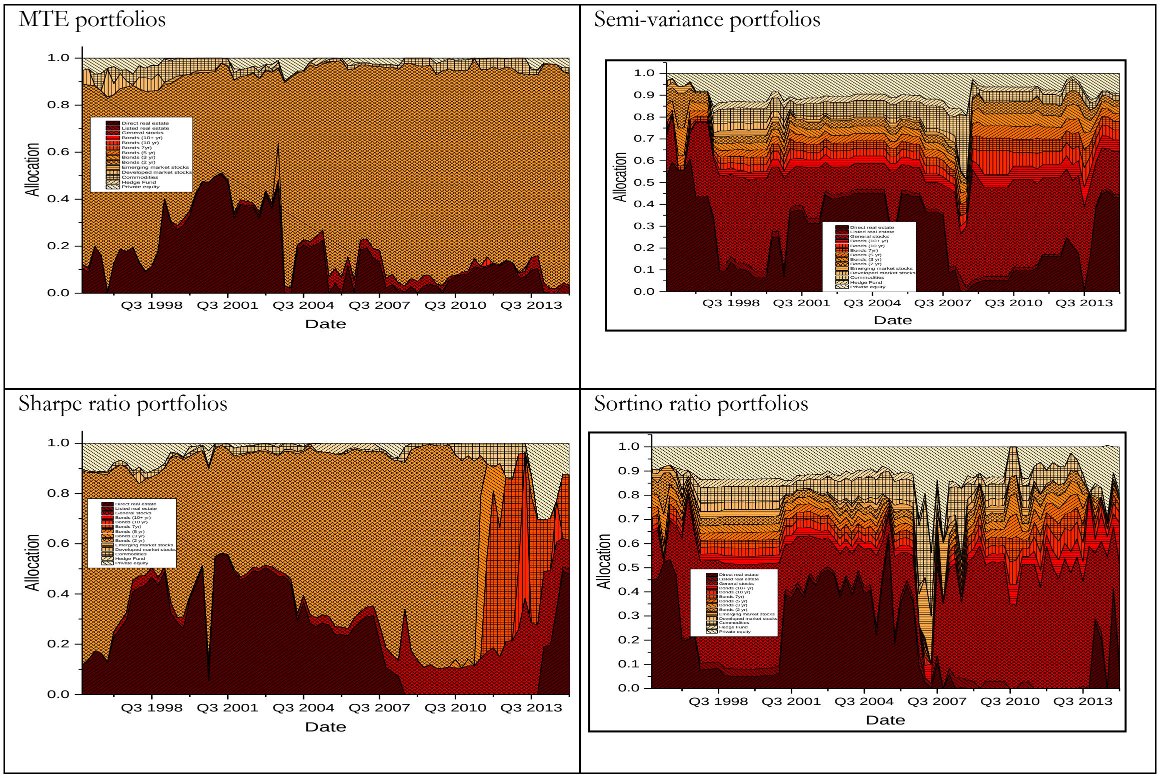
As observed in-sample, bonds still dominated the allocations within the various inflation and interest rate hedging portfolios especially within portfolios based on tracking error variance. Bonds received an average allocation of 47% within mean-tracking error and Sharpe ratio portfolios. The suggested allocation was as high as 77% for mean-tracking error portfolios hedged against T-bill interest rate. Bond allocations within portfolios based on semi-variance and Sortino ratio portfolios ranged from 19% to 51%.

Apart from bonds, real estate also received significant allocations across most of the models examined, receiving allocations that ranged from 16% to 34%. The mean tracking error and mean semi-variance models suggested an allocation of between 16% and 34% to direct real estate while the Sharpe and Sortino ratio portfolios suggest an allocation between 20% and 30% depending on the specific inflation/interest rate benchmark being hedged against.

Consistent with the results obtained in-sample, we observed that stocks received the biggest allocation of between 33% and 35% within Sortino ratio portfolios. However, mean-tracking error model allocates no more than 3% to stocks. An optimal stock allocation of between 16% and 27% is suggested by the mean-semi-variance model.

As with stocks, alternative assets received more allocation in the two downside risk portfolios (semi-variance and Sortino ratio portfolios). The allocation suggested by both downside risk portfolios ranged from 13% to 26% whiles mean-tracking error and Sharpe ratio portfolios allocated between 5% and 10% to alternative assets.

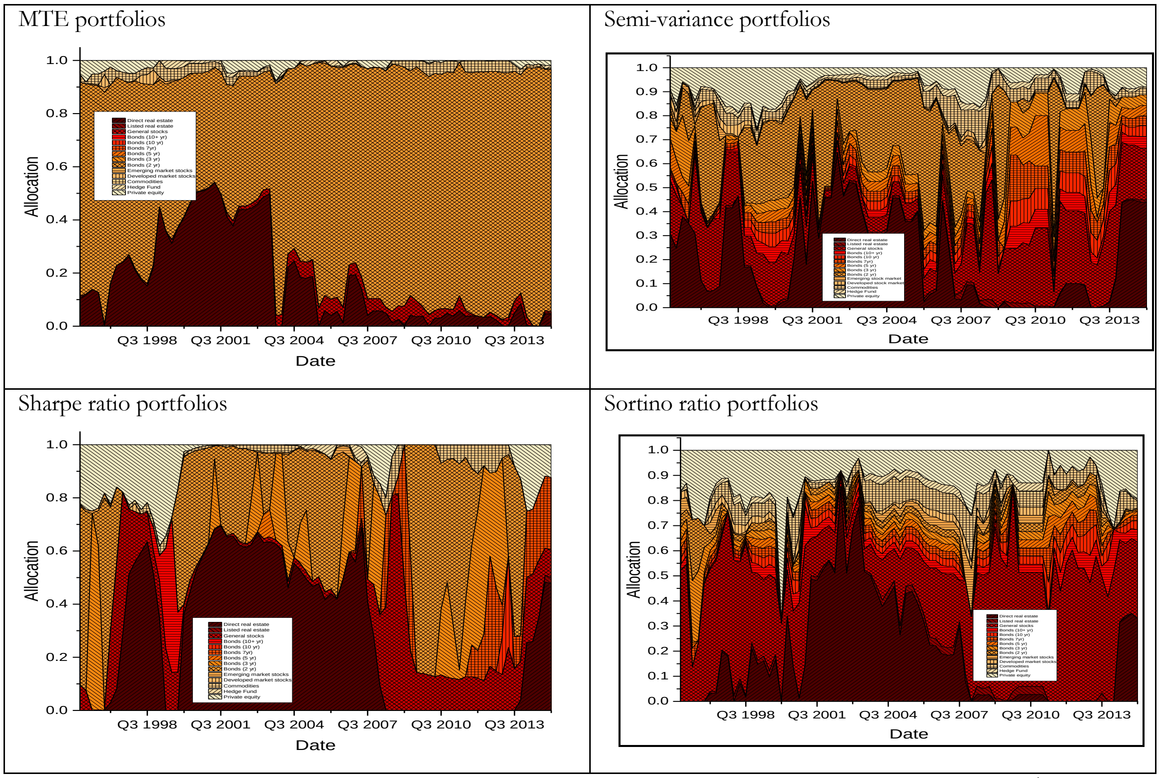
Figure 8(1): Inflation Hedging Portfolio (Consumer Price Inflation)



Looking at the pattern of allocations in Figure 8(1), we observe that the allocations within portfolios hedged against the two inflation rates tend to be remarkably similar to each other, so are the portfolios hedged against the two interest rates. A close inspection reveals some subtle differences, especially between the two inflation rate hedging portfolios. A comparison of the portfolios produced by the various optimisation models however show significant differences. An implication of this result is that the investment objective being pursued drives the pattern in allocation than the specific inflation or interest rate benchmark being hedged against. It is also clear from Figures 8(1) and 8(2) that portfolios based on downside risk produced more diversified portfolios than those based on tracking error variance. For example, two-year bonds dominate the mean-tracking error and Sharpe ratio portfolios which use the tracking error variance as the measure of risk. However, the allocations within mean-semi-variance and Sharpe ratio portfolios over time show a wider array of assets over time.

Real estate received significant allocations irrespective of the investment objective being pursued especially between 1995 and 2004 or in some cases, between 1995 and 2007. The allocation to real estate however falls sharply between 2007 and 2012 especially in the models that maximise risk-adjusted returns. This result also implies that real estate would continue to play a significant role in inflation and interest rate hedging portfolios, unless in periods where real estate returns shift from the fundamentals.

Figure 8(2): Interest Rate Hedging Portfolios (LIBOR)



Note: MTE = Portfolios constructed to minimise the tracking error between the portfolio returns and the selected inflation/interest rate; Semi-variance portfolios = Portfolios constructed to minimise the downside risk between portfolio returns and the selected inflation/interest rate; Sharpe ratio portfolios = Portfolios constructed to maximise risk adjusted returns; Sortino ratio portfolio = Portfolio constructed to maximise the risk-adjusted downside risk

8.3.4 OUT-OF-SAMPLE PORTFOLIO RISK AND RETURN

Table 8(II) shows that all the mean-tracking error and Sharpe ratio portfolios produced returns that were nearly symmetrically distributed. On the other hand, mean semi-variance and Sortino ratio portfolios produced returns that were negatively skewed. This is indicative of the fact that minimising the downside risk increases the negative skewness of the returns, implying lower downside risk. Our results are similar to Chen (2001) who also found the returns of semi-variance portfolios to be negatively skewed.

In terms of risk, mean tracking error models had the lowest standard deviation, commensurate with their low returns. The standard deviation of Sharpe ratio portfolios were lower than those of Sortino and Semi-variance portfolios. Interestingly however, we found that mean tracking error and Sharpe ratio portfolios produced lower semi-variance out-of-sample than mean semi-variance and Sortino ratio portfolios. We believe this is largely due to the fact that the portfolios based on downside were heavily invested in high-volatility assets such as stocks and alternative assets. This is also evidenced by their high average returns. Moreover, the analysis of the return distributions carried out earlier show that downside risk portfolios do indeed provide significant downside risk protection, evidenced by the significant negative skewness.

Table 8(II): Descriptive Statistics - Out-of-sample Portfolios

		CPI	RPI	LIBOR	TBILL
MTE	Average returns	1.44	1.48	1.44	1.42
	Standard deviation	1.01	1.11	0.98	0.96
	Median	1.40	1.42	1.46	1.35
	Maximum	4.06	4.36	3.70	3.51
	Minimum	-1.83	-1.76	-1.90	-1.92
	Skewness	-0.19	-0.49	-0.11	-0.52
	Kurtosis	3.73	3.67	3.36	3.66
	Jarque-Bera	2.15	4.50	0.56	4.91
	Probability	0.34	0.11	0.76	0.09
MSV	Average returns	2.33	2.49	2.06	1.79
	Standard deviation	4.54	3.62	3.06	3.56
	Median	2.62	2.86	2.27	1.85
	Maximum	12.06	10.59	8.97	8.36
	Minimum	-23.98	-12.11	-14.17	-22.79
	Skewness	-2.33	-1.77	-1.08	-4.09
	Kurtosis	15.81	12.03	6.24	30.31
	Jarque-Bera	595.99	301.65	48.61	2607.84
	Probability	0.00	0.00	0.00	0.00
Sharpe	Average returns	1.83	1.76	2.41	2.36
	Standard deviation	1.84	2.62	4.97	4.67
	Median	2.14	2.20	2.25	2.26
	Maximum	6.42	7.01	20.16	20.09
	Minimum	-6.87	-16.03	-20.59	-19.55
	Skewness	-1.60	-0.42	-4.07	-0.38
	Kurtosis	9.39	11.35	28.54	11.99
	Jarque-Bera	163.51	226.04	2305.02	261.17
	Probability	0.00	0.00	0.00	0.00
Sortino	Average returns	2.40	2.65	2.68	2.96
	Standard deviation	5.01	4.38	5.23	5.86
	Median	2.87	3.11	3.32	3.21
	Maximum	12.73	12.68	19.59	29.33
	Minimum	-23.43	-12.78	-15.22	-18.14
	Skewness	-1.72	-0.53	-0.44	0.66
	Kurtosis	10.70	4.57	5.45	9.22
	Jarque-Bera	228.18	11.47	21.79	129.82
	Probability	0.00	0.00	0.00	0.00

As expected, Sortino ratio portfolios produced the highest average return of the four models examined. These portfolios produced between 2.40% and 2.96% per quarter over the period examined. Mean-tracking-error portfolios produced the lowest expected return of between 1.42% and 1.48% depending on the inflation or interest rate benchmark being hedged against. Mean semi-variance portfolios produced returns that were greater than Sharpe ratio portfolios when inflation rates were being hedged against, but not when interest rates were being hedged against.

In order to determine how well the various inflation and interest rate hedging portfolios perform, we compared the returns of these portfolios first to the inflation/interest rate benchmark being hedged against. We also compared the returns of the optimised portfolios to a traditional 80-20 stock-bond allocation, which reflects the historical allocations within DC pension portfolios.

It is clear from the results from the return evolutions in Figure 8(3) that returns from the various inflation and interest rate hedging portfolios were always higher than the returns on the respective inflation/interest rate benchmarks. An implication of this result is that, over the long run, a DC fund that constructs its investment portfolios using any of the models employed in this study would be able to deliver cumulative minimum return rates that exceed the respective inflation or interest rate.

Apart from the mean-tracking error portfolio hedged against CPI inflation, all the other portfolios out-performed the traditional 80-20 stock-bond portfolio in terms of expected returns. Of the various optimised portfolios, mean-tracking error portfolios produced the lowest cumulative returns. Whiles an investment in 3-month Treasury bills at the beginning of 1991 would have yielded an ending value of £28,137 in 2015, a mean-tracking error portfolio hedged against T-bills would have grown to a slightly higher value of £28,754 over the same period. An investment in the Sortino ratio portfolio hedged against the T-bill rate over the same period would however have grown to £80,290.14.

As explained earlier, the relevant risk measure when a benchmark is being hedged against is the tracking error. From Appendix 8(Q) we see that in all cases, the tracking error of the various inflation hedging portfolios were lower than those observed for the 80-20 stock-bond portfolios. The same result is obtained when we measure risk in term the standard deviation of returns. Here again, for each benchmark, the standard deviation observed for the 80-20 portfolio exceeded the standard deviation of all the various inflation hedging and interest rate hedging portfolios.

The results also show that, although the composition of the various optimised portfolios did not change significantly when the specific inflation or interest rate is altered, we observed that, in terms of terminal value, there were some significant differences. For example, portfolios hedged against RPI inflation often provided higher terminal values than those hedged against CPI inflation. Similarly, LIBOR hedging portfolios also provided higher returns than T-bill hedging portfolios. For example, a £10,000 investment in the MTE portfolio hedged against CPI inflation at the start of 1991 would produce an ending value of £29,335 by 2015 whiles the same amount invested in the MTE portfolio hedged against RPI would have produced £30,030. If the same amounts were invested in Sortino ratio portfolios, the CPI hedging portfolio would produce £54,839 and the RPI portfolio would have an ending value of £67,902.

8.3.5 THE ROLE OF REAL ESTATE IN INFLATION/INTEREST RATE HEDGING PORTFOLIOS

In order to analyse the role that real estate plays within the various portfolios, we drop real estate from the opportunity set and re-run the optimisation models. The results of the analysis without real estate are compared to the earlier results that include real estate. The summary statistics of the various optimisations without real estate are shown in Table 8(III).

We can see from a comparison of Table 8(II) and Table 8(III) that across all portfolios and benchmarks, the portfolios containing direct real estate consistently had lower tracking errors relative to the benchmarks against which they are hedged. The standard deviation of the portfolios that include direct real estate were also lower than the standard deviation of the portfolios that do not include direct real estate

We however found that including direct real estate in inflation and interest rate hedging portfolios does not necessarily lead to improved returns. A return improvement is seen in mean-tracking error and mean semi-variance models. However, for their risk maximising counterparts, the Sharpe and Sortino maximising portfolios, including direct real estate led to a fall in returns in most cases. This is probably due to the fact that direct real estate mostly replaced bonds in the risk-minimising portfolios. Since direct real estate returns are higher than bond returns, this leads to an increase in returns in the returns of those portfolios. However, including direct real estate in Sharpe and Sortino maximising portfolios results in a fall in the allocation to high earning assets such as stocks and alternative assets, which contribute a significant part to the returns of these portfolios. Consequently, this places a drag on the returns of these portfolios.

