CRANFIELD UNIVERSITY

Anandadeep Mandal

An Empirical Investigation of the Determinants of Asset Return Comovements

Cranfield School of Management
Doctorate Programme

PhD Thesis
Academic Year: 2014-15

Supervisor
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(NB. This section can be removed if the award of the degree is based solely on examination of the thesis)

An Empirical Investigation of the Determinants of Asset Return Comovements

ABSTRACT

Understanding financial asset return correlation is a key facet in asset allocation and investor's portfolio optimization strategy. For the last decades, several studies have investigated this relationship between stock and bond returns. But, fewer studies have dealt with multi-asset return dynamics. While initial literature attempted to understand the fundamental pattern of comovements, later studies model the economic state variables influencing such time-varying comovements of primarily stock and bond returns.

Research widely acknowledges that return distributions of financial assets are non-normal. When the joint distributions of the asset returns follow a non-elliptical structure, linear correlation fails to provide sufficient information of their dependence structure. In particular two issues arise from this existing empirical evidence. The first is to propose a more reliable alternative density specification for a higher-dimensional case. The second is to formulate a measure of the variables' dependence structure which is more instructive than linear correlation.

In this work I use a time-varying conditional multivariate elliptical and non-elliptical copula to examine the return comovements of three different asset classes: financial assets, commodities and real estate in the US market. I establish the following stylized facts about asset return comovements. First, the static measures of asset return comovements overestimate the asset return comovements in the economic expansion phase, while underestimating it in the periods of economic contraction. Second, Student t-copulas outperform both elliptical and non-elliptical copula models, thus confirming the

dominance of Student t-distribution. Third, findings show a significant increase in asset return comovements post August 2007 subprime crisis.

Next, the thesis examines the determinants of time varying dependence structure of the return comovements of three different asset classes using Markov Switching Stochastic Volatility (MSSV) model. The dependence structures are estimated using conditional Student-t copula. This study provides a number of significant findings. First, I confirm that the dependence structures of asset return comovements of all asset pairs show significant regime-switching behaviour both in terms of statistical and economic significance. Second, I find that amongst the macro-economic factors, interest rate and inflation have significant effect on the return comovements during the economic contraction regime, whilst risk aversion plays a significant role in the economic expansion regime. On the other hand, the non-macro factors i.e., output uncertainty, bond illiquidity and depth of recession contribute significantly in explaining the return comovements in both economic contraction and expansion regimes. Third, the findings suggest that the return comovements of the real estate-oil pair are influenced by only macroeconomic factors. Finally, the model fit worsens considerably when the non-macro factors are dropped for the equity-bond and equity-oil pairs.

Using multivariate time-varying conditional copula, I analyze the time variation of the joint dependence structure of the non-linear asset returns. This research is important because it presents the first empirical evidence examining the factors that drive the joint return distribution of different asset classes. I find that non-macro variables have significant influence on the return comovements. The findings show that among the non-macroeconomic variables, uncertainty and illiquid variables play a dominant role in both contractionary and expansionary phases of the economy. Further, I observe that among

the macro-economic variables, inflation and risk aversion positively impact the return comovements. Finally, my examination of the factor contributions reveals that the model fit worsens considerably when the non-macro factors are dropped from the estimation model.

This work also studies the economic sources of extreme stock return comovements of the emerging Indian equity market and the developed equity markets of US, UK, Germany, France, and Canada. The findings show that the probability of extreme comovements in the economic contraction regime is relatively higher than in the economic expansion regime. Further, I show that increase in stock market volatility in the developed markets during the economic contraction phase does not adversely impact the Indian stock market returns. Overall, I show that 3-month Treasury bill rate of developed economies, inflation uncertainty and dividend yields are the main drivers of the asymmetric return comovements.

An additional contribution of this thesis relates to the practical applications of this research study. The findings show that MSSV framework enhances the flexibility in the model accommodating the persistence of volatility shocks. Moreover, the Markov switching model is able to capture the 'pressure smoothening' effects of those shocks that are not persistent and are followed by low volatility regimes. Overall, the findings indicate that the dynamic strategy employed by the developed regime switching framework outperforms the multivariate conditional covariance strategy. This, therefore, justifies that understanding the dynamics and the influence of macroeconomic and non-macroeconomic factors on asset return comovements enhances asset allocation decisions.

Keywords: Markov Switching stochastic volatility model, dependence structure, Student-t copula, asset return comovements, emerging Indian equity market

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CHAPTER 1

Introduction

In the wake of the economic downturn during 2007-08, returns of different asset classes have shown evidence of strong linkages. Declining house prices in the US led to the collapse of various financial institutions, triggering a steep decline in equity markets, commodity prices and real estate values globally. The oil prices also witnessed high volatility with prices reaching US$147 per barrel in July 2008 and dropping below US$60 per barrel within the next four months (Chan et al., 2011). In addition, the stimulated response by the Federal Reserve led to extremely low interest rates in many economies, driving up the demand for government bonds and causing a steep decline in yields. On the other hand, corporate bond spreads widened appreciably whilst the gold prices reached new highs.