Another issue which we seek to explore in this chapter is whether the real estate return series, and for that matter, the vehicle used to access the real estate market has an effect on the composition and performance of inflation hedging portfolios. We use four different real estate series to represent the different real estate vehicles: The AREF/IPF Unlisted fund index represents exposure to the real estate market through unlisted funds whiles the IPD All Property Index represents direct exposure to the real estate market. In addition to the actual IPD All Property Index, we use an unsmoothed IPD All

Property Index to account for the perceived appraisal smoothing associated with appraisal based return series. We also make use of a blended real estate consisting of 80% AREF/Unlisted fund and 20% listed real estate. This represents exposure to the direct real estate market through blended/hybrid real estate products such as those offered by Legal and General. A detailed discussion of these products is in Chapter 6.

A visual inspection that the portfolios constructed using the various real estate series did not reveal any obvious differences. However, when we compared the out-of-sample returns of the various optimised portfolios constructed using the different real estate vehicles, we observed that the returns of the portfolios constructed using the AREF/IPD unlisted fund return series to proxy real estate investments were remarkably similar to those of the IPD All Property Index return series. Similarly, the portfolios constructed using the blended/hybrid real estate return series also generated returns that were very similar to the returns of the unsmoothed IPD All Property Index series. This is possibly because the both the unsmoothing process and the addition of listed real estate to a direct real estate portfolio serve to induse some volatility in the real estate portfolios. A practical implication of this result is that using blended/hybrid property return series has the same or similar effect as unsmoothing the IPD All Property Index returns. These results are consistent with the results obtained by Baum (2006) who found that using direct real estate data or unlisted fund data did not result in significant differences in allocations. Significant differences were however found when listed real estate returns were instead used in portfolio optimisation models to gain access to real estate.

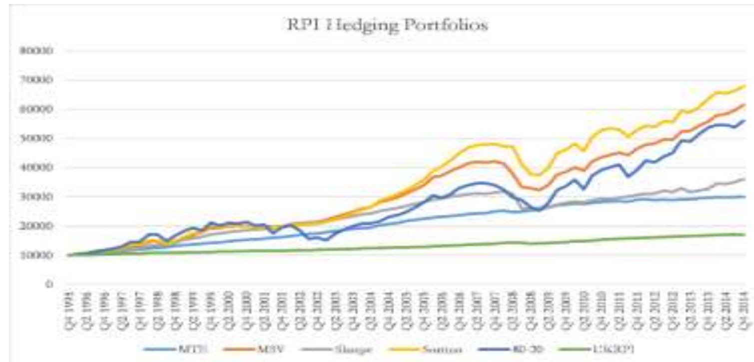
Table 8(III): Out-of-Sample Returns – Portfolios with no Direct Real Estate

		MTE	MSV	Sharpe	Sortino	80-20
CPI	Average returns	1.3266	2.5381	1.8645	2.5226	2.5484
	Index value	26783.99	60747.44	39495.08	59596.49	56118.53
	Tracking error	1.265	4.591	2.321	5.090	6.8262
	Standard deviation	1.103	4.665	2.280	5.124	6.8097
	Average excess returns	0.827	2.038	1.365	2.023	2.0484
	Semi-deviation	1.030	4.912	2.454	5.216	7.3188
	Sharpe ratio	0.653	0.444	0.588	0.397	0.3001
	Sortino	0.803	0.415	0.556	0.388	0.2799
	Maximum	4.256	11.287	10.591	15.163	16.9879
	Minimum	-1.819	-12.434	-6.874	-12.027	-15.9182
	Success ratio	0.740	0.714	0.818	0.701	0.6753
RPI	Average returns	1.309	2.267	1.843	2.950	2.5484
	Index value	26427.11	50350.45	38143.92	79341.56	56118.53
	Tracking error	1.3217	4.3377	3.1130	5.9346	6.7430
	Standard deviation	1.1945	4.3959	3.1354	5.9766	6.8097
	Average excess returns	0.8088	1.7666	1.3430	2.4499	1.8488
	Semi-deviation	1.1921	5.2597	4.3426	5.3526	7.1985
	Sharpe ratio	0.6119	0.4073	0.4314	0.4128	0.2742
	Sortino	0.6785	0.3359	0.3093	0.4577	0.2568
	Maximum	4.7305	11.2388	13.1992	28.8202	16.9879
	Minimum	-1.8196	-12.5204	-16.0324	-12.1753	-15.9182
	Success ratio	0.7532	0.7532	0.8052	0.7273	0.6623
LIBOR	Average returns	1.2821	1.9068	2.4207	3.0753	2.5484
	Index value	25933.0	40062.0	53978.0	87487.0	56118.53
	Tracking error	1.2114	3.2274	5.6779	5.8095	6.8310
	Standard deviation	1.0070	3.2645	5.6916	5.8473	6.8097
	Average excess returns	0.7821	1.4069	1.9207	2.5753	1.5914
	Semi-deviation	1.0772	3.5705	6.1989	5.6360	7.5148
	Sharpe ratio	0.6456	0.4359	0.3383	0.4433	0.2330
	Sortino	0.7261	0.3940	0.3099	0.4569	0.2118
	Maximum	3.8751	16.1575	26.3232	25.1349	16.9879
	Minimum	-1.9570	-10.6391	-20.5886	-16.9891	-15.9182
	Success ratio	0.7662	0.7792	0.7792	0.7143	0.6623
TBILL	Average returns	1.2860	1.8408	2.3833	3.2745	2.5484
	Index value	26006.0	37483.0	53074.0	95538.0	56118.53
	Tracking error	1.2285	3.7587	5.4408	7.0062	6.8461
	Standard deviation	1.0179	3.7820	5.4586	7.0472	6.8097
	Average excess returns	0.7860	1.3409	1.8834	2.7746	1.6393
	Semi-deviation	1.0722	5.1818	5.9074	7.2360	7.4975
	Sharpe ratio	0.6398	0.3567	0.3462	0.3960	0.2395
	Sortino	0.7331	0.2588	0.3188	0.3834	0.2186
	Maximum	3.6896	17.0284	26.3232	28.4204	16.9879
	Minimum	-1.9774	-19.3072	-19.5451	-27.3876	-15.9182
	Success ratio	0.7662	0.7922	0.7922	0.7143	0.6623

Figure 8(3): Out-of-sample returns

UK CPI

UK RPI



LIBOR

TBILL

Note: MTE = Mean- tracking error portfolio; MSV = Mean-semi-variance portfolio; Sharpe = Sharpe ratio portfolio; Sortino = Sortino ratio maximizing portfolio; UKCPI = UK Consumer Price Index; UK RPI = UK Retail Price Index; TBILL = 3 month Treasury bill rate

8.4 CONCLUSION

In this study, we have analysed the composition and performance of various portfolios constructed to provide returns that help to preserve the purchasing power of the pension pot of DC investors. The optimal allocation to real estate and other alternative assets as well as the allocation to stocks and bonds were also analysed. We proceeded to discuss the risk and return implications of the various inflation/interest rate hedging portfolios. We compared the risk and return features of the the various inflation/interest rate hedging portfolios to the risk and return features of a traditional stock-bond portfolio which invests 80% to stocks and 20% to bonds. In order to analyse the portfolio role of real estate, we initially run all the analysis with real estate and then re-run our analysis without direct real estate. Building on the preceding chapters, the chapter also explores how the choice of real estate vehicle affects the allocation and performance of the resulting portfolios. Four real estate return series representing different real estate vehicles are used in our analysis: the AREF/IPF Unlisted fund index, the IPD UK All Property index (actual), an unsmoothed IPD UK All Property Index and a blended/hybrid real estate index. Here, we find that the optimisation Results obtained from using the IPD series are quite similar to those obtained when the AREF balanced fund series was used. Similarly, a 70:30 hybrid real estate series produced results identical to an unsmoothed real estate series. A practical implication of this result is that, as with using unsmoothed real estate returns in portfolio construction, using the returns of a hybrid/blended real estate series could potentially help avoid the issue of over-allocation to real estate within portfolios. This approach may be more practical for investors as the blended/hybrid portfolios are investible and hence the risk and returns are likewise realisable.

On the whole, we find that the optimisation (investment) objective being pursued is has is of more significance than the specific inflation or interest rate benchmark being hedged against. In the UK case, we find that once a DC pension scheme decides on whether to hedge against inflation or hedge against a risk-free rate, it does not appear to matter whether the specific inflation or risk-free interest rate they use. In terms of portfolio risk, we find that tracking error and Sharpe ratio portfolios provided lower standard deviation than semi-variance and Sortino ratio portfolios. However, we find that, semi-variance and Sortino ratio portfolios provided more downside risk protection than their counterpart tracking error and Sharpe ratio portfolios.

A close examination of the composition of the various portfolios shows that the portfolios constructed using semi-variance as the measure of risk shows remarkable diversification than those that use tracking error. In particular, bonds dominate mean – tracking error and Sharpe ratio portfolios. This result holds both in-sample and out-of-sample.

We find that real estate receives significant allocations in the various portfolios. However, in almost all these portfolios, we observe a sharp fall in real estate allocations following the recent global financial crisis (2007-2008) possibly due to the fact that real estate returns deviated significantly from the fundamentals as observed by Lizieri (2013). In-sample analysis covering the entire 1990 – 2015 sample period show a fall in the real estate allocations, compared to higher allocations obtained when the sub-sample period (1990 – 2006) was analysed. This result is confirmed by the suggested allocations within out-of-sample portfolios which also show very little allocation to real estate between 2007 and 2013.

Again, we find that stocks and alternative assets receive very little allocations within portfolios that employ downside risk measures (semi-variance and Sortino ratio) than within portfolios based on tracking error (mean-tracking error and Sharpe ratio).

A comparison of the returns of the various inflation and interest rate hedging portfolios and the inflation/interest rate benchmarks against which they are hedged shows that all the optimised portfolios produced cumulative returns higher than their respective benchmarks. This means that in all cases, it is better for DC pension funds to construct optimised portfolios hedged against the various benchmarks than to invest in the benchmarks themselves. For example, it is better to invest in the mean-tracking error portfolio that is hedged against T-bills than to directly invest in T-bills as the former provided less than a third of the returns that the latter delivered. This is especially true as the tracking error of the various portfolios relative to the various benchmarks are reasonably low, implying that the mean-tracking error portfolios do a good job of mimicking T-bill return patterns.

Further, we compared the out-of-sample returns of the various optimised portfolios to a traditional 80-20 stock-bond portfolio and found that almost all the inflation hedging portfolios out-performed the traditional 80-20 stock-bond portfolios. In terms of risk also, the tracking error of the 80-20 stock bond portfolio was higher for an 80-20 stock-bond portfolio than for the various optimised portfolios. This shows that the portfolios optimised portfolios do a better job of tracking the inflation and interest rates than a naïve 80-20 stock-bond portfolio. The standard deviation for the 80-20 portfolios were also higher than the standard deviation of all the various inflation and interest rate hedging portfolios.

Including real estate in inflation and interest rate hedging portfolios was found to always lead to lower tracking error and standard deviation. However, in terms of returns, we find that including real estate did not always lead to improved returns. We used alternative real estate vehicles to see if this affected the performance of the various portfolios. We found that the vehicle that is used to access the real estate market did not significantly affect the performance of the resulting portfolios as all the portfolios had similar risk-return characteristics. In particular, we found that the returns obtained from portfolios that created using the IPD All-Property portfolio were more like the portfolios constructed using the

AREF/IPF unlisted fund return series. On the other hand, the unsmoothed IPD All-property portfolio return series produced returns that were similar to the Blended/Hybrid property real estate portfolio that contains a 20% allocation to listed real estate. This result implies that investment managers who wish to avoid some of the problems associated with using the IPD All property portfolio could use the blended/hybrid real estate in their optimisations given that adding listed real estate to a property portfolio induces volatility - similar to results of unsmoothing the appraisal-based IPD property portfolio returns.

A limitation of this study is that we do not consider transaction costs and the fees that an investment manager charges for managing the various portfolios in this study. Future studies can model the cost of rebalancing and how this would impact on the allocations and performance of the various portfolios.

APPENDICES

Appendix 8(A) Descriptive Statistics (1990 – 2015)

	Mean	Median	Max	Min	Std. Dev.	Skew	Kurtosis	JB Test	Prob.
Real Estate									
AREF unlisted real estate funds	1.78	2.26	8.04	-13.44	3.13	-1.9	9.08	207.47	0
Blended/hybrida real estate	1.95	2.36	13.04	-13.18	4.16	-1.07	5.32	40.08	0
IPD all property portfolio	2.09	2.44	12.06	-12.96	3.17	-1.33	9.07	177.68	0
Unsmoothed IPD all property	2.19	2.04	23.94	-25.15	5.33	-0.85	13.75	478.64	0
Listed real estate	2.64	4.86	33.08	-34.18	11.68	-0.65	3.72	8.95	0.01
Stocks									
Oil and gas	2.74	4.09	25.58	-26.64	9.07	-0.47	3.53	4.7	0.1
Basic materials	2.95	4	27.93	-43.8	13.07	-0.83	4.29	17.81	0
Industrials	3.29	4.15	29.3	-31.35	10.86	-0.49	3.98	7.82	0.02
Construction	2.8	4.18	22.66	-24.64	10.41	-0.34	2.59	2.59	0.27
Industrial goods and services	2.91	3.15	22.51	-26.94	9.51	-0.53	3.62	6.12	0.05
Consumer goods	3.71	4.21	32.95	-32.27	10.63	-0.05	4.01	4.16	0.12
Health care	2.88	3.36	24.49	-14.59	7.17	0.07	3.41	0.77	0.68
Consumer services	2.55	3.26	21.2	-21.88	8.75	-0.52	3.45	5.24	0.07
Telecommunications	3.12	3.74	46.02	-25.2	12.57	0.46	4.38	11.11	0
Technology	4.5	4.82	127.04	-54.61	20.82	1.77	14.44	579.36	0
Utilities	3.47	3.94	21.36	-13.67	7.11	0	2.62	0.58	0.75
Banks	3.44	4.01	40.54	-38.79	13.75	-0.16	3.92	3.81	0.15
Insurance	3.07	5.09	29.47	-30.84	11.54	-0.43	3.27	3.25	0.2
Financial Services	3.26	4.76	23.04	-23.75	10.34	-0.39	2.92	2.44	0.3
Bonds									
10+ year bonds	2.41	1.84	15.96	-9.29	4.49	0.23	2.98	0.87	0.65
10 year bonds	2.19	2.38	11.52	-8.26	3.68	0.04	3.21	0.2	0.91
7 year bonds	2.04	2.02	8.61	-5.58	2.91	-0.06	2.86	0.13	0.94
5 year bonds	1.79	1.7	7.51	-4.57	2.39	-0.02	3.04	0.01	1
3 year bonds	1.63	1.5	5.69	-2.11	1.62	0.47	2.99	3.54	0.17
2 year bonds	1.44	1.17	5.03	-1.12	1.3	0.87	3.47	13.26	0
Alternatives									
Emerging market stocks	2.94	3.83	34.53	-40.62	14.22	-0.24	3.01	0.97	0.62
Developed market stocks	2.29	3.4	21.55	-32.68	9.67	-0.78	4.08	14.6	0
Commodities - Oil	2.18	3.65	45.23	-57.68	18.27	-0.35	3.62	3.5	0.17
Commodities - Gold	1.22	1.28	20.78	-24.2	8.31	-0.11	3.01	0.19	0.91
Hedge fund	1.57	1.89	15.02	-27.25	6.11	-1.04	6.96	80.72	0
US private equity	3.58	4.33	22.04	-31.3	7.67	-0.92	6.49	63.1	0
US venture capital	4.26	4.22	80.51	-28.78	12.54	2.3	16.03	771.31	0
Developed ex-US private equity	3.64	3.9	31.8	-37.07	11	-0.45	4.83	16.74	0
Emerging market private equity	1.81	2.1	27.82	-33.01	8.36	-0.51	6.15	44.32	0
Benchmarks									
CPI Inflation	0.57	0.47	4.72	-0.73	0.66	2.62	17.2	925.57	0
RPI Inflation	0.7	0.6	2.15	-2.13	0.68	-0.47	5.23	23.65	0
LIBOR	1.15	1.28	2.99	0.13	0.69	0.09	2.71	0.47	0.79
3- month T-bill rate	1.11	1.22	3.18	0.09	0.7	0.2	3.01	0.63	0.73

Appendix 8(B) Descriptive Statistics (1990 – 2015)

	MEAN	STD. DEV	TRACKING ERROR				CORRELATION			
			CPI	RPI	LIBOR	TBILL	CPI	RPI	LIBOR	TBILL
Real Estate										
AREF Real Estate Funds	1.78	3.13	3.28	3.08	3.28	3.31	-0.12	0.19	-0.12	-0.16
Blended/Hybrid real estate	1.95	4.16	4.22	4.07	4.27	4.29	-0.06	0.18	-0.11	-0.13
IPD All Property	2.09	3.17	3.28	3.09	3.33	3.36	-0.09	0.21	-0.15	-0.19
Unsmoothed IPD All Property	2.19	5.33	5.34	5.27	5.43	5.45	0.01	0.12	-0.13	-0.15
Listed real estate	2.64	11.68	11.68	11.63	11.75	11.75	0.04	0.11	-0.07	-0.07
Stocks:										
Oil and gas	2.74	9.07	9.04	9.06	9.05	9.08	0.08	0.04	0.06	0.02
Basic materials	2.95	13.07	12.91	12.88	13.06	13.09	0.27	0.31	0.05	0.01
Industrials	3.29	10.86	10.79	10.80	10.87	10.88	0.14	0.11	0.01	0.00
Construction	2.8	10.41	10.30	10.33	10.45	10.45	0.19	0.15	-0.02	-0.03
Industrial goods and services	2.91	9.51	9.43	9.43	9.52	9.53	0.17	0.15	0.03	0.02
Consumer goods	3.71	10.63	10.51	10.58	10.62	10.63	0.22	0.11	0.05	0.04
Health care	2.88	7.17	7.15	7.29	7.14	7.12	0.08	-0.12	0.10	0.12
Consumer services	2.55	8.75	8.73	8.74	8.76	8.76	0.07	0.05	0.02	0.02
Telecommunications	3.12	12.57	12.59	12.60	12.54	12.55	0.01	-0.01	0.07	0.06
Technology	4.5	20.82	20.86	20.78	20.82	20.84	-0.04	0.08	0.02	-0.01
Utilities	3.47	7.11	7.12	7.13	7.03	7.02	0.03	0.02	0.16	0.18
Banks	3.44	13.75	13.75	13.74	13.68	13.67	0.03	0.05	0.13	0.15
Insurance	3.07	11.54	11.55	11.56	11.56	11.55	0.02	0.00	0.00	0.01
Financial Services	3.26	10.34	10.32	10.26	10.37	10.39	0.06	0.15	-0.02	-0.04
Bonds:										
10+ year bonds	2.41	4.49	4.58	4.75	4.46	4.44	-0.06	-0.32	0.13	0.15
10 year bonds	2.19	3.68	3.73	3.93	3.62	3.60	0.01	-0.28	0.18	0.21
7 year bonds	2.04	2.91	2.95	3.15	2.83	2.80	0.06	-0.26	0.23	0.28
5 year bonds	1.79	2.39	2.44	2.65	2.31	2.27	0.06	-0.26	0.25	0.31
3 year bonds	1.63	1.62	1.69	1.92	1.49	1.44	0.09	-0.29	0.40	0.45
2 year bonds	1.44	1.3	1.40	1.63	1.10	1.04	0.10	-0.29	0.53	0.60
Alternatives:										
Emerging market stocks	2.94	14.22	14.16	14.09	14.26	14.29	0.12	0.22	-0.03	-0.08
Developed market stocks	2.29	9.67	9.63	9.51	9.70	9.74	0.09	0.26	-0.02	-0.07
Commodities - Oil	2.18	18.27	18.24	18.02	18.24	18.28	0.06	0.39	0.07	0.01
Commodities - Gold	1.22	8.31	8.27	8.17	8.42	8.46	0.11	0.24	-0.12	-0.17
Hedge fund	1.57	6.11	6.09	5.95	6.10	6.16	0.08	0.29	0.07	-0.01
US private equity	3.58	7.67	7.62	7.52	7.72	7.77	0.12	0.27	-0.02	-0.09
US venture capital	4.26	12.54	12.54	12.48	12.50	12.54	0.02	0.12	0.09	0.03
Developed ex-US private equity	3.64	11	10.95	10.82	11.01	11.06	0.10	0.29	0.01	-0.06
Emerging market private equity	1.81	8.36	8.31	8.23	8.49	8.53	0.12	0.22	-0.14	-0.21

Appendix 8(C) Descriptive Statistics (1990 – 2006)

			Tracking error				Correlations			
	Avg. Ret	St. Dev.	CPI	RPI	LIBOR	TBILL	CPI	RPI	LIBOR	TBILL
Real Estate										
AREF Real Estate Funds	2.49	1.96	2.25	2.06	2.26	2.30	-0.27	0.00	-0.56	-0.63
Blended/hybrid real estate	2.72	2.89	3.05	2.98	3.10	3.14	-0.12	-0.04	-0.39	-0.47
IPD All Property	2.69	2.15	2.39	2.21	2.41	2.45	-0.22	0.04	-0.51	-0.56
Unsmoothed IPD All Property	2.86	3.73	3.87	3.74	3.88	3.89	-0.10	0.07	-0.26	-0.26
Listed real estate	3.65	9.82	9.81	9.88	9.89	9.92	0.05	-0.06	-0.13	-0.18
Stocks:										
Oil and gas	3.36	7.83	7.84	7.88	7.88	7.90	0.02	-0.05	-0.08	-0.12
Basic materials	3.32	10.32	10.19	10.31	10.35	10.36	0.21	0.04	-0.05	-0.07
Industrials	3.65	11.73	11.64	11.76	11.71	11.72	0.16	-0.02	0.08	0.04
Construction	3.66	10.20	10.05	10.19	10.27	10.27	0.25	0.05	-0.12	-0.12
Industrial goods and services	3.05	9.80	9.68	9.81	9.73	9.74	0.20	0.01	0.17	0.15
Consumer goods	3.85	12.09	11.89	12.03	12.03	12.05	0.33	0.12	0.15	0.11
Health care	f3.24	7.39	7.27	7.43	7.25	7.25	0.21	-0.03	0.32	0.31
Consumer services	2.89	8.96	8.90	8.99	8.89	8.90	0.13	-0.03	0.17	0.14
Telecommunications	3.00	14.01	13.99	14.04	13.93	13.93	0.05	-0.02	0.20	0.18
Technology	4.65	24.54	24.60	24.55	24.50	24.52	-0.06	0.01	0.11	0.05
Utilities	4.07	7.69	7.66	7.75	7.60	7.59	0.09	-0.06	0.22	0.23
Banks	5.45	12.10	12.05	12.22	12.04	12.04	0.11	-0.16	0.15	0.15
Insurance	3.25	11.41	11.39	11.49	11.34	11.35	0.06	-0.10	0.16	0.14
Financial Services	4.05	10.52	10.52	10.57	10.55	10.58	0.05	-0.04	-0.04	-0.09
Bonds:										
10+ year bonds	2.62	4.12	4.16	4.28	4.00	3.98	0.02	-0.20	0.32	0.34
10 year bonds	2.37	3.53	3.53	3.66	3.39	3.36	0.09	-0.14	0.36	0.41
7 year bonds	2.27	2.86	2.84	3.00	2.72	2.68	0.14	-0.14	0.38	0.44
5 year bonds	2.01	2.38	2.39	2.55	2.25	2.21	0.12	-0.16	0.36	0.44
3 year bonds	1.93	1.59	1.61	1.80	1.46	1.41	0.18	-0.17	0.42	0.51
2 year bonds	1.79	1.23	1.26	1.46	1.08	1.02	0.24	-0.15	0.51	0.61
Alternatives:										
Emerging market stocks	3.61	14.19	14.16	14.19	14.27	14.31	0.07	0.03	-0.15	-0.22
Developed market stocks	2.86	8.58	8.60	8.58	8.63	8.67	0.02	0.05	-0.07	-0.16
Commodities - Oil	4.09	17.31	17.40	17.22	17.43	17.46	-0.11	0.17	-0.23	-0.29
Commodities - Gold	1.09	7.81	7.91	7.79	7.99	8.01	-0.10	0.08	-0.35	-0.39
Hedge fund	2.40	5.42	5.47	5.35	5.48	5.54	-0.01	0.17	-0.10	-0.20
US private equity	4.38	6.82	6.84	6.73	6.90	6.95	0.02	0.20	-0.14	-0.24
US venture capital	5.46	14.17	14.21	14.15	14.15	14.19	-0.03	0.06	0.07	-0.02
Developed ex-US private equity	4.80	10.37	10.37	10.23	10.45	10.50	0.04	0.27	-0.13	-0.24
Emerging market private equity	1.47	6.93	6.95	6.86	7.02	7.07	0.01	0.15	-0.18	-0.27

Appendix 8(D) Mean Tracking Error Portfolios: In-sample Allocations

	1990 - 2006				1990 - 2015			
	CPI	**RPI**	**LIBOR**	**T-bill**	**CPI**	**RPI**	**LIBOR**	**T-bill**
Real Estate:								
Direct real estate	19%	28%	18%	16%	11%	18%	10%	10%
Listed real estate	0%	0%	0%	0%	0%	0%	0%	0%
Total real estate	**19%**	**28%**	**18%**	**16%**	**11%**	**18%**	**10%**	**10%**
Stocks:								
Oil and gas	0%	0%	0%	0%	0%	0%	0%	0%
Basic materials	0%	0%	0%	0%	1%	0%	0%	0%
Industrials	0%	0%	0%	0%	0%	0%	0%	0%
Construction	0%	0%	0%	0%	0%	0%	0%	0%
Industrial goods and services	0%	0%	0%	0%	0%	0%	0%	0%
Consumer goods	2%	1%	0%	0%	1%	0%	0%	0%
Health care	0%	0%	0%	1%	1%	0%	0%	0%
Consumer services	0%	0%	0%	0%	0%	0%	0%	0%
Telecommunications	0%	0%	0%	0%	0%	0%	0%	0%
Technology	0%	0%	1%	0%	0%	0%	1%	1%
Utilities	0%	0%	0%	0%	0%	0%	0%	0%
Banks	0%	0%	0%	0%	0%	0%	0%	0%
Insurance	0%	0%	0%	0%	0%	0%	0%	0%
Financial Services	0%	0%	0%	0%	0%	0%	0%	0%
Total stocks	**2%**	**1%**	**1%**	**1%**	**3%**	**0%**	**1%**	**1%**
Bonds:								
10+ year bonds	0%	0%	0%	0%	0%	0%	0%	0%
10 year bonds	0%	0%	0%	0%	0%	0%	0%	0%
7 year bonds	0%	0%	0%	0%	0%	0%	0%	0%
5 year bonds	0%	0%	0%	0%	0%	0%	0%	0%
3 year bonds	0%	0%	0%	0%	0%	0%	0%	0%
2 year bonds	74%	66%	77%	78%	81%	74%	85%	86%
Total bonds	**74%**	**66%**	**77%**	**78%**	**81%**	**74%**	**85%**	**86%**
Alternatives:								
Emerging market stocks	1%	0%	0%	0%	0%	0%	0%	0%
Developed market stocks	0%	0%	0%	0%	0%	0%	0%	0%
Commodities - Oil	1%	1%	1%	1%	1%	2%	2%	2%
Commodities - Gold	1%	1%	0%	1%	2%	2%	0%	0%
Hedge fund	0%	0%	0%	0%	0%	0%	2%	1%
US private equity	0%	0%	0%	0%	0%	0%	0%	0%
US venture capital	0%	0%	0%	0%	0%	0%	0%	0%
Developed ex-US private equity	0%	1%	0%	0%	0%	0%	0%	0%
Emerging market private equity	2%	1%	3%	2%	2%	1%	0%	0%
Total alternatives	**5%**	**4%**	**4%**	**4%**	**5%**	**5%**	**4%**	**3%**

Appendix 8(E) Mean Semivariance Portfolios: In-Sample Allocations

	1990 - 2006				1990 - 2015			
	CPI	**RPI**	**LIBOR**	**T-bill**	**CPI**	**RPI**	**LIBOR**	**T-bill**
Real Estate:								
Direct real estate	17%	17%	12%	13%	7%	5%	1%	1%
Listed real estate	0%	0%	0%	0%	1%	1%	0%	0%
Total real estate	**17%**	**17%**	**12%**	**13%**	**8%**	**6%**	**1%**	**1%**
Stocks:								
Oil and gas	1%	1%	1%	1%	0%	0%	0%	0%
Basic materials	1%	1%	0%	0%	2%	2%	0%	0%
Industrials	0%	0%	0%	0%	0%	0%	0%	0%
Construction	1%	1%	1%	1%	0%	0%	0%	0%
Industrial goods and services	0%	0%	0%	0%	0%	0%	0%	0%
Consumer goods	1%	1%	1%	1%	0%	0%	0%	0%
Health care	3%	3%	3%	2%	2%	2%	2%	2%
Consumer services	0%	0%	0%	0%	1%	1%	1%	0%
Telecommunications	0%	0%	0%	0%	0%	0%	0%	0%
Technology	0%	0%	0%	0%	0%	0%	0%	0%
Utilities	4%	4%	2%	2%	0%	0%	0%	0%
Banks	0%	0%	0%	0%	1%	1%	0%	0%
Insurance	3%	3%	1%	1%	1%	1%	0%	0%
Financial Services	0%	0%	0%	0%	1%	1%	0%	0%
Total stocks	**14%**	**14%**	**9%**	**8%**	**8%**	**8%**	**3%**	**2%**
Bonds:								
10+ year bonds	6%	6%	3%	3%	21%	0%	0%	0%
10 year bonds	6%	6%	4%	3%	0%	0%	0%	0%
7 year bonds	6%	6%	5%	4%	0%	0%	0%	0%
5 year bonds	6%	6%	5%	4%	0%	0%	0%	0%
3 year bonds	5%	5%	5%	5%	37%	71%	16%	0%
2 year bonds	10%	10%	44%	47%	5%	6%	74%	92%
Total bonds	**39%**	**39%**	**66%**	**66%**	**63%**	**77%**	**90%**	**92%**
Alternatives:								
Emerging market stocks	0%	0%	0%	0%	0%	0%	0%	0%
Developed market stocks	1%	1%	1%	1%	2%	1%	0%	0%
Commodities - Oil	3%	3%	1%	1%	0%	0%	2%	1%
Commodities - Gold	3%	3%	1%	1%	3%	2%	1%	1%
Hedge fund	4%	4%	2%	2%	0%	0%	0%	0%
US private equity	5%	5%	2%	2%	5%	1%	0%	0%
US venture capital	4%	4%	1%	1%	3%	2%	1%	1%
Developed ex-US private equity	6%	6%	1%	1%	2%	1%	0%	0%
Emerging market private equity	3%	3%	2%	2%	3%	1%	0%	0%
Total alternatives	**29%**	**29%**	**11%**	**11%**	**18%**	**8%**	**4%**	**3%**

Appendix 8(F) Sharpe Ratio Portfolios: In-sample allocations (1990 – 2006 and 1990 – 2015)