These developments provide anecdotal evidence of increased linkages between financial, commodities and real estate markets, triggering a renewed interest amongst academics and practitioners in examining asset allocation strategies for effective diversification of risk during turbulent economic conditions. However, asset allocation strategies can be properly executed only if the nature of return comovements of various asset returns is well understood. Guidolin and Timmermann (2007) show that since asset return comovements are time varying and dynamic in nature, investors require information about conditional distribution of the asset returns for implementing dynamic asset allocation strategies.

It is well known that asset return comovements are not time-invariant but tend to be rather dynamic in nature. Investors, therefore, require information about conditional distribution of the asset returns to implement dynamic asset allocation strategies. Information regarding whether the returns of two or more assets are positively related in certain circumstances but negatively related in others may have key implications in portfolio diversification and asset allocation strategies. Thus, understanding asset return correlation, i.e. dependence structure, is a key aspect of asset allocation and portfolio optimization strategy. For the last decade, several studies have examined the stock and bond return comovements (Wainscott, 1990; Shiller and Beltratti, 1992; Connolly et al., 2007; Baele et al., 2010). But, fewer studies have dealt with multi-asset return dynamics. In this work I refer to multi-assets as a combination of three or more assets. It is fair to say that investors no longer invest in only conventional financial assets such as equities and bonds but in a wide range of alternative instruments including commodities and real estate. Thus, examining multi-asset asset dependence structures has important implications for asset management. Furthermore, extant literature primarily uses linear dependence structure to explore the return dynamics of the assets. While the linear dependence structure is widely used, this measure of association is too simple to accurately characterize the non-normal distribution of the financial returns. Also, under non-normal conditions, it becomes very difficult to characterize the joint distribution of multi-asset returns (Jondeau and Rockinger, 2006). Under these circumstances, the copula functions approach may be an effective alternative to overcome the limitations of a linear dependence structure measure such as the correlation coefficient.

The copula method has significant advantages over other parametric methods in capturing the uncertainty associated with the dependence pattern of financial return series. First, the copula functions approach can be efficiently employed to examine dependence structure beyond linear measure of association. The copula models also provide a higher degree of flexibility, which allows capturing of the dynamic non-linear characteristics of multi-asset return dependence structure. Second, unlike the traditional parametric approach, copula method does not require any probabilistic normal distribution assumptions. Third, the copula approach preserves the dependence structure during the non-linear transformation of the random variables. In other words, the marginal and the joint distribution models can be estimated separately without loss of information. Fourth, copulas are best suited to examine the dynamic nature of multivariate random variables. Effectively, copula provides a more efficient method of modelling the joint distribution of financial assets under non-linear dynamic environment.

Further, asset return comovements change due to changes in economic conditions and/or changes in non-macroeconomic factors. For example, Piplack and Straetmans (2010) show that asset return comovements change during periods of market stress. Thus, in constructing an optimal portfolio, it is critical to identify the economic circumstances and understand the impact of macroeconomic and non-macroeconomic factors on asset return comovements. A model identifying variations in the asset market linkages and decomposing the effects of macroeconomic and non-macro factors influencing the dependence structure of different asset return comovements is critical for accurately estimating the portfolio risk. Further, identifying the determinants of asset return comovements across different asset classes has significant implications for policymakers and financial regulators. If different assets show positive comovements especially during periods of economic contraction, then an understanding of key determinants of their dependence structures will aid in implementation of appropriate interventions by the policy makers. There is plenty of literature on stock-bond return comovement; however, research on linkages amongst other asset classes is relatively scarce. Despite the significant importance of understanding the determinants of the linkages between various asset return comovements, relatively little work has been done in this area.

Against this backdrop, the key objectives of my research are: i) to examine the bivariate comovement of the asset return dynamics in the US market, ii) to statistically test the performance of elliptical and non-elliptical copula models for both the constant and the dynamic dependence structures, iii) to analyse if the dependence structures exhibit evidence of regime switching behaviour, iv) to identify macro and non-macro factors and examine their impact on the dependence structure of the asset return comovements, v) to investigate whether the impact of these factors on dependence structures is the same in different regimes and finally vi) to extend the work in identifying various channels of equity market linkages between emerging Indian equity market and the developed economies.

1.1 The distinct features of the work

This empirical work has a number of distinct features. In this study I adopt an alternative approach to overcome the limitations of simple linear correlations to examine the dependence structure of the multi-asset return comovements. The proposed approach models the dependence structure of the returns across three different asset classes using dynamic conditional copula models. In this research, all the five asset returns follow a non-normal distribution. I analyze and identity the determinants of both the general and the tail dependence structures of the bivariate asset pairs and the joint comovement of the multi-asset returns. My empirical findings contribute to the literature along several dimensions.

1. The dataset not only includes conventional financial assets, i.e. equities and bonds, but also commodities and real estate. Further, the period of analysis is from 1987 to 2012 (1st August 1987 to 1st September 2012), which allows me to capture the effects of economic downturns caused by several financial crises on the behaviour of different asset classes.
2. I examine the dynamics of the general and the tail dependence structures for the ten bivariate combinations of asset pairs and extend the modeling of dependence structure to capture the time-varying evolutionary effect of the return comovements especially during the crisis period. Further, I examine the joint dependence structure by combining all the asset classes. With the ever rising uncertainty in the financial markets, investors do not solely invest in only one or two assets but in a portfolio of assets. Therefore, this examination of the joint dependence structure of the multi-asset return comovement yields important information for portfolio diversification and asset allocation. To the best of my knowledge this is the first study, which attempts to examine such an issue.
3. This study compares and statistically tests the performance of various elliptical and non-elliptical copula models. This enables proper selection of a superior model to understand more complex return dynamics, especially during periods of financial turbulences.

4. I consider a wide range of macroeconomic factors and non-macroeconomic factors[1] to explore the determinants of the dynamics of the dependence structures for the 11 combinations of asset pairs. The state variables include interest rates, output gap and inflation and also risk aversion measure based on Campbell and Cochrane's (1995) model. I also consider macroeconomic uncertainty measures to accommodate for economic uncertainties as shown by David (2008) and Bekaert et al. (2009a). Additionally, the research includes other non-macroeconmic variables such as liquidity, variance premium and depth of recession. It is, to the best of my knowledge, the first study that comprehensively examines the macroeconomic and non-macroeconomic determinants of the dependence structure for three different asset classes.
5. In examining the dynamics of the state variables using Markov Switching Stochastic Volatility (MSSV) model, I impose structural restrictions inspired by New-Keynesian dynamics[2]. My regime-switching model accommodates for heteroskedastic shocks in the state variables. I, further, decompose the performance of the model to examine the impact of macroeconomic and the non-macroeconomic factors. This provides useful insights in identifying the key determinants of multi-asset return comovements.

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[1] The variables that affect the whole economy of a nation rather than a few selected investors or individuals are considered as macroeconomic variables. The macroeconomic variables considered in this study feature in the standard macroeconomic models. The variables include, output gap, inflation and short rate. The factors other than the standard/pure macroeconomic variables are termed/considered as non-macroeconomic variables in this study. These variables include economic risk premium proxies (such as economic uncertainty measures and non-liner component of risk aversion factor) and stock and bond market illiquidity variables.

2 The New-Keynesian dynamics links the New Classical macroeconomics with Keynesian school of thoughts. The two key assumptions of the New Keynesian models are i) markets react to rational expectations, ii) there exists imperfect competition which means that prices and wages do not adjust instantaneously to changes in the economy. As a consequence, the New-Keynesian dynamics thrives on non-neutrality of monetary policy implying optimal behaviour of microeconomic agents.

6. This study also examines the forecasting performance and the economic value of understanding asset return comovements. Specifically, I present the forecasting analysis of the Markov switching stochastic volatility models that capture the dynamic behaviour of the asset return comovements. Further, I check whether regime switching forecast provides more accurate results than a single regime stochastic volatility model. This adds to the robustness of the application of the developed regime switching models.
7. India's well established trade links with the world is next only to China. Thus, there is little doubt that amongst the emerging economies, India is going to play an increasingly important role in shaping the world's economy in coming years. An understanding of the causes of extreme comovements will therefore provide greater insights to both Indian policy makers and international investors. This study aims to achieve this by investigating the economic sources of stock return comovements of the emerging Indian equity market and the developed equity markets of US, UK, Germany, France, and Canada.

1.2 The key findings of the work

This work reports several key findings.

1. The time-varying copula models provide superior dependence structure measures compared to the static copula models. This illustrates that asset allocation based on simple linear correlation of asset returns will result in underperforming portfolios.
2. The findings show that lower tail dependence is much higher than upper tail dependence. This suggests that there is high probability of extreme comovements in

economic contractionary period. The higher dependence measure implies that some of the diversification benefits are lost during the contraction periods, which are characterized by increased risk.

3. The bivariate dependence structures: The findings provide significant evidence of regime switching behavior. The dependence structures tend to rise faster than they fall, which corroborates the anecdotal evidence of contagion in financial markets across different asset classes. The results show that during the economic contraction regime, the non-macro factors play a significant role in defining the dependence structure, whereas during the economic expansion regime the macroeconomic factors seem to have a greater impact on the dependence structures. The significant impact of the liquidity factors provide evidence for “flight-to-liquidity” phenomenon as reported in the previous literature (Connolly et al., 2005). This indicates that when risk aversion is high during periods of economic contraction, interest rates may be low, increasing the bond prices, but stocks which are positively correlated with interest rate shocks during the times of economic contraction may witness fall in prices. Further, the significant influence of the economic uncertainty measures indicates that higher the uncertainty about future economic state variables, the more swiftly the investors are likely to react to news. This in turn affects both the variances and the covariance of the asset returns. This study therefore makes a significant contribution to the literature on the learning models as proposed by Veronesi (1999) and David and Veronesi (2008).
4. Joint Dependence Structure (JDS): The findings show significant regime-switching behaviour both in terms of statistical and economic significance. The two regimes identified represent economic expansion and economic contraction phases. The