	1990 - 2006				1990 - 2015			
	CPI	**RPI**	**LIBOR**	**T-bill**	**CPI**	**RPI**	**LIBOR**	**T-bill**
Real Estate:								
Direct real estate	32%	32%	35%	35%	16%	15%	7%	8%
Listed real estate	0%	0%	0%	0%	0%	0%	0%	0%
Total real estate	**32%**	**32%**	**35%**	**35%**	**16%**	**15%**	**7%**	**8%**
Stocks:								
Oil and gas	0%	0%	2%	1%	0%	0%	0%	0%
Basic materials	0%	0%	0%	0%	0%	0%	0%	0%
Industrials	0%	0%	0%	0%	0%	0%	0%	0%
Construction	0%	0%	0%	0%	0%	0%	0%	0%
Industrial goods and services	0%	0%	0%	0%	0%	0%	0%	0%
Consumer goods	0%	0%	1%	1%	1%	1%	2%	2%
Health care	0%	0%	0%	0%	2%	3%	7%	6%
Consumer services	0%	0%	0%	0%	0%	0%	0%	0%
Telecommunications	0%	0%	0%	0%	0%	0%	0%	0%
Technology	0%	0%	0%	0%	1%	1%	1%	1%
Utilities	0%	0%	0%	0%	1%	2%	8%	7%
Banks	0%	0%	0%	0%	0%	0%	0%	0%
Insurance	0%	0%	0%	0%	0%	0%	0%	0%
Financial Services	0%	0%	0%	0%	0%	0%	0%	0%
Total stocks	**0%**	**0%**	**3%**	**2%**	**5%**	**7%**	**18%**	**16%**
Bonds:								
10+ year bonds	0%	0%	0%	0%	0%	0%	0%	0%
10 year bonds	0%	0%	0%	0%	0%	0%	0%	0%
7 year bonds	0%	0%	0%	0%	0%	0%	18%	9%
5 year bonds	0%	0%	0%	0%	0%	0%	0%	0%
3 year bonds	0%	0%	0%	0%	6%	26%	42%	55%
2 year bonds	64%	64%	58%	59%	68%	47%	0%	0%
Total bonds	**64%**	**64%**	**58%**	**59%**	**74%**	**73%**	**60%**	**64%**
Alternatives:								
Emerging market stocks	0%	0%	0%	0%	0%	0%	0%	0%
Developed market stocks	2%	2%	0%	0%	0%	0%	0%	0%
Commodities - Oil	1%	1%	1%	1%	1%	1%	2%	2%
Commodities - Gold	0%	0%	0%	0%	0%	0%	0%	0%
Hedge fund	0%	0%	0%	0%	0%	0%	0%	0%
US private equity	0%	0%	2%	1%	3%	4%	10%	9%
US venture capital	0%	0%	0%	1%	1%	1%	3%	3%
Developed ex-US private equity	0%	0%	1%	1%	0%	0%	0%	0%
Emerging market private equity	0%	0%	0%	0%	0%	0%	0%	0%
Total alternatives	**3%**	**3%**	**4%**	**4%**	**5%**	**6%**	**15%**	**14%**

Appendix 8(G) Sortino Ratio Portfolios: In-Sample Allocations

	1990 - 2006				1990 - 2015			
	CPI	**RPI**	**LIBOR**	**T-bill**	**CPI**	**RPI**	**LIBOR**	**T-bill**
Real Estate:								
Direct real estate	32%	34%	32%	33%	3%	3%	3%	3%
Listed real estate	0%	0%	0%	0%	1%	1%	1%	1%
Total real estate	**32%**	**34%**	**32%**	**33%**	**4%**	**4%**	**4%**	**4%**
Stocks:								
Oil and gas	1%	1%	1%	1%	0%	0%	0%	0%
Basic materials	1%	1%	1%	1%	2%	2%	2%	2%
Industrials	0%	0%	0%	0%	4%	4%	4%	3%
Construction	2%	2%	2%	2%	0%	0%	0%	0%
Industrial goods and services	0%	0%	0%	0%	1%	1%	1%	1%
Consumer goods	3%	3%	3%	3%	0%	0%	0%	0%
Health care	3%	3%	3%	3%	3%	3%	3%	3%
Consumer services	0%	0%	0%	0%	1%	1%	1%	1%
Telecommunications	0%	0%	0%	0%	0%	0%	0%	0%
Technology	0%	0%	0%	0%	0%	0%	0%	0%
Utilities	5%	5%	5%	5%	0%	0%	0%	0%
Banks	5%	4%	5%	5%	1%	1%	1%	1%
Insurance	0%	0%	0%	0%	1%	1%	1%	1%
Financial Services	0%	0%	0%	0%	1%	1%	1%	1%
Total stocks	**20%**	**19%**	**20%**	**20%**	**14%**	**14%**	**14%**	**13%**
Bonds:								
10+ year bonds	5%	5%	5%	5%	24%	23%	23%	22%
10 year bonds	4%	4%	4%	5%	0%	0%	0%	0%
7 year bonds	4%	4%	4%	4%	0%	0%	0%	0%
5 year bonds	3%	3%	4%	4%	0%	0%	0%	0%
3 year bonds	3%	3%	3%	3%	46%	48%	49%	50%
2 year bonds	3%	3%	3%	3%	1%	1%	0%	0%
Total bonds	**22%**	**22%**	**23%**	**24%**	**71%**	**72%**	**72%**	**72%**
Alternatives:								
Emerging market stocks	0%	0%	0%	0%	0%	0%	0%	0%
Developed market stocks	0%	0%	0%	0%	1%	1%	1%	1%
Commodities - Oil	4%	4%	4%	4%	2%	2%	2%	2%
Commodities - Gold	0%	0%	0%	0%	1%	1%	1%	1%
Hedge fund	1%	1%	1%	1%	0%	0%	0%	0%
US private equity	6%	6%	6%	6%	2%	2%	2%	2%
US venture capital	7%	6%	7%	7%	3%	3%	3%	3%
Developed ex-US private equity	6%	6%	6%	6%	1%	1%	1%	1%
Emerging market private equity	0%	0%	0%	0%	0%	0%	0%	0%
Total alternatives	**24%**	**23%**	**24%**	**24%**	**10%**	**10%**	**10%**	**10%**

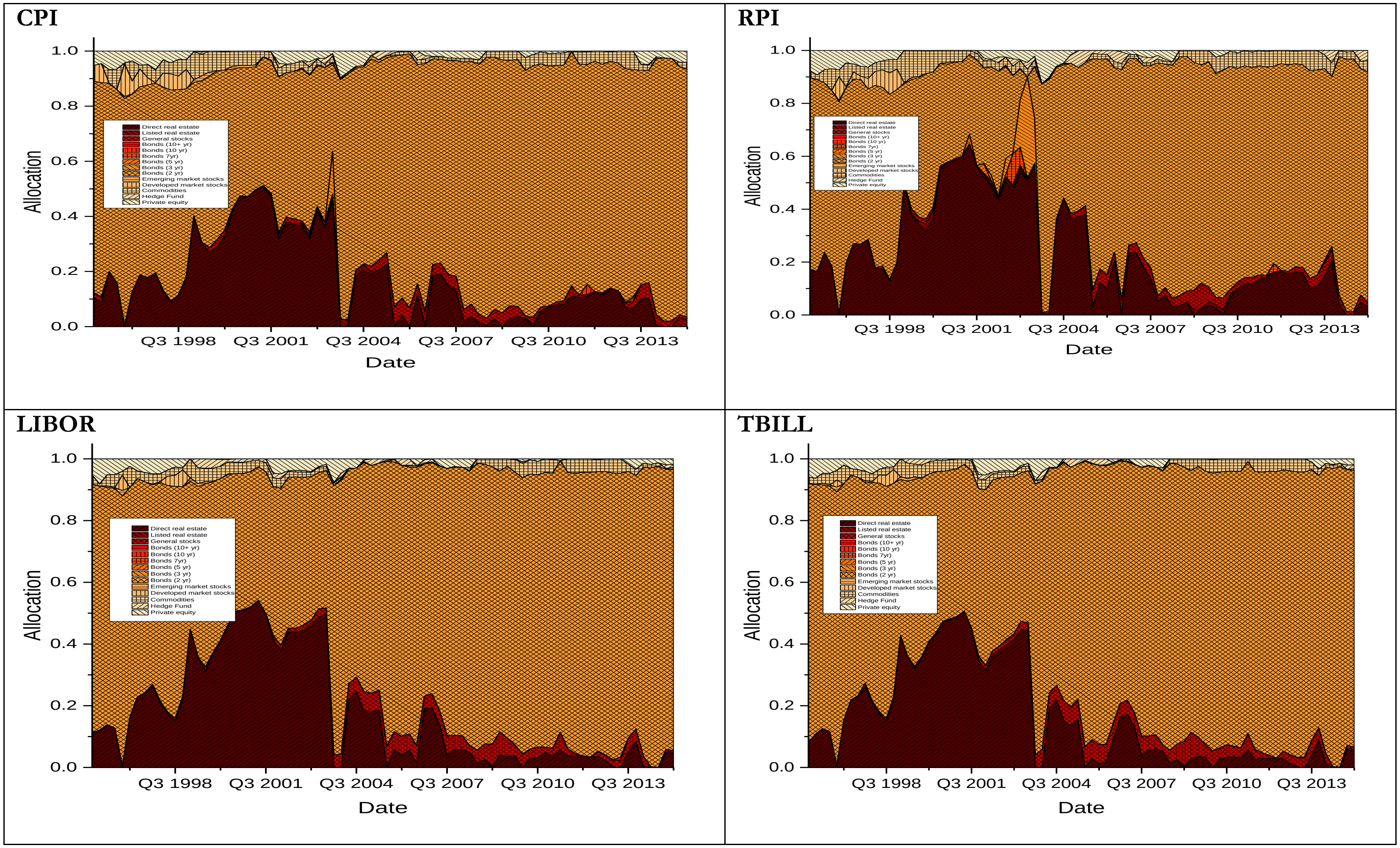
Appendix 8(H) Average Out-of-Sample Allocations – Mean-Tracking Error and Mean-Semi-Variance Portfolios

	Mean-Tracking Error Model				Mean-Semi-Variance Model			
	CPI	**RPI**	**LIBOR**	**T-bill**	**CPI**	**RPI**	**LIBOR**	**T-bill**
Real Estate:								
Direct real estate	16%	22%	17%	16%	27%	32%	21%	19%
Listed real estate	0%	0%	0%	0%	2%	1%	1%	1%
Total real estate	**17%**	**23%**	**17%**	**16%**	**29%**	**34%**	**21%**	**20%**
Stocks:								
Oil and gas	0%	0%	0%	0%	2%	2%	2%	2%
Basic materials	0%	0%	0%	0%	1%	1%	1%	1%
Industrials	0%	0%	0%	0%	2%	1%	1%	1%
Construction	0%	0%	0%	0%	2%	1%	1%	1%
Industrial goods and services	0%	0%	0%	0%	2%	1%	1%	1%
Consumer goods	0%	0%	0%	0%	3%	2%	2%	1%
Health care	0%	0%	0%	0%	4%	3%	3%	2%
Consumer services	0%	0%	0%	0%	2%	1%	1%	1%
Telecommunications	0%	0%	0%	0%	2%	2%	1%	1%
Technology	0%	0%	0%	0%	2%	2%	2%	2%
Utilities	0%	0%	1%	1%	3%	3%	2%	2%
Banks	0%	0%	0%	0%	1%	1%	1%	0%
Insurance	0%	0%	0%	0%	1%	1%	1%	1%
Financial Services	0%	0%	0%	0%	1%	1%	1%	1%
Total stocks	**2%**	**2%**	**3%**	**3%**	**27%**	**23%**	**18%**	**16%**
Bonds:								
10+ year bonds	0%	0%	0%	0%	4%	4%	4%	3%
10 year bonds	0%	0%	0%	0%	4%	4%	4%	4%
7 year bonds	0%	0%	0%	0%	4%	4%	5%	5%
5 year bonds	0%	0%	0%	0%	4%	4%	5%	5%
3 year bonds	0%	1%	0%	0%	4%	4%	6%	6%
2 year bonds	75%	66%	75%	77%	4%	5%	22%	28%
Total bonds	**75%**	**68%**	**75%**	**77%**	**25%**	**25%**	**46%**	**51%**
Alternatives:								
Emerging market stocks	0%	0%	0%	0%	1%	1%	1%	0%
Developed market stocks	1%	1%	0%	0%	1%	1%	1%	1%
Commodities - Oil	1%	2%	1%	1%	3%	2%	3%	3%
Commodities - Gold	2%	2%	1%	1%	3%	2%	2%	2%
Hedge fund	0%	1%	0%	0%	2%	2%	2%	1%
US private equity	0%	0%	0%	0%	3%	3%	2%	2%
US venture capital	1%	0%	1%	0%	2%	3%	2%	2%
Developed ex-US private equity	0%	0%	0%	0%	2%	2%	2%	2%
Emerging market private equity	1%	1%	1%	1%	2%	2%	2%	1%
Total alternatives	**6%**	**7%**	**5%**	**5%**	**19%**	**18%**	**15%**	**13%**

Appendix 8(I) Average Out-of-Sample Allocations – Sharpe Ratio and Sortino Ratio Portfolios

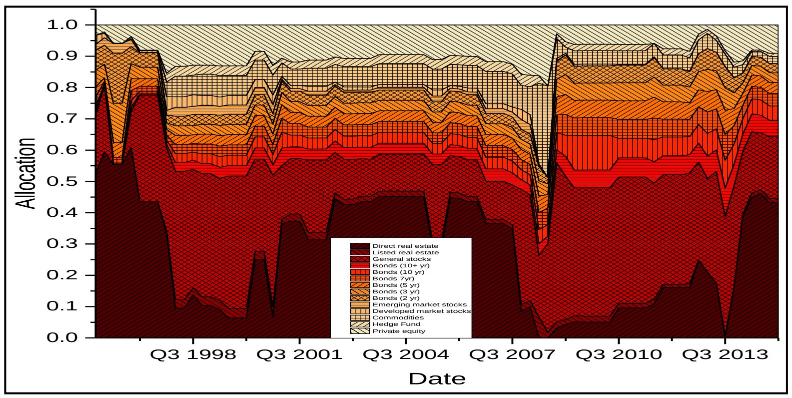
	Sharpe Ratio Portfolios				Sortino Ratio Portfolios			
	CPI	**RPI**	**LIBOR**	**T-bill**	**CPI**	**RPI**	**LIBOR**	**T-bill**
Real Estate:								
Direct real estate	24%	26%	30%	29%	18%	22%	19%	20%
Listed real estate	0%	0%	0%	0%	2%	2%	1%	1%
Total real estate	**24%**	**26%**	**30%**	**29%**	**20%**	**24%**	**20%**	**21%**
Stocks:								
Oil and gas	0%	0%	2%	2%	3%	4%	4%	6%
Basic materials	1%	1%	2%	1%	3%	3%	2%	2%
Industrials	0%	0%	0%	0%	2%	2%	2%	1%
Construction	0%	0%	0%	0%	2%	2%	2%	2%
Industrial goods and services	0%	0%	0%	0%	2%	2%	2%	1%
Consumer goods	1%	2%	1%	1%	3%	3%	3%	2%
Health care	1%	1%	1%	1%	3%	3%	3%	3%
Consumer services	0%	0%	0%	0%	2%	2%	2%	1%
Telecommunications	0%	0%	0%	0%	2%	2%	2%	2%
Technology	2%	2%	2%	2%	3%	4%	6%	6%
Utilities	2%	3%	5%	4%	3%	3%	3%	3%
Banks	0%	0%	0%	0%	1%	1%	2%	2%
Insurance	0%	0%	0%	0%	2%	2%	1%	1%
Financial Services	0%	0%	0%	0%	2%	1%	1%	1%
Total stocks	**8%**	**9%**	**13%**	**12%**	**33%**	**33%**	**35%**	**35%**
Bonds:								
10+ year bonds	0%	0%	2%	2%	4%	4%	4%	4%
10 year bonds	1%	2%	1%	1%	4%	3%	3%	3%
7 year bonds	7%	6%	5%	4%	3%	3%	3%	3%
5 year bonds	0%	0%	0%	0%	3%	3%	3%	3%
3 year bonds	2%	3%	12%	10%	3%	3%	3%	3%
2 year bonds	51%	47%	27%	33%	3%	3%	3%	3%
Total bonds	**61%**	**58%**	**47%**	**49%**	**21%**	**19%**	**19%**	**19%**
Alternatives:								
Emerging market stocks	0%	0%	0%	0%	3%	2%	2%	2%
Developed market stocks	0%	0%	0%	0%	1%	1%	1%	1%
Commodities - Oil	1%	1%	1%	1%	4%	3%	3%	4%
Commodities - Gold	1%	2%	1%	1%	4%	3%	3%	3%
Hedge fund	1%	0%	0%	0%	2%	2%	2%	1%
US private equity	2%	2%	2%	2%	4%	4%	4%	3%
US venture capital	2%	2%	5%	5%	3%	3%	6%	7%
Developed ex-US private equity	0%	0%	0%	0%	4%	3%	3%	3%
Emerging market private equity	0%	0%	0%	0%	2%	2%	2%	2%
Total alternatives	**7%**	**8%**	**10%**	**10%**	**26%**	**24%**	**26%**	**25%**

Appendix 8(J) MTE Portfolios: Out-of-Sample Allocations

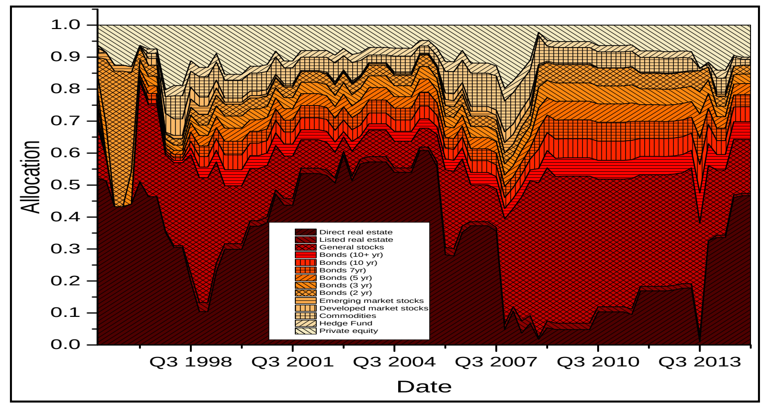


Appendix 8(K) MSV Portfolios: Out-of-Sample Allocations

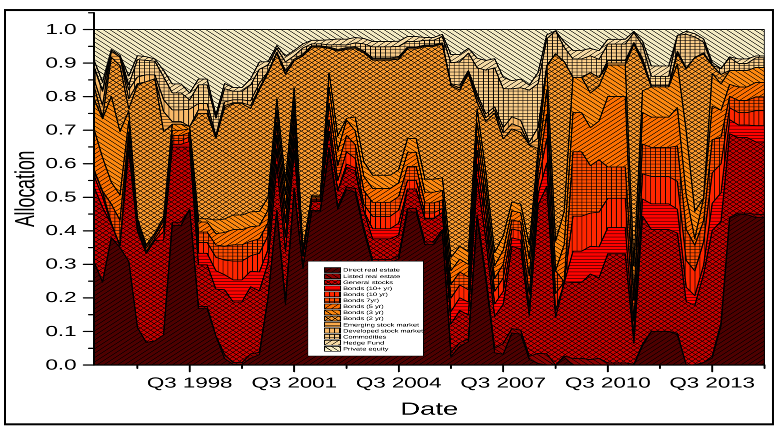
CPI



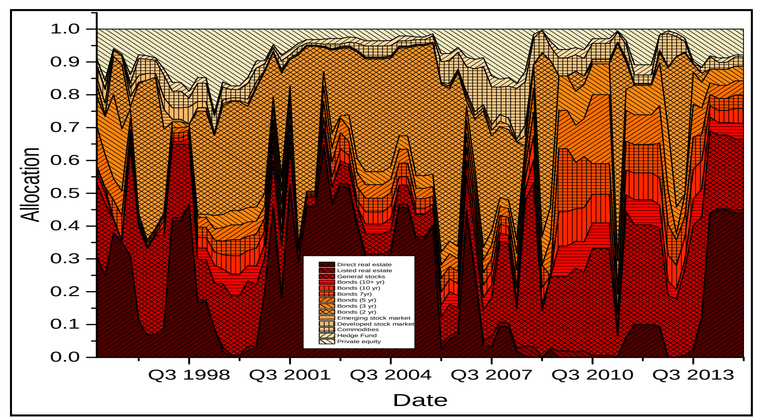
RPI



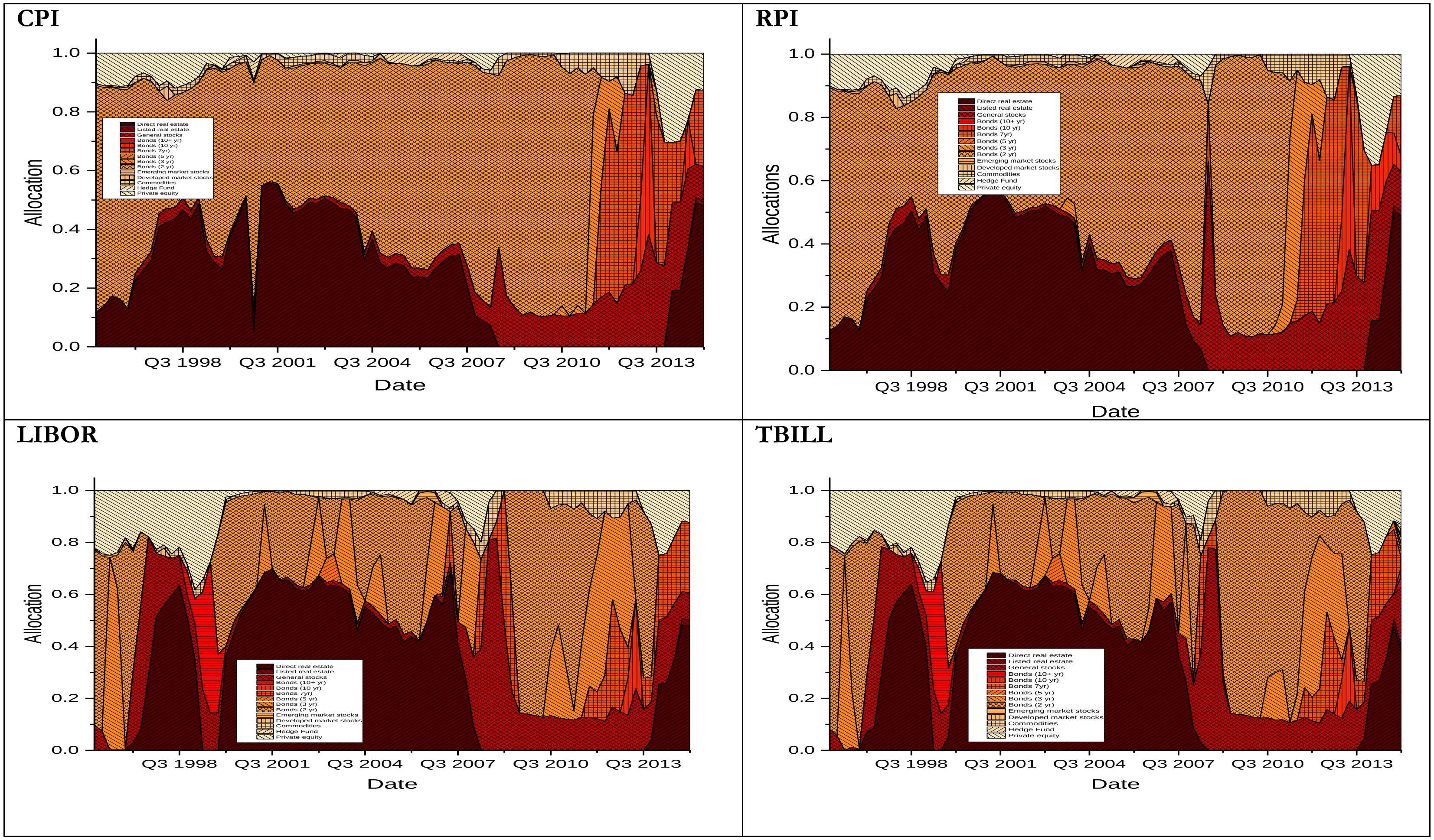
LIBOR



TBILL

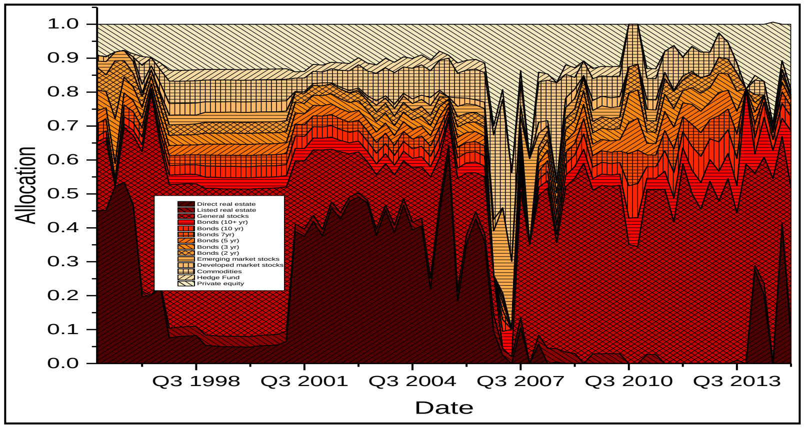


Appendix 8(L) Sharpe Ratio Portfolios: Out-of-Sample Allocations

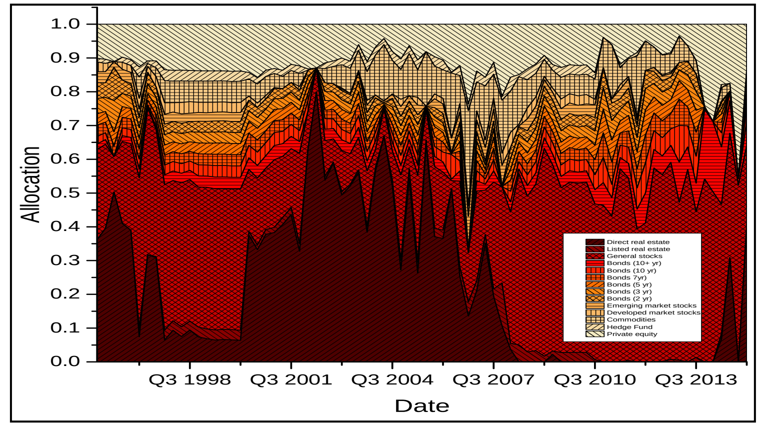


Appendix 8(M) Sortino Ratio Portfolios: Out-of-Sample Allocations

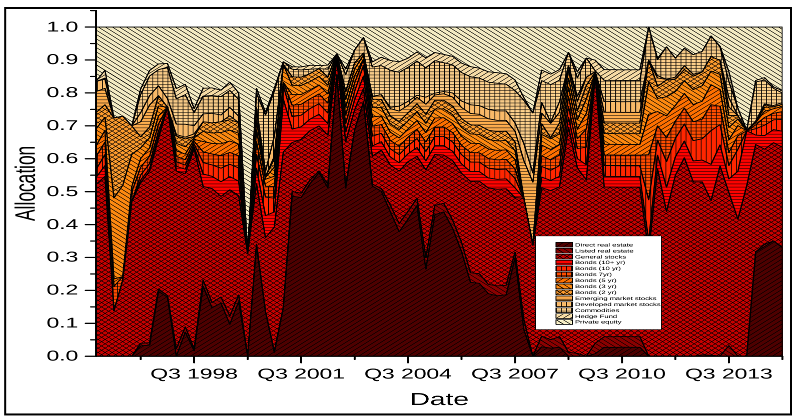
CPI



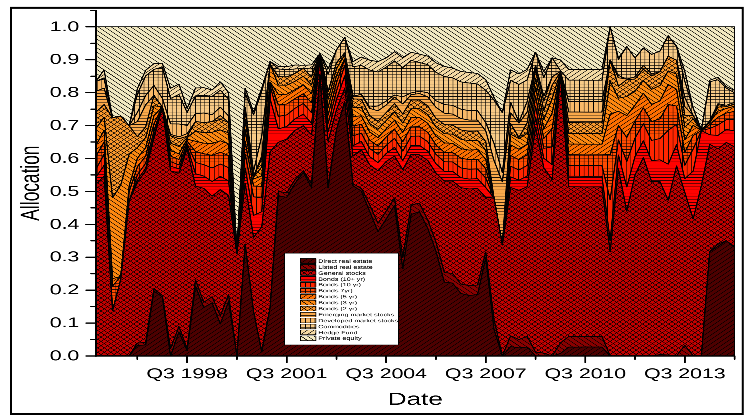
RPI



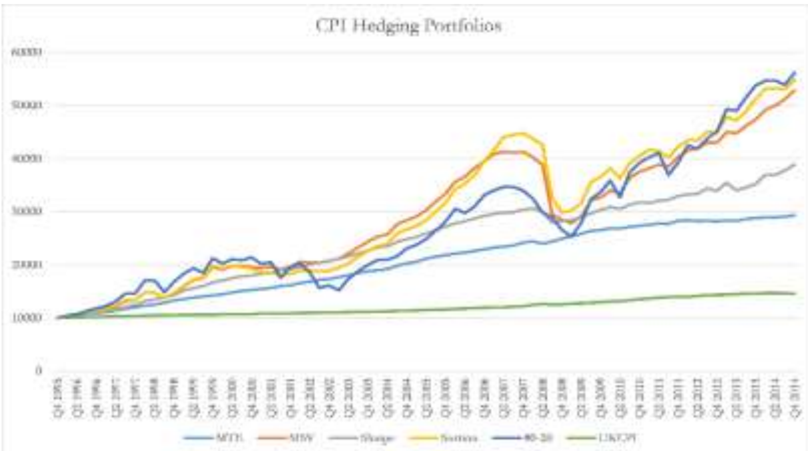
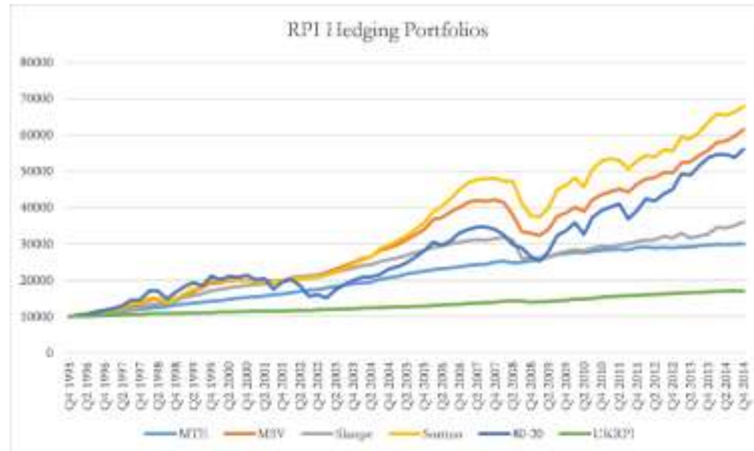
LIBOR

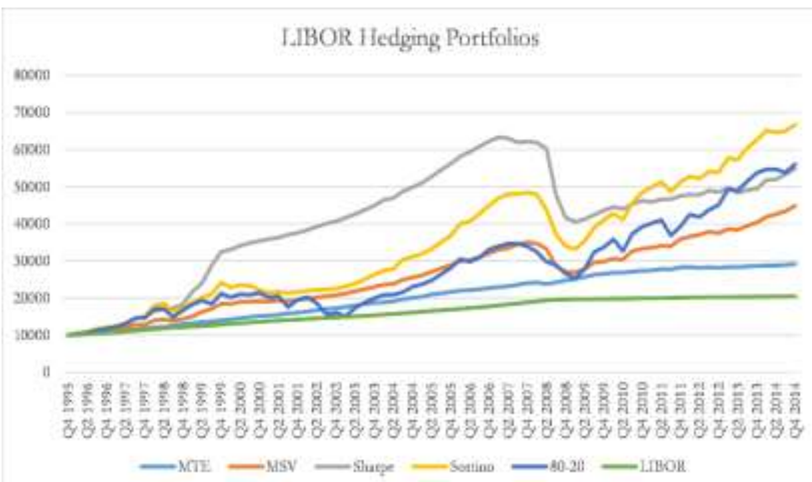
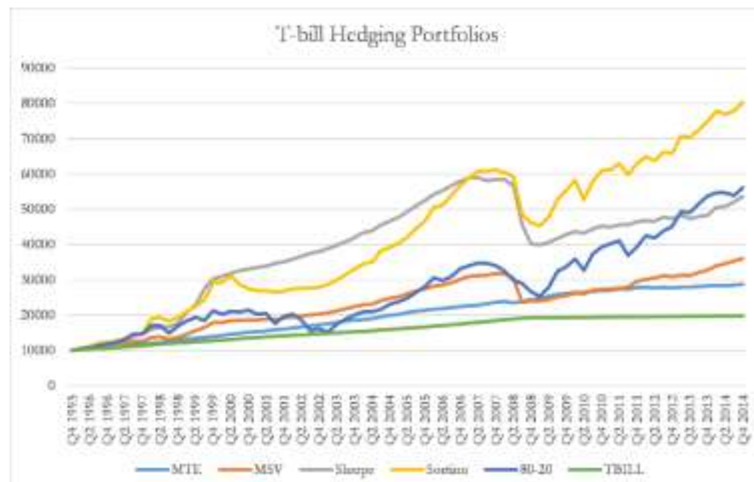