results show that among the macroeconomic variables, inflation plays a central role (positive influence) during both the phases of the economy. Also, risk aversion is positively significant during the economic contraction phase, whereas risk free rate negatively affects the JDS during the economic expansion period. Among the non-macroeconomic variables, uncertainty variable and bond illiquid play a dominant role in both the phases of the economy. The findings show that output uncertainty and bond illiquidity have the highest coefficient values. The significant impact of the liquidity factor provides evidence for “flight-to-liquidity” phenomenon. While more research is accounted for in the field of “flight-to-liquidity” and its interaction with liquidity, some previous studies give credence to these findings. For instance, Li (2007) shows that systematic liquidity risk is priced in bond markets. However, they do not conduct study for other financial assets. Further, examining the factor contributions, the study finds that the model fit worsens considerably when the non-macro factors are dropped. Thus, it is fair to say that the non-macroeconomic factors play a vital role in explaining the variations in the JDS. The results are also conclusive from the quartile regressions and other robust tests.

5. The study shows that JDS fails to show any significant extreme comovements during either phases of the economy. This reinstates the diversification benefits of investing in assets other than conventional stocks and bonds. However, the results also show an increase in JDS since the August 2007 subprime crisis. An important implication of high dependence measure is that otherwise-diversified portfolios, which combine safe assets such as bonds and gold, witness loss in diversification benefits during periods of economic decline.

6. Emerging Indian equity market and developed economies: Consistent with existing literature (Yilmaz, 2010; Kenourgios et al., 2011) the findings show that probability of extreme comovements in the economic contraction regime is relatively higher. The study finds that both Indian and international inflation uncertainty are likely to adversely affect international portfolio's risk diversification potential since they positively impact the return comovements. The results show that an increase in the international interest rates has a positive impact on the return comovements. This suggests that both international and Indian equity markets are adversely affected by the hike in international interest rates. However, while an increase in the Indian interest rates negatively affects its stock market, it has no impact on the international equity markets. The results also indicate that rise in stock market volatility in the developed markets during the economic contraction phase does not adversely impact the Indian stock market returns. The results indicate that Indian dividend yield (DY) and price-to-earnings (PE) ratios seem to have a greater positive impact on return comovements during the economic expansion phase as compared to the economic contraction phase. However an increase in international dividend yield during the economic contraction phase increases the return comovements suggesting that it fails to uplift the investors' sentiments in both international and Indian equity markets.
7. Contributions to practice: The findings show that developed Markov switching framework enhances the flexibility in the model accommodating the persistence of volatility shocks. For instance, if shocks are more persistent in periods of economic contraction than in periods of economic recovery, this can be captured by the specific regime parameters. Moreover, the Markov switching model is also able to capture the 'pressure smoothening' effects of those shocks that are not persistent and are followed

by low volatility regimes. The results also indicate that the dynamic strategy which considers the factors that drive the return comovements outperforms the portfolio returns constructed based on multivariate conditional covariance strategy.

The rest of the thesis is organized as follows: Chapter 2 reviews the literature on asset market linkages. Chapter 3 provides the research question examined in this work. Chapter 4 discusses the proposed approach to model the joint dependence structure of the multi-asset returns and develops the dependence structure models. Chapter 5 provides a description of the data used and discusses the empirical findings of the bivariate and joint dependence structure. Chapter 6 discusses the methodology used to model the dynamics of the dependence structure models and provides a description of the macro and non-macroeconomic variables used in the study. Chapter 7 discusses the empirical findings of the determinants of the bivariate dependence structures. Chapter 8 discusses the empirical findings of the determinants of the joint dependence structure and examines the practical applications of the empirical models developed. Chapter 9 examine the equity market linkages between emerging Indian and developed economies and finally Chapter 10 concludes the thesis work.

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CHAPTER 2

Literature Review

2.1 Introduction

Following the financial crisis of 2007, academics as well as practitioners have been keen to understand the behaviour of financial assets in turbulent economic conditions. Asset allocation has attracted the attention of investors and researchers in the domain of portfolio return prediction and forecasting. The key requirements for understanding the approach to asset allocation are return, risk and the correlation of the asset classes. Ever since the seminal work of Markowitz (1952) asset correlation has been the prime focus of portfolio management.

Efficient pricing suggests that any news about future cash flows and the required rate of returns is reflected on security prices at once. This adds to the challenges faced by portfolio risk management professionals and long-term investment holders. Engle (2004) shows that information arrives in huddles, which leads to clusters in pricing volatility affecting different financial assets differently. For instance, negative news about the economic cycle may impact equity prices adversely but will have an insignificant effect on the returns of real estate investment companies. This is because the cash flows of real estate investments come from leases with long term maturity and have fixed terms. Thus, differential news impacts drive the return correlation of different asset classes not to be time-invariant. Consequently, correlation of assets is decisive for risk management and control.