TBILL



Appendix 8(N) Out-of-Sample Returns

CPI	RPI
	

LIBOR	TBILL
	

Appendix 8(O) Descriptive Statistics - Out-of-sample Portfolios with Direct Real Estate

		CPI	RPI	LIBOR	TBILL
MTE	Average returns	1.44	1.48	1.44	1.42
	Standard deviation	1.01	1.11	0.98	0.96
	Median	1.40	1.42	1.46	1.35
	Maximum	4.06	4.36	3.70	3.51
	Minimum	-1.83	-1.76	-1.90	-1.92
	Skewness	-0.19	-0.49	-0.11	-0.52
	Kurtosis	3.73	3.67	3.36	3.66
	Jarque-Bera	2.15	4.50	0.56	4.91
	Probability	0.34	0.11	0.76	0.09
MSV	Average returns	2.33	2.49	2.06	1.79
	Standard deviation	4.54	3.62	3.06	3.56
	Median	2.62	2.86	2.27	1.85
	Maximum	12.06	10.59	8.97	8.36
	Minimum	-23.98	-12.11	-14.17	-22.79
	Skewness	-2.33	-1.77	-1.08	-4.09
	Kurtosis	15.81	12.03	6.24	30.31
	Jarque-Bera	595.99	301.65	48.61	2607.84
	Probability	0.00	0.00	0.00	0.00
Sharpe	Average returns	1.83	1.76	2.41	2.36
	Standard deviation	1.84	2.62	4.97	4.67
	Median	2.14	2.20	2.25	2.26
	Maximum	6.42	7.01	20.16	20.09
	Minimum	-6.87	-16.03	-20.59	-19.55
	Skewness	-1.60	-0.42	-4.07	-0.38
	Kurtosis	9.39	11.35	28.54	11.99
	Jarque-Bera	163.51	226.04	2305.02	261.17
	Probability	0.00	0.00	0.00	0.00
Sortino	Average returns	2.40	2.65	2.68	2.96
	Standard deviation	5.01	4.38	5.23	5.86
	Median	2.87	3.11	3.32	3.21
	Maximum	12.73	12.68	19.59	29.33
	Minimum	-23.43	-12.78	-15.22	-18.14
	Skewness	-1.72	-0.53	-0.44	0.66
	Kurtosis	10.70	4.57	5.45	9.22
	Jarque-Bera	228.18	11.47	21.79	129.82
	Probability	0.00	0.00	0.00	0.00

Appendix 8(P) Descriptive Statistics – Out-of-Sample Portfolios without Direct Real Estate

		MTE	MSV	SHARPE	SORTINO
CPI	Mean	1.3266	2.5381	1.8645	2.5226
	Median	1.2651	2.8770	1.6397	2.9107
	Std. Dev.	1.1107	4.6958	2.2946	5.1572
	Maximum	4.2558	11.2870	10.5912	15.1628
	Minimum	-1.8188	-12.4337	-6.8735	-12.0269
	Skewness	0.0659	-0.7584	0.0393	-0.3895
	Kurtosis	3.5307	4.3585	7.3516	3.7364
	Jarque-Bera	0.9593	13.3028	60.7754	3.6869
	Probability	0.6190	0.0013	0.0000	0.1583
RPI	Mean	1.3088	2.2665	1.8429	2.9498
	Median	1.1903	2.4887	1.6642	3.1158
	Std. Dev.	1.2023	4.4248	3.1560	6.0158
	Maximum	4.7305	11.2388	13.1992	28.8202
	Minimum	-1.8196	-12.5204	-16.0324	-12.1753
	Skewness	0.0587	-0.9195	-1.6166	0.8041
	Kurtosis	3.5784	5.1552	16.8051	6.9731
	Jarque-Bera	1.1175	25.7527	644.9817	58.9451
	Probability	0.5719	0.0000	0.0000	0.0000
LIBOR	Mean	1.2821	1.9068	2.4207	3.0753
	Median	1.2151	1.9396	1.8166	3.3488
	Std. Dev.	1.0136	3.2859	5.7289	5.8856
	Maximum	3.8751	16.1575	26.3233	25.1349
	Minimum	-1.9570	-10.6391	-20.5886	-16.9891
	Skewness	-0.1363	0.3467	0.5019	0.0507
	Kurtosis	3.6485	8.9267	10.0323	5.9175
	Jarque-Bera	1.5878	114.2373	161.8961	27.3421
	Probability	0.4521	0.0000	0.0000	0.0000
TBILL	Mean	1.2860	1.8408	2.3833	3.2745
	Median	1.1460	1.7425	1.7282	3.6034
	Std. Dev.	1.0246	3.8068	5.4944	7.0934
	Maximum	3.6896	17.0284	26.3233	28.4204
	Minimum	-1.9774	-19.3072	-19.5451	-27.3876
	Skewness	-0.0990	-1.1808	0.7372	-0.2700
	Kurtosis	3.5273	17.1156	10.8166	8.2542
	Jarque-Bera	1.0180	657.1507	202.9998	89.5058
	Probability	0.6011	0.0000	0.0000	0.0000

Appendix 8(Q) Out-of-sample returns – Portfolios with Direct Real Estate

		MTE	MSV	Sharpe	Sortino	80-20
CPI	Average returns	1.4426	2.3255	1.8323	2.4013	2.5484
	Index value	29334.77	52828.98	38854.80	54838.63	56118.53
	Tracking error	1.2043	4.4909	1.8944	4.9539	6.8262
	Standard deviation	1.0089	4.5441	1.8414	5.0060	6.8097
	Average excess returns	0.9426	1.8256	1.3323	1.9013	2.0484
	Semi-deviation	1.0258	5.9428	2.5236	6.0487	7.3188
	Sharpe ratio	0.7827	0.4065	0.7033	0.3838	0.3001
	Sortino	0.9189	0.3072	0.5279	0.3143	0.2799
	Maximum	4.0644	12.0618	6.4181	12.7270	16.9879
	Minimum	-1.8308	-23.9830	-6.8735	-23.4255	-15.9182
	Success ratio	0.7792	0.7403	0.8312	0.7143	0.6753
RPI	Average returns	1.4763	2.4881	1.7563	2.6538	2.5484
	Index value	30029.58	61597.03	36160.56	67902.40	56118.53
	Tracking error	1.3123	3.4884	2.5168	4.1860	6.7430
	Standard deviation	1.1085	3.6193	2.6179	4.3818	6.8097
	Average excess returns	0.7767	1.7885	1.0567	1.9541	1.8488
	Semi-deviation	0.8692	5.0005	4.1548	4.1456	7.1985
	Sharpe ratio	0.5918	0.5127	0.4199	0.4668	0.2742
	Sortino	0.8935	0.3577	0.2543	0.4714	0.2568
	Maximum	4.3551	10.5902	7.0141	12.6773	16.9879
	Minimum	-1.7598	-12.1095	-16.0324	-12.7820	-15.9182
	Success ratio	0.6623	0.8312	0.7922	0.7143	0.6623
LIBOR	Average returns	1.4386	2.0573	2.4088	2.6840	2.5484
	Index value	29191.86	44899.03	54878.56	66783.38	56118.53
	Tracking error	0.8717	3.0345	4.7923	5.1953	6.8310
	Standard deviation	0.9759	3.0637	4.9661	5.2282	6.8097
	Average excess returns	0.4816	1.1003	1.4518	1.7270	1.5914
	Semi-deviation	0.9067	4.0285	6.3784	5.8797	7.5148
	Sharpe ratio	0.5525	0.3626	0.3029	0.3324	0.2330
	Sortino	0.5311	0.2731	0.2276	0.2937	0.2118
	Maximum	3.7032	8.9672	20.1626	19.5903	16.9879
	Minimum	-1.9029	-14.1734	-20.5886	-15.2211	-15.9182
	Success ratio	0.7403	0.7403	0.7792	0.7013	0.6623
TBILL	Average returns	1.4178	1.7884	2.3612	2.9551	2.5484
	Index value	28754.09	36055.41	53573.33	80290.14	56118.53
	Tracking error	0.8414	3.5850	4.5473	5.8174	6.8461
	Standard deviation	0.9616	3.5582	4.6719	5.8648	6.8097
	Average excess returns	0.5088	0.8793	1.4521	2.0460	1.6393
	Semi-deviation	0.8557	5.5850	5.8656	5.4578	7.4975
	Sharpe ratio	0.6046	0.2453	0.3193	0.3517	0.2395
	Sortino	0.5945	0.1574	0.2476	0.3749	0.2186
	Maximum	3.5108	8.3610	20.0901	29.3253	16.9879
	Minimum	-1.9206	-22.7907	-19.5451	-18.1433	-15.9182
	Success ratio	0.7532	0.7273	0.7662	0.6753	0.6623

Appendix 8(R) Out-of-Sample Returns – Portfolios with no Direct Real Estate

		MTE	MSV	Sharpe	Sortino	80-20
CPI	Average returns	1.3266	2.5381	1.8645	2.5226	2.5484
	Index value	26783.99	60747.44	39495.08	59596.49	56118.53
	Tracking error	1.265	4.591	2.321	5.090	6.8262
	Standard deviation	1.103	4.665	2.280	5.124	6.8097
	Average excess returns	0.827	2.038	1.365	2.023	2.0484
	Semi-deviation	1.030	4.912	2.454	5.216	7.3188
	Sharpe ratio	0.653	0.444	0.588	0.397	0.3001
	Sortino	0.803	0.415	0.556	0.388	0.2799
	Maximum	4.256	11.287	10.591	15.163	16.9879
	Minimum	-1.819	-12.434	-6.874	-12.027	-15.9182
	Success ratio	0.740	0.714	0.818	0.701	0.6753
RPI	Average returns	1.309	2.267	1.843	2.950	2.5484
	Index value	26427.11	50350.45	38143.92	79341.56	56118.53
	Tracking error	1.3217	4.3377	3.1130	5.9346	6.7430
	Standard deviation	1.1945	4.3959	3.1354	5.9766	6.8097
	Average excess returns	0.8088	1.7666	1.3430	2.4499	1.8488
	Semi-deviation	1.1921	5.2597	4.3426	5.3526	7.1985
	Sharpe ratio	0.6119	0.4073	0.4314	0.4128	0.2742
	Sortino	0.6785	0.3359	0.3093	0.4577	0.2568
	Maximum	4.7305	11.2388	13.1992	28.8202	16.9879
	Minimum	-1.8196	-12.5204	-16.0324	-12.1753	-15.9182
	Success ratio	0.7532	0.7532	0.8052	0.7273	0.6623
LIBOR	Average returns	1.2821	1.9068	2.4207	3.0753	2.5484
	Index value	25933.0	40062.0	53978.0	87487.0	56118.53
	Tracking error	1.2114	3.2274	5.6779	5.8095	6.8310
	Standard deviation	1.0070	3.2645	5.6916	5.8473	6.8097
	Average excess returns	0.7821	1.4069	1.9207	2.5753	1.5914
	Semi-deviation	1.0772	3.5705	6.1989	5.6360	7.5148
	Sharpe ratio	0.6456	0.4359	0.3383	0.4433	0.2330
	Sortino	0.7261	0.3940	0.3099	0.4569	0.2118
	Maximum	3.8751	16.1575	26.3232	25.1349	16.9879
	Minimum	-1.9570	-10.6391	-20.5886	-16.9891	-15.9182
	Success ratio	0.7662	0.7792	0.7792	0.7143	0.6623
TBILL	Average returns	1.2860	1.8408	2.3833	3.2745	2.5484
	Index value	26006.0	37483.0	53074.0	95538.0	56118.53
	Tracking error	1.2285	3.7587	5.4408	7.0062	6.8461
	Standard deviation	1.0179	3.7820	5.4586	7.0472	6.8097
	Average excess returns	0.7860	1.3409	1.8834	2.7746	1.6393
	Semi-deviation	1.0722	5.1818	5.9074	7.2360	7.4975
	Sharpe ratio	0.6398	0.3567	0.3462	0.3960	0.2395
	Sortino	0.7331	0.2588	0.3188	0.3834	0.2186
	Maximum	3.6896	17.0284	26.3232	28.4204	16.9879
	Minimum	-1.9774	-19.3072	-19.5451	-27.3876	-15.9182
	Success ratio	0.7662	0.7922	0.7922	0.7143	0.6623

Appendix 8(S) Out-of-Sample Returns – CPI Hedging Portfolios with Different Direct Real Estate Vehicles

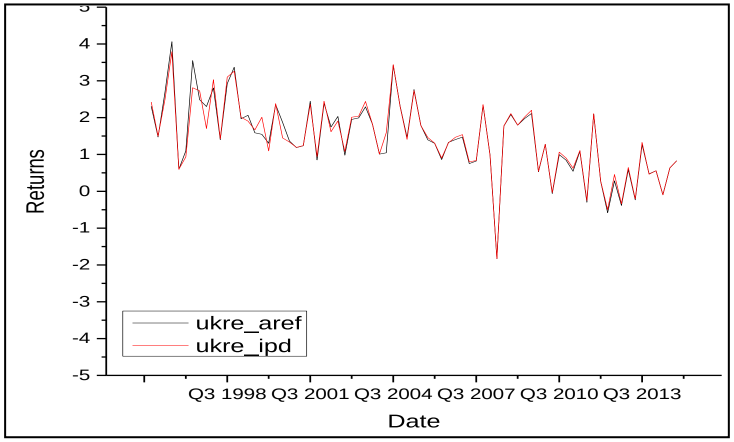
		UK unlisted funds	UK IPD direct real estate	Unsmoothed UK IPD direct real estate	Blended real estate
MTE	Average returns	1.4426	1.4478	1.3442	1.3650
	Index value	29334.77	29425.13	27160.03	27588.76
	Tracking error	1.2043	1.1764	1.2383	1.2531
	Standard deviation	1.0089	0.9772	1.0576	1.0715
	Average excess returns	0.9426	0.9478	0.8443	0.8650
	Semi-deviation	1.0258	0.9964	1.0916	1.0307
	Sharpe ratio	0.7827	0.8057	0.6818	0.6903
	Sortino	0.9189	0.9512	0.7734	0.8392
	Maximum	4.0644	3.7911	4.1148	4.2527
	Minimum	-1.8308	-1.8259	-1.8424	-1.7529
	Success ratio	0.7792	0.7792	0.7662	0.7532
MSV	Average returns	2.3255	2.1919	1.7668	2.3451
	Index value	52828.98	46766.63	35532.00	54748.57
	Tracking error	4.4909	4.8340	3.6447	3.7584
	Standard deviation	4.5441	4.8947	3.6872	3.7652
	Average excess returns	1.8256	1.6920	1.2668	1.8451
	Semi-deviation	5.9428	6.8718	4.6941	4.1646
	Sharpe ratio	0.4065	0.3500	0.3476	0.4909
	Sortino	0.3072	0.2462	0.2699	0.4431
	Maximum	12.0618	10.8448	9.6885	11.3445
	Minimum	-23.9830	-27.0465	-15.1164	-12.1084
	Success ratio	0.7403	0.7403	0.7273	0.7403
Sharpe	Average returns	1.8323	1.8361	1.8163	1.8839
	Index value	38854.80	38971.37	38137.08	40075.16
	Tracking error	1.8944	1.8777	2.1563	2.2982
	Standard deviation	1.8414	1.8198	2.1374	2.2660
	Average excess returns	1.3323	1.3361	1.3163	1.3839
	Semi-deviation	2.5236	2.5894	2.5239	2.5306
	Sharpe ratio	0.7033	0.7116	0.6105	0.6022
	Sortino	0.5279	0.5160	0.5215	0.5469
	Maximum	6.4181	6.2209	10.4223	11.5718
	Minimum	-6.8735	-6.6641	-6.8768	-6.8768
	Success ratio	0.8312	0.8442	0.8312	0.8312
Sortino	Average returns	2.4013	2.4658	2.5612	2.4136
	Index value	54838.63	58509.25	62686.45	50772.85
	Tracking error	4.9539	4.6151	4.4857	6.2533
	Standard deviation	5.0060	4.6494	4.5378	6.3307
	Average excess returns	1.9013	1.9659	2.0612	1.9137
	Semi-deviation	6.0487	5.1092	4.6616	9.0014
	Sharpe ratio	0.3838	0.4260	0.4595	0.3060
	Sortino	0.3143	0.3848	0.4422	0.2126
	Maximum	12.7270	12.6984	13.1434	13.0617
	Minimum	-23.4255	-17.4062	-12.0023	-37.9640
	Success ratio	0.7143	0.7143	0.7273	0.7273