As such, one key follow up question that arises is whether investors should include all possible financial assets in their portfolio to gain maximum diversification benefits.

Given that these multi-asset portfolios act in different ways to hedge against various risks associated with the economic conditions, the primary issue is to realize the return co-movements of these various financial instruments.

Against this backdrop, the aim of this chapter is threefold. First, it provides a sound literature review that is central to the research issue. It forms the foundation for developing an informed conceptual model that will enable to build on and contribute to existing knowledge in the relevant fields. Second, the review of the existing theoretical and empirical knowledge reveals potential research gaps for further investigation. This leads to the advancement of the research questions. Third, it informs the theoretical foundation and methodological approaches which will be subsequently used in the following chapters.

In addition to providing a sound literature review, my approach in examining the extant literature has two key distinctive features. First, I carry out an empirical analysis on the conventional financial assets, i.e. stocks and bonds, to illustrate the distinctive aspects of the time-varying phenomena. Second, the review provides four boundaries that inform the empirical work necessary for further enquiry in the relevant field of multi-asset return co-movements.

2.2 Asset Return Comovements

The extant literature examines the relationship of various financial in small subsets. Some authors examine the stock and bond return relationship, while others investigate the relationship between equity markets and certain commodities or real estate. None of the existing studies examine the determinants of the comovements of a range of financial, commodity and real estate assets that we study in this paper.

The literature on the determinants of the asset market linkages focuses on different pairs of financial assets. For example, in one of the earlier studies Hamilton (1983) show that an increase in oil prices negatively affects corporate expenses causing future stock returns to increase. In other words, the study reports that increase in oil prices has a negative impact on the expected stock returns, i.e. on the equity market. In more recent studies, Driesprong et al. (2008) and Jones and Kaul (2012) examine the relationship between oil price and stock return co-movements. Jones and Kaul (2012) explore this relationship for U.S., U.K., Canada, and Japan. They conclude that only for U.S. and Canada, the global oil shocks significantly influence the equity prices. On the other hand, Driesprong et al. (2008) show that oil price movements significantly predict equity returns in both developed and emerging economies. Their findings also demonstrate that time-varying risk premia fail to explain the predictive phenomenon because oil price movements significantly affect excess negative returns. While these studies try to establish the link between oil shocks and stock returns, they do not provide insights on the determinants of the return comovements of oil and stock returns. In other words, the impacts of macro and non-macroeconomic variables remain unexplained and unexamined.

Interestingly, despite the importance of gold as a hedge and/or a safe haven, studies investigating the dependence structure of gold returns and other assets are rare. Amongst them, the prominent studies by Tully and Lucey (2007) and Batten and Lucey (2009) model the volatility of gold futures market, while Baur (2012) examine the asymmetric nature of gold volatility. These studies analyze some specific the volatility characteristics of gold, but do not focus on examining the dependence structure, i.e. return comovements, of gold returns with other assets. Far fewer studies examine the relationship between gold and other financial assets. Exceptions include Baur and Lucey (2010) and Baur and McDermott (2010). They demonstrate that gold acts as a safe-haven investment in volatile market conditions. Yet, in extreme market conditions Treasury bond returns and not gold are negatively correlated to stock returns (Piplack and Straetmans, 2010). Fewer studies examine the correlation between gold and other asset returns. Cashin et al. (2002) show that there exists significant correlation between oil and gold for the period 1960 to 1985. Pindyck and Rotemberg (1990) confirm similar findings for oil and gold price levels. Šimáková (2011) show that there exists a long term relationship between gold and oil prices. However, research examining the relationship between gold and other asset returns through the common factors is far less common. Most of these studies exhibit the link between gold and oil prices through inflation channel. The studies empirically show that when inflation rises, the price of gold as a good also rises (Hooker, 2002; Hunt, 2006). Furlong et al. (1996) find that rise in oil prices increases price of other assets. Most interestingly, none of these existing studies analyse the extreme comovements of gold asset returns. Therefore, a model identifying the variations in the asset market linkages between gold and other financial assets and the effects of macroeconomic and non-macro factors influencing the dependence structures of the return comovements is critical for examining the benefits and portfolio diversification. For instance, if market linkages between gold and other financial assets increases in times of economic crisis, then the effectiveness of gold as safe haven may be compromised. Alternatively, if the dependence decreases in periods of economic contraction, the effectiveness of investing in gold is enhanced. It is thus essential to examine the dependence structure of gold returns and examine the economic sources that significantly influence the market linkages during extremes.

Concerning real-estate, the relationship between real estate and stock market is mixed. On one hand studies show that the in US the real estate market is segmented from the stock market due to eternal barriers such as information quality and cost of real estate. This leads to the findings that real estate and stock market returns are not statistically significant (Liu et al., 1990; Quan and Titman, 1999). In contrary, Peterson and Hsieh (1997) show that equity and real estate risk premiums are significantly related to the three factor Fama-French model, while mortgaged real estate risk premiums are associated with bond factors. Further, Ling and Naranjo (1999) use a multi-factor asset pricing model and confirm that the real estate securities market is integrated with U.S. stock markets and their linkage significantly increase during 1990s. But in a more recent work, Downs and Patterson (2005) show that real estate returns cannot be fully explained by stock and bond returns. However, it is worth noting that none of these studies try to examine the determinants of the return comovements of real estate and other assets. Primarily, the existing studies examine whether asset returns of either stocks or bonds have an influence over the real estate returns. To emphasize, previous studies do not investigate what we achieve in this work.

Alternatively, authors have used the concept of cointegration to examine long-run relationship between real estate and capital market prices. Glascock et al. (2000) show evidence of bivariate cointegration between real estate security and S&P 500 index for the period 1992 to 1996. But, the relationship fails to be statistically significant for later years 1972 to 1996. During the period 1992-1996, the findings also show significant cointegration between real estate security and bond market. The study reveals decreasing diversification benefits of real estate securities and equity investors after 1992. In contrast, Chaudhry et al. (1999) show multivariate cointegration between the real estate market, the equity market, the bond market and the Treasury bills. Allowing structural breaks in cointegration tests, Wilson et al. (1998) show that U.S., U.K. and Australian real estate and stock markets are not cointegrated. Employing fractional cointegration tests, Okunev and Wilson (1997) show that there exists non-linear relationship between real estate and stock markets. Still, the results provide no significant evidence for a long-term relationship using conventional tests. In a similar vein, Liow and Yang (2005) provide evidence for Japan, Hong Kong, Singapore and Malaysia. They show the existence of short-term dynamics and long-term co-movement between the equity market and real estate securities.

Authors have used other time-series techniques to examine the time-varying relationship between real estate and general financial markets. Conducting structural break tests, Kallberg et al. (2002) report return and volatility regime shifts in real estate and equity market for eight Asian countries. Cotter and Stevenson (2006) employ a bivariate GARCH model to conclude that real estate and stock return correlation increased during the period 1999-2005. Huang and Zhong (2011) employ a multivariate GARCH technique to examine the daily conditional correlation between real estate security and the U.S. stock market. They claim that the correlation follows a positive trend for the period 1999 to 2005. Using a similar approach, Case et al. (2012) examine the monthly conditional relationship between real estate security and the U.S. equity market for the period 1972 to 2008. They explore the implications for portfolio diversification. Yet, none of the studies aim to model the joint distribution of multi-asset returns, allowing the distribution to be dynamic over states or regimes. The only studies which explores in similar lines as this work does are by Chan et al. (2011) and Clayton and Mackinnon (2003). The former use a Markov regime switching model and report contagion effects across stock, oil and real estate returns during economic recession. However, these studies fail to examine the determinants of contagion across various assets returns. Such an analysis may provide novel insights for researchers, investors and policy makers. The closest paper to answering these questions is the latter one. It reports that those economic factors which drive large market capitalization U.S. stocks also influence real estate prices. Similar to the previous discussed literature, these studies do not examine the impact of non-macroeconomic variables. Further, they do not examine the impact of the determinants during periods of economic expansion and contraction[3].

It is interesting to note that the existing studies examine these relationships either based on asset pricing model or time series analysis. For example, Huang and Zhong (2011) examine the time variation in diversification benefits of commodities and real estate. Using data from 1970 to 2010, the study reports that investments in commodities and real estate cannot be substituted and hence they provide diversification benefits. As expected, they show that the diversification benefits are time varying and are dependent on the time-varying correlation. The authors show that dynamic conditional correlation model outperforms other correlation structures, namely constant correlation and historical rolling correlation. While this finding is not surprising as the commodities and real estate show evidence of time-varying asymmetric returns, the authors fail to address limitations

[3] Economic expansion refers to the phase of the business cycle which witness an increase in the level of economic activities. Economic expansion is a period of economic growth which is often measured by a rise in gross domestic product. In contrast, economic contraction refers to the phase of the business cycles that witnesses a decline in the level of economic activity. During economic contraction the economic slows down leading to a fall in gross domestic product and rise in unemployment.

of using Multivariate Generalized Auto-Regressive Conditional Heteroskedasticity (MGARCH) framework, which are presented in the following sub section. Further, similar to majority of the existing literature, the study does not consider the economic cycles and the determinants of return comovements in examining the correlation structure. In a seemingly related study Yang et al. (2009) use a multivariate GARCH model to examine the dynamic conditional correlation between S&P 500, US corporate bonds and real estate returns. They provide evidence for asymmetric volatility in real estate returns. In contrast to the previous study they show reduced hedging benefits of real estate against bearish equity market returns. This can be related to the evidence of strong asymmetric conditional covariance between real estate and stock returns. The study also shows that investment in bonds provide diversification benefits for stocks and real estates. In examining what drives the asymmetric return correlation, they report that default spread and stock market volatility play a significant role. In light of examining the determinants of return comovements, this research remains inconclusive because of several reasons. First, they do not consider the impact of macroeconomic and non-macroeconomic variables. Second, the study does not consider the differential impact of the explanatory variables during the economic contraction and economic expansion phases. Since the factors can have a more dominant role in either of the phases of the economy, there is likelihood that the results will be biased and inconsistent if the whole sample is taken into consideration while examining the drivers of return comovements. The third imitation relates to the use of multivariate GARCH models in examining retune comovements. I discuss the limitation of these models in the next sub-section.