Appendix 8(T) Out-of-Sample Returns – Libor Hedging Portfolios with Different Direct Real Estate Vehicles

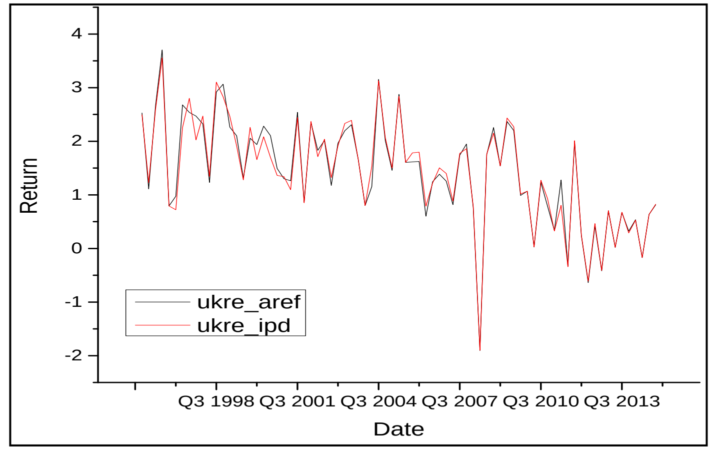
		UK unlisted funds	UK IPD direct real estate	Unsmoothed UK IPD direct real estate	Blended real estate
MTE	Average returns	1.4386	1.4313	1.3143	1.3186
	Index value	29191.86	29041.32	26578.41	26666.48
	Tracking error	0.8717	0.8641	0.9530	0.9405
	Standard deviation	0.9759	0.9618	0.9930	0.9864
	Average excess returns	0.4816	0.4742	0.3573	0.3616
	Semi-deviation	0.9067	0.9019	0.8581	0.8888
	Sharpe ratio	0.5525	0.5489	0.3749	0.3844
	Sortino	0.5311	0.5258	0.4164	0.4068
	Maximum	3.7032	3.5544	3.8793	3.8793
	Minimum	-1.9029	-1.8976	-1.9578	-2.0038
	Success ratio	0.7403	0.7403	0.6234	0.6364
MSV	Average returns	2.0573	1.7934	1.8627	1.7434
	Index value	44899.03	35951.98	37448.83	33986.55
	Tracking error	3.0345	3.8388	3.9916	4.1855
	Standard deviation	3.0637	3.8598	4.0207	4.2415
	Average excess returns	1.1003	0.8364	0.9057	0.7864
	Semi-deviation	4.0285	5.6824	6.0354	6.8495
	Sharpe ratio	0.3626	0.2179	0.2269	0.1879
	Sortino	0.2731	0.1472	0.1501	0.1148
	Maximum	8.9672	8.6378	9.7746	11.3414
	Minimum	-14.1734	-24.5682	-24.6120	-28.4169
	Success ratio	0.7403	0.7013	0.7273	0.7403
Sharpe	Average returns	2.4088	2.1791	2.3318	2.3894
	Index value	54878.56	46743.59	50797.74	53077.44
	Tracking error	4.7923	4.4171	5.3782	5.3626
	Standard deviation	4.9661	4.5755	5.5430	5.5315
	Average excess returns	1.4518	1.2221	1.3748	1.4324
	Semi-deviation	6.3784	6.2031	5.4366	5.1975
	Sharpe ratio	0.3029	0.2767	0.2556	0.2671
	Sortino	0.2276	0.1970	0.2529	0.2756
	Maximum	20.1626	19.9391	26.3248	26.3248
	Minimum	-20.5886	-20.5886	-20.5886	-20.5886
	Success ratio	0.7792	0.7662	0.6883	0.6623
Sortino	Average returns	2.6840	2.9689	2.7029	3.0931
	Index value	66783.38	83888.19	69888.74	86907.98
	Tracking error	5.1953	4.8194	4.4028	6.3197
	Standard deviation	5.2282	4.8727	4.4287	6.4060
	Average excess returns	1.7270	2.0119	1.7459	2.1361
	Semi-deviation	5.8797	4.8051	4.5346	5.5723
	Sharpe ratio	0.3324	0.4175	0.3965	0.3380
	Sortino	0.2937	0.4187	0.3850	0.3833
	Maximum	19.5903	14.8197	12.3127	34.9356
	Minimum	-15.2211	-11.5963	-12.0513	-18.5009
	Success ratio	0.7013	0.7013	0.6753	0.6623

Appendix 8(U) Out-of-sample returns – MTE Portfolios using Different Direct Real Estate Vehicles

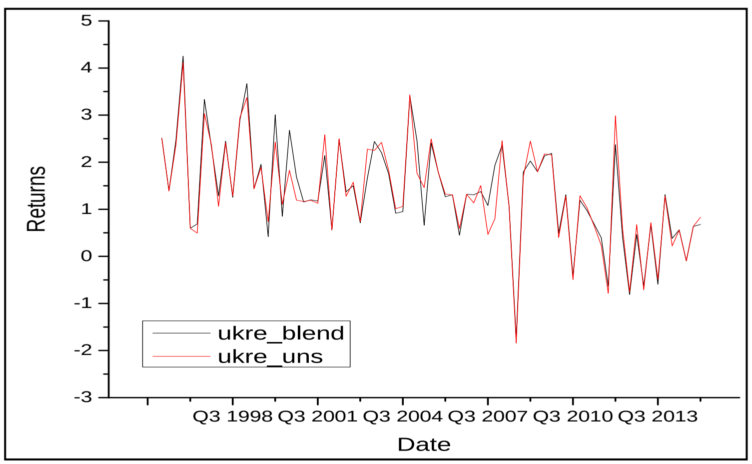
CPI Hedging



LIBOR Hedging



CPI Hedging



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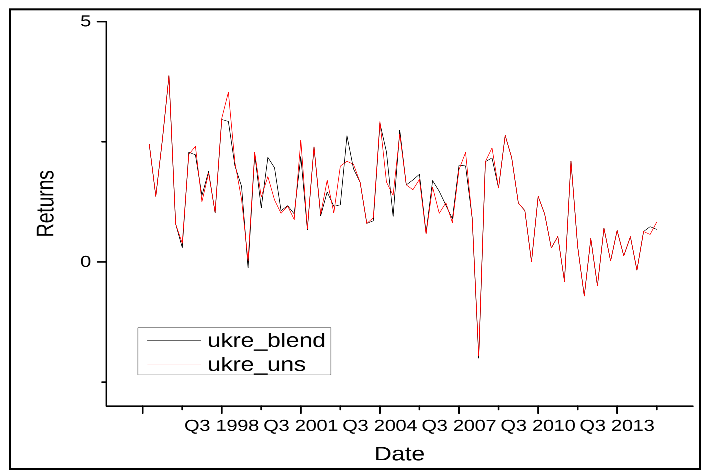
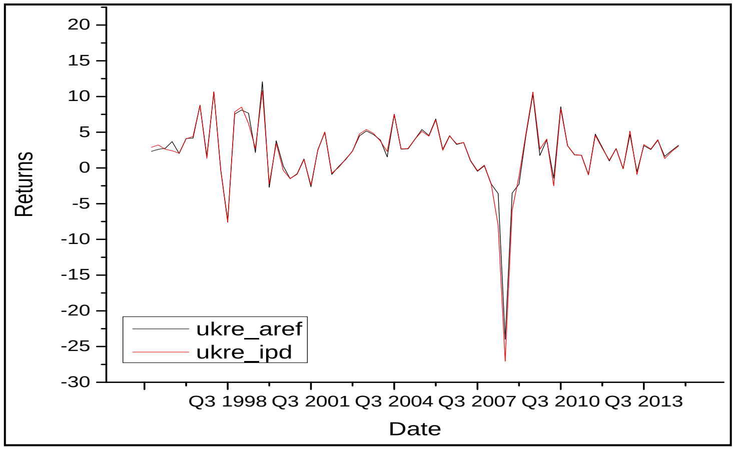
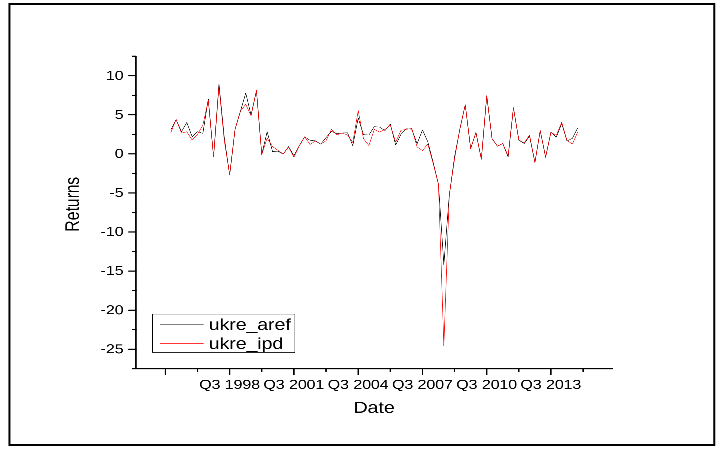


Appendix 8(V) Out-of-sample allocations – MSV Portfolios using Different Direct Real Estate Vehicles

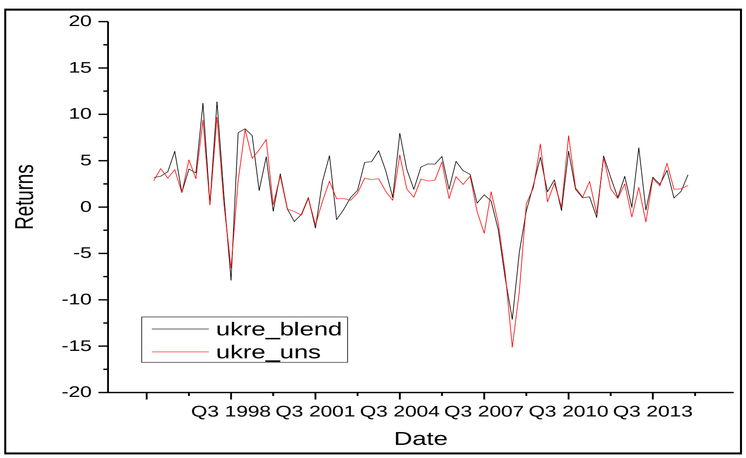
CPI Hedging



LIBOR Hedging



CPI Hedging



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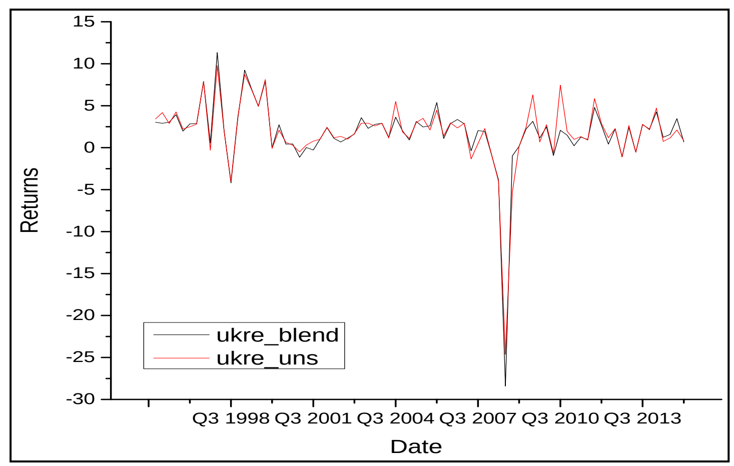

CHAPTER NINE – CONCLUSIONS

9.0 MOTIVATION FOR AND OBJECTIVES OF THE THESIS

With the increase in the significance of Defined Contribution (DC) pensions within the pension industry of most countries, there are concerns among regulatory agencies that contributors may not have adequate income replacement at retirement given that the amount of pension income is not known with certainty. Concerns exist also regarding the impact that increased competition can have on the amount of risk that these funds take as they try to produce superior returns than their counterparts (Ibbotson, 2007; Ruloff, 2005; Harrison et al., 2014). These concerns were explored in Chapter 2. One of the proposals that has been put forward to manage risk within DC pension funds industry is the establishment of minimum return guarantees (Antolin et al., 2012; Piggott and Sane, 2009; Dorfman et al., 2009). The goal of these minimum return guarantees is primarily to preserve the purchasing power of the pension pot to ensure that at the very least, contributors would not be left with a pension amount that is less in real terms than the value of their accumulated contributions.

By their nature, defined contribution pension schemes do not provide any assurance that a certain amount would be given to contributors at retirement. This is contrary to how defined benefit pension schemes operate – the amount of money that would be received at retirement is reasonably certain. The amount of money that a contributor receives under defined contribution pension arrangement is dependent on the total amount contributed and the returns that have been earned on these contributions less any fees. It is possible therefore that the pensioner could end up with less than what he/she contributed under defined contribution schemes. As discussed by Chapter 2, this concern has led many regulatory agencies to establish minimum return guarantees. In some cases, the DC pension fund guarantees the nominal amount of the member's total contribution. Yet such an arrangement only guarantees the monetary value of the contributions and not the value of goods and services that can be obtained. Hence, some other regulatory agencies require that the real value of the contributions should be guaranteed. This means that that the total contribution should be increased periodically by the rate of inflation. Again, some other regulatory agencies believe that the contributions should earn the risk-free rate of interest and not merely keep pace with inflation.

In addition to producing returns which ensure that the purchasing power of DC contributions are preserved, there is an increasing emphasis on liquidity as a key objective among DC pension funds.

One of the main attractions of real estate is its ability to produce returns that keep pace with inflation. Defined benefit pension funds have historically allocated a significant proportion of their portfolios to direct real estate and other real estate assets. With the increasing focus on liquidity however, many DC pension funds have found themselves in a position where they are unable to include real estate in their portfolios because of its perceived illiquidity. Expert interviews conducted as part of this thesis revealed that the restriction on illiquid assets for UK DC funds is not as a result of any regulation per say, but is a function of how the DC pension funds carry out their investment activities. The majority of DC pension funds carry out their investment activities through external fund management firms. Many of these funds who are subject to UCITs rules. UCITs rules explicitly prohibit investment in assets, such as real estate, that are deemed to be illiquid.

Regulators in some countries also have limits on the amount that can be invested in specific assets. Given that the recent financial crisis (2007-2008) originated from the housing market, limits on real estate investments, especially direct real estate investments, have been put in place by regulators in many countries. Indirect real estate investments such as REITs are still permitted in most jurisdictions. This raises the question of whether the benefits of direct real estate can be obtained by investing indirectly. Or if it is possible to earn property-like returns without being fully invested in properties. This subject was pursued in Chapters 2 and 5.

The objectives of this thesis were twofold: One was to determine the optimal allocation within DC pension real estate portfolios in the light of increasing liquidity requirement by pension trustees and regulatory agencies. The second is to determine the optimal combination of real estate and other alternative assets, along with stocks and bonds that would help pension funds protect the purchasing power of DC pension investors.