In contrast to the above discussed body of literature on return comovements of different financial assets, considerable body of empirical research examines the stock and bond return comovements. Most studies confirm that stock and bond return correlation varies inversely with stock market volatility. Some authors relate this to the ‘flight – to-safety’ phenomenon (Connolly et al., 2005; 2007). Unlike the literature on other financial assets, authors have examined the variables that have an impact on the stock and bond return comovements. In majority of the studies the authors claim that real interest rate and inflation volatilty influence the stock-bond return correlation (e.g. d’Addona and Kind, 2006, Boyd et al., 2005 and Andersen et al., 2007).

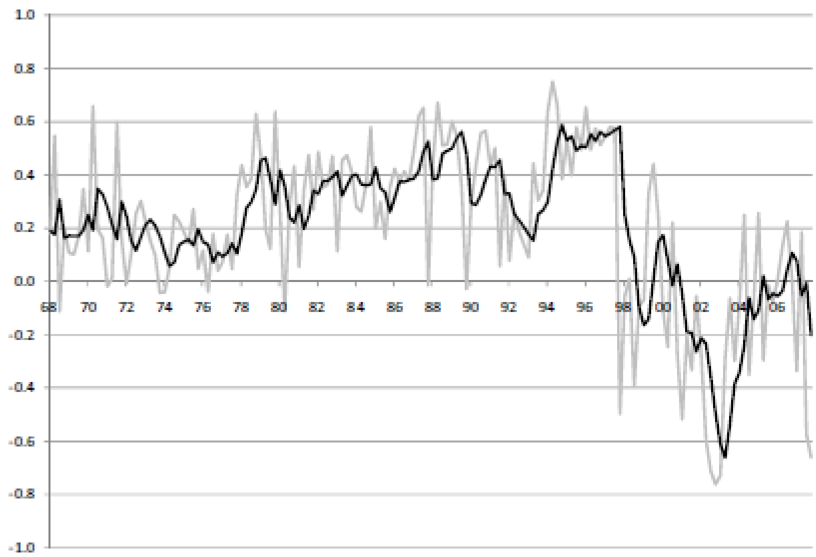
However, whether the stock-bond return correlation is significatly higher in the bull phase and in the bear periods is ambiguous. For instance, Ilmanen (2003) finds that returns are positively correlated during economic expansion whereas the correlation declines during economic contraction. In contrast, Jensen and Mercer (2003) show that stock and bond return correlations are higher during recession and lower during the expansion phase. The existing studies show two major limitations. First, they do not consider other variables such as output and inflation uncertainty, illiquidity factors, depth of recession along with risk aversion and other macroeconomic variables and second, these studies are mostly based on linear measure of association, which does not accommodate for the asymmetric characteristics of the return distributions. Baele et al.’s (2010) model considers macro-economic variables and non-macro factors, e.g. liquidity to account for stock-bond return correlation. Though their model addresses the former limitation, it does rely on the unrealistic normality assumption of the asset returns. Other studies that aim to overcome the second limitation, such as Chan et al. (2011), do not consider the determinants of the return comovements. This study, unlike the existing studies, addresses both these limitations. The work, therefore, contributes to the filling of the on-going research and existing literature gap’s on the determinants of asset return linkages. In particular, my approach analyses the differential impacts of macro and non-macroeconomic variables on asset return comovements of three different asset classes during economic contraction and economic expansion regimes.

The extant literature primarily uses linear dependence structure to explore the asset return dynamics. In the following sub-section I present the modelling techniques primarily used in examining asset return comovements.

2.3 Modelling the asset return co-movement

Majority of the studies in asset return comovements examines conventional financial assets, i.e. stocks and bonds. For instance Baele et al. (2010) report that post-1968 to 2009 U.S. stock and bond markets show 19 percent correlation between stock and bond returns. However, previous researches have provided inconsistent findings. For example, Shiller and Beltratti (1992) underestimate the empirical stock-bond correlation by imposing constant discount rates in their present value model. In contrast, Bekaert et al. (2009) overestimate the co-movements employing a consumption based asset pricing model. Yet, these methods provide substantial evidence of significant correlation. Previous findings show (cf. Figure 2-1) that stock-bond (New York Stock Exchange index returns and 10 years government benchmark bond index returns) correlation is as high as 60 percent in the late nineties to as low as negative 60 percent in 2005. An increasing number of authors have documented this time-varying phenomenon using sophisticated statistical models (Guidolin and Timmermann, 2005), but much less research has been done to unravel the underpinning economic sources.