This thesis contributes to the real estate financial literature across three different areas: inflation hedging, strategic asset allocation and the management of liquidity risk. In this thesis, we implement an approach which constructs investment portfolios that provide returns hedged against inflation and interest rate changes while, at the same time, ensuring that they incorporate the liquidity needs of DC pension trustees and regulators. As suggested by Dessner et al. (2012), the objective of inflation-protection has to be pursued without compromising other investment objectives such as liquidity, target returns and volatility constraints.

As discussed in Chapter 3, while several studies have examined the ability of real estate and other assets prior to the 2008 financial crisis, few studies have revisited this issue following the crisis. With the changing interdependency between assets and macroeconomic variables, we find it important to analyse the inflation and interest rate hedging ability of different assets. This is particularly important given the increasing dominance of DC pension funds whose primary objective is to protect the purchasing power of members' contributions. A review of the statements of investment principles of several Master trust pension funds in the UK shows that most of them have inflation and interest rate protection as a key investment objective. Outside the UK, we show that several regulatory agencies, especially in countries where DC pension funds are mandatory, have introduced some form of minimum return requirement tied to inflation and interest rate measures.

Ling and Naranjo (1997) noted that most of the empirical studies on the inflation hedging, especially within the real estate literature, have focused on examining the relationship of various assets and the macro-economy. Dessner et al. (2012) believe that instead of identifying the assets that possess the ability to hedge against inflation, a diversified approach should be adopted by investors. Our study contributes to the limited literature on the construction of inflation and interest rate hedging portfolios.

An aspect of this thesis is dedicated to examining the optimal allocation within real estate fund portfolios in light of the increasing emphasis on liquidity by DC pension trustees, regulators and even contributors when choosing where to allocate capital. Our study is one of the first to explicitly examine the optimal allocation within hybrid/blended real estate funds. Previous studies have focused on the performance implication of the current allocation within open-ended real estate funds that have added cash and/or listed real estate to a their property portfolios. In this thesis, we do not take the current allocations as given. Instead, we consider the possibility of expanding the liquid asset universe to include cash, listed real estate, general stocks and bonds of various maturities.

9.1 SUMMARY, FINDINGS AND POLICY IMPLICATIONS

Chapters 1 through 4 set the foundation for the empirical analysis conducted in Chapters 5 to 8. Chapter one introduces the thesis. In addition to presenting the objective of this PhD project and the motivations for the various studies, this chapter also provides a general introduction to pensions and highlight the changes that have occurred on the pension landscape globally. The issues of liquidity and capital perseveration within the context of DC pension funds are also touched on.

Chapter 2 extends the context provided on pension funds by focusing on the occupational UK pension sector. In this chapter, we provided what can be described as styled facts on the UK pension market. After giving an overview of the occupational pension sector in the United Kingdom and the main changes that have taken place, we proceed to do two sets of analysis. We first analysed the annual reports and Statements of Investment Principles of selected master trust pension funds. The analysis revealed that most of these funds have explicit objectives regarding capital preservation and also regarding how liquid they want their investments to be. We found that funds such as NEST have return objectives tied to CPI inflation whiles funds such as NOW Pensions have risk-free interest rates such as SONIA and T-bill interest rate as their benchmark. A second set of analysis was conducted to understand the differences in allocations to various assets within the portfolios of DB and DC pension funds. We analysed survey results from the Pension Protection Fund, Schroders and UBS. An analysis of the asset allocation patterns shows that the portfolios of DC pension funds were less diversified than their counterpart DB pensions. DC pension funds had allocations in excess of 80% to equities alone at the beginning of 2013, confirming the concerns raised by DCIF and other analysts. However, there are indications that these funds are increasing their allocations to bonds, real estate and other alternative assets.

In Chapter 3, we carry out a review of the empirical studies on the role that real estate plays within the portfolios of institutional investors such as pension funds. We identified two strands of literature – one that examines the role of real estate within multi-asset portfolios and a second strand that looks at the inflation hedging characteristics of real estate investments. For the first strand that considers the inflation-hedging ability of real estate, we found that the classic regression analysis of Fama & Schwert (1977) and cointegration analysis have dominated the literature. We review the limitations of these approaches and discuss newer approaches that have been proposed to deal with these limitations. In particular, we found the autoregressive lag model of Pesaran et al. (2001) has received increased attention as it is able to accommodate variables irrespective of their level of integration. Again, we find that the mean-variance model of Markowitz (1952) has been used extensively in analyzing the portfolio role of real estate. The real estate allocations suggested by these models have been found to be greater than what was observed in practice. Also, these models were found to have challenges relating to parameter uncertainty and the distribution properties of the various assets. We went on to review several studies that have been proposed and used to determine the portfolio role of real estate. Most of these models produced allocations which were much lower than the mean-variance framework. The results of these studies have also been found to be more robust.

In Chapter 4, we present the data used in this thesis. We also explore the time series features of the returns of the various assets as well as the selected inflation/interest rates. We observed that most of these series suffer from non-normality. Real estate and the other private market assets were found to exhibit serial correlations. Stationarity tests further confirmed that while many return indices were stationary at levels I(0), a few were stationary in first difference I(1). After gaining an insight into the time series features of the data series, we proceeded to select the appropriate models for the empirical analysis we conduct subsequently. We provide a detailed background to these models in the second part of Chapter 4.

The goal of Chapter 5 is to help us understand the liquidity issues that DC pension funds are faced with and how this affects their investment to illiquid asset classes such as DC pension funds. The chapter highlights the multi-faceted nature of liquidity and its causes. We explore different measures that can be used to estimate the different aspects or dimensions of liquidity such as tightness, depth, resilience, breadth and immediacy. We were able to map each measure of liquidity to the different aspects/dimensions of liquidity. We found through an extensive review of the literature that apart from REITs, application of the different measures of liquidity within the field of real estate has been quite limited. Some measures have not yet been applied at all to real estate investments. An exploration of these measures would improve an understanding of the real estate market. We also explored different ways in which DC pension funds can manage liquidity within their investment portfolios. We identified the incorporation of liquidity matrices into asset allocation techniques and the use of derivative/hybrid instruments that allow investors to access illiquid asset classes without bearing all the liquidity risk inherent in these investments. Other approaches include the use of debt and sensitivity/stress test analysis.

The focus of Chapter 6 is on one of the approaches that DC pension funds adopt to manage liquidity within their investment portfolios – the holding of blended/hybrid investment products. This chapter analyses the optimal mix of liquid assets within hybrid/blended real estate portfolios that contain a certain amount of liquid assets. We expand the liquid asset universe to include cash, listed real estate, general stocks and bonds of various maturities. The goal is to combine these assets in a way that both enhances liquidity as well as delivers property-like returns. The Mean-Tracking error optimisation model is used to create portfolios that minimise the tracking error between direct real estate returns and the returns of the hybrid/blended real estate portfolios. Compared to the current practice of limiting the liquid asset universe to cash and/or listed real estate, we find that expanding the liquid asset universe results in lower tracking errors than those obtained by using only cash or listed real estate. The returns obtained from these portfolios are also higher than those from a cash-only liquidity buffer. We observe however that the returns obtained from the minimum tracking error portfolios tend to be lower than the returns obtained from a pure property portfolio. To avoid this, minimum return constraints are imposed to ensure that the returns obtained from the hybrid/blended portfolios match the returns that could be obtained from a pure property portfolio. Understandably, imposing a minimum return constraint results in higher tracking error and lower correlation with the underlying property portfolio. An examination of the allocation within the blended portfolios shows that the unconstrained mean-tracking error portfolios are invested heavily in cash especially prior to 2007. This may explain the current allocation within open-ended real estate funds which mostly have cash as the only liquidity buffer. With the imposition of a minimum return constraint, the liquid-asset allocations become more diversified. In addition to cash, other liquid assets such as listed real estate, general stocks and long-term bonds receive significant allocations.

In Chapter 7, we reassess the inflation and interest rate hedging characteristics of real estate using contemporary approaches that take into the account the different levels of integration of variables. The autoregressive distributed lag model of Pesaran et al. (2001) is used to test the long-run cointegration relationship between inflation and asset returns whiles the Toda & Yamamoto (1995) approach for testing for Granger Causality is used for testing the short-run causal relationship between the variables. In addition to these approaches, we also use the dynamic conditional correlation within a GARCH framework to examine the relationship between asset returns and inflation/interest rates.

Overall, the results show that several assets possess the ability to hedge against inflation and interest rate changes over the long-run. However, the real problem appears to be finding assets that can offer an inflation-hedge over the short-run. The policy implication of this result is that an insistence by regulators and pension trustees that the fund managers should deliver returns in line with inflation on a period-to-period basis could result in a lack of diversification of those portfolios. This could result in an over-investment in assets that are perceived to be inflation hedges such as index-linked bonds, inflation swaps etc. As noted by Amenc et al. (2009) this is expensive in the long-run as these investments typically offer low returns and are subject to counterparty risk. Most of these assets are thinly traded, resulting in liquidity concerns. A lack of diversification is a risk in itself as a market shock could prove catastrophic. We find that real estate is a good hedge against almost all the inflation and interest rates analysed in Chapter 7. The results were consistent over both the long-run and short-run. We found also that real estate investment vehicle used does not alter or diminish the inflation/interest rate hedging ability of real estate. This result implies that irrespective of the inflation or interest rate being hedged against, DC pension funds would benefit from holding real estate as part of their investment portfolios. Surprisingly, most of the tests did not find index-linked gilts to be a complete hedge against inflation/interest rate changes. Although index-linked gilts were a good hedge over the long-run, they were not found to be a hedge over the short-run. The lagged indexation phenomenon has been blamed for the inability of index-linked gilts to offer a short-term hedge against inflation. Although the returns of these bonds are supposed to change with any change in inflation rate, in practice, the returns of index-linked bonds are adjusted 3 to 8 months after the official declaration of the inflation rate (Schofield, 1996). Several stock sectors were found to be a good hedge over the long-term as they were found to be cointegrated with at least one inflation and/or interest rate. However, very few stock sectors exhibited a short-term causal relationship with the inflation/interest rates.

Over the short-run however, we found several alternative assets possess the ability to offer a hedge against inflation, witnessed by a causality in at least one direction by several alternative assets. This result is confirmed by the fact that the error-correction coefficients of some alternative assets were also quite high. In fact, private equity sectors had error-correction coefficients that exceeded most UK domiciled assets. We also investigate the effect of appraisal smoothing on the results of our analysis. We found that the conclusions reached on the inflation and interest rate hedging ability of these assets did not change when the unsmoothed IPD real estate sector and private market alternative asset return series were analysed. The the speed of adjustment to equilibrium (error-correction coefficient) increased remarkably. Hoesli et al. (1997) observed that this shows that private market assets do not adjust that quickly to market information. Similarly, we found that conversion of the returns of alternatives from USD to GBP did not alter the conclusion of the various tests.

In Chapter 8, we construct different inflation and interest rate hedging portfolios. The composition and the risk and return features of the various optimisation models are analysed. The effect on portfolio composition and the risk-return features of portfolios hedged against alternative inflation and interest rates are also discussed. We then compare the risk and return features of these portfolios to a traditional stock-bond portfolio. The role of real estate within the various portfolios is also investigated. As an add-on, we analyse the effect of using different real estate investment vehicles on the risk and return of the respective portfolios. We find that given the same optimisation framework, the use of CPI or RPI inflation rates do not produce portfolios that show any significant differences in composition or risk-return features. Similarly, using LIBOR interest rate or T-bill interest rates did not result in different portfolio structures. Portfolios based on semi-variance as a measure of risk were far more diversified than those that utilise tracking error of returns. The tracking-error portfolios were heavily invested in bonds and real estate. These portfolios produced remarkably low tracking errors out-of-sample. However, their returns were among the lowest of the various models. We feel that these portfolios are appropriate for periods where DC asset managers wish to pursue a low-risk investment strategy. The allocation within this portfolio accords with the practice within the asset management industry where investment managers gradually move the accumulated funds of the DC contributor into bonds as they get close to retirement. Some funds also use this strategy when the DC member has just started saving to help them accumulate enough funds before they pursue a riskier strategy in the growth phase. The belief is that investing in new DC members' assets in risky assets could discourage them if the strategy backfires and they lose even part of their contribution. We also found that the cumulative returns of the various inflation and interest rate hedging portfolios exceeded the cumulative inflation and interest rate growth. A practical application of this result is that it is better to construct an optimised portfolio than to invest in T-bills or inflation-indexed bonds that deliver the benchmark returns with more certainty. For example, between 1991 and 2015, an investment in T-bills would have produced just about a third of the cumulative returns of the low-risk tracking error portfolio. We also found that the optimised portfolios out-performed the traditional 80-20 portfolios in all cases. This result also means that the current 80-20 equity-bond allocation within DC pension funds is sub-optimal at best. Adding real estate to the portfolio leads to improved tracking error relative to all the inflation and interest rate benchmarks. This means that real estate improves the hedging ability of the various portfolios. However, we found that omitting real estate from the portfolio did not always result in a fall in the returns of the portfolios. Understandably, the returns depends on the asset that replaces real estate when real estate is omitted from a particular optimisation process. From this, we can conclude that the primary role that real estate plays within the inflation and interest rate hedging portfolios is to enhance the ability of the portfolio to hedge or closely track the inflation or interest rate.

9.2 LIMITATIONS AND AREAS OF FUTURE RESEARCH

Many of the issues discussed in this thesis are relevant not just to the United Kingdom but to other jurisdictions as well. The analysis in this thesis can be applied to countries, especially those where there are strict regulations such as those regarding minimum returns and those limiting the amount that can be invested in some asset classes. However, the analysis in this thesis has been limited to the United Kingdom. The UK was used primarily because of data availability and also because DC funds in the United Kingdom are free to select their own performance benchmarks. Consequently, using the UK as a case study has allowed us to explore a range of benchmarks and liquidity requirements.

Although Chapter 5 explores a large number of liquidity measures that can be applied to understand the how liquidity is measured in DC pension portfolios, we did not actually apply them in the chapter. In Chapter 6, we focused on blended/hybrid real estate investments as a route through which DC pension funds can gain access to the real estate market. Future studies could directly incorporate the liquidity measures explored in this chapter to understand the differences between proposed and actual allocation to real estate investment managers. We believe this could result in more realistic allocation to real estate than observed in previous studies.

In Chapter 6, we considered the possibility of adding liquid, publicly traded assets to a portfolio of UK properties. This analysis assumes that the investor is only interested in UK assets. Here again, it is possible to expand the liquid asset universe beyond UK assets. Obviously, this would mean dealing with foreign exchange risk and regulations that exist in the target country. The analysis in this chapter can also be applied to other illiquid assets such as commodities, farmland, infrastructure etc. It is also possible to create a fund which combines different illiquid assets and liquid, publicly traded assets to enable investors have access different alternative assets.

An obvious problem with the econometric models used in the analysis in Chapter 7 is that although they help in identifying assets that have short and long-run association with the selected inflation and interest rates, they do not provide any guidance on how an investor should combine these assets in a portfolio to obtain optimal inflation protection. This limitation is addressed in Chapter 8 which proposes and implements a number of portfolio optimisation techniques that help construct inflation and interest rate hedging portfolios. Other techniques may exist that can also enable investors address this issue of optimal allocation within inflation and interest rate hedging portfolios. Future studies could build on the ideas in this thesis and implement other models and techniques in the construction of portfolios to hedge against inflation and interest rate changes.

Also, the econometric models used in Chapter 7 do not consider the effects of possible structural breaks and non-linear relationship between asset returns and the inflation/interest rate benchmarks. This represents an area of future research which could be explored. State-space models could also be used to explore the time-varying nature of the relationship between asset returns and macroeconomic variables such as inflation and interest rates.

The analysis in the portfolio chapter were also undertaken without incorporating transaction costs and other rebalancing costs. Obviously, these could have an effect on the allocation to different assets as the post-transaction cost returns may be different, especially if the transaction costs in the various markets are significantly different from each other. Future studies could consider the effects of transaction costs incurred on various investment strategies to determine the options that would be in the best interest of investors.

These limitations notwithstanding, the present study makes important contributions to the literature on designing portfolios that could help Defined Contribution pensions to address the issue of liquidity within their investment portfolios. The techniques proposed in this Chapter could also be applied within DC pension funds for the selection of assets to offer an optimal hedge against inflation and interest rate changes.

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