Figure 2-1: Stock-Bond Return Correlation



Source: adopted from Baele et al. (2010)

In the extant literature researchers have used different techniques to capture the asset return comovements. The studies show that despite the limitations of linear correlation, it has been most frequently used to examine the asset market linkages. Alternatively, researchers have also proposed autoregressive and multivariate GARCH frameworks to capture the dynamic return comovements. For example, Schwert (1990) uses 12th order autoregressive predictive models[4] to examine why volatilities of stock and bond returns change over time. While this paper does not examine the return comovements, it is one of the seminal studies to examine the time varying return volatilities of asset returns. In a similar vein, Downing et al. (2009) adopt a bivariate vector autoregressive (VAR) model[5]

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[4] $\left|\hat{\varepsilon}_t\right| = \sum_{i=1}^{12} \gamma_i D_{it} + \sum_{i=1}^{12} \rho_i \left|\hat{\varepsilon}_{t-i}\right| + \mu_t$, where ε_t denotes the standard deviation and D_{it} is the capital gain including the dividends.

[5] $z_t = c + \sum_{i=1}^{L} b_i R_{B,t-i} + \sum_{i=1}^{L} S_i R_{S,t-i} + \varepsilon_i$, where Z_t is the vector $\left[R_{B,t}, R_{S,t}\right]'$, $R_{B,t}$ is the bond return and $R_{S,t}$ is the stock return.

to examine the relationship between stock and bond returns. However, such examinations have major limitations i) the use of VAR models lead to identification problem. In specific, the combination of past values of the endogenous and exogenous variables leads to predetermined values of the reduced form model. In other words, the number of reduced form coefficients and the number of structural parameters will not be equal. This leads to either over or under identification of the model, ii) the VAR models fail to differentiate between correlation and causation (with the exception of structural VARs). Thus, they, i.e. the reduced form VARs and recursive VARs, are not suitable for structural inference or policy analysis, iv) the standard VARs (reduced form VARs and Recursive VARs) are nonlinear and suffer from conditional heteroskedastic issues, leading to the estimation of inefficient parameters. Therefore, they are unstable and hence are poor predictors, v) the timing conventions in the VARS may be misleading and do not necessarily reflect the real-time data availability. As an example, assumption regarding inflation is non-responsive (sticky) to monetary shocks over a given period of time is valid for a single day/ short time period, but becomes less plausible over a month/longer period. Such assumptions are generally made for structural VARs, vi) if some of the variables are highly persistent in the VAR model, then the standard errors of the impulse response functions leads to misinterpretation or results, vii) there is a high likelihood that the appropriateness of the lag length (either by information criteria or cross-equation restriction) leads to inconsistency of the results, viii) the number of parameters to be estimated is large (proportional to the square of the number of variables). Therefore, even for small sample size the degrees of freedom are rapidly reduced/ used up. This leads to increased standard errors and wide confidence intervals.

In contrast, Wainscott (1990) calculates the correlations based on rolling averages for the periods of one, three, five and ten years. He examines these correlations to test the predictive power of the future relations based on the historical relations. The study shows that extrapolating the past correlations to predict future return comovement leads to unsatisfactory results. Ilmanen (2003) uses the dividend discount model[6] to find the correlation of the factors with the pricing of the asset classes. To examine the stock-bond return comovement, the study uses 26-week rolling correlation to explain and predict the future return dynamics. In line with the previous studies, this paper clearly fails to accommodate the limitations of using simple measures of association.

An alternative to the use of linear correlation is the use of multivariate GARCH models in examining the covariance structure of return series. In recent years several authors have increasingly relied on such approaches to analyse asset return comovements. For example, Scruggs and Glabadanidis (2003) use multivariate GARCH model to examine the dynamic covariance between stocks and bonds. Their approach is nested within Kroner and Ng's (1998) asymmetric dynamic covariance (ADC) proposed model. In particular the ADC is an extension of the generalized dynamic covariance model that allows the impact of lagged returns shocks to be defined by the sign and the magnitude of the shocks. The key advantage of using multivariate GARCH models is that it to accommodate for the volatility clustering and the time-varying correlation characteristics of the asset return comovements. A key contribution of the paper is that the authors reject

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[6] $P_S = E\left|\sum_{t=1}^{T}\left(1+g/1+Y+ERP_t\right)^T \times D\right|$, where P_s is price of a stock, g is growth rate, D is dividends, Y is short-term interest rate and ERP is the equity risk premium.

the constant correlation constraint in examining the dynamic covariance structure of the return comovements. Other significant studies using multivariate GARCH approaches include Brenner et al. (2009) and Berben and Jansen (2009). Brenner et al. (2009) use Engle's (2002) dynamic conditional correlation multivariate model GARCH model to analyse the asset return comovements. Berben and Jansen (2009) employ Berben and Jansen's (2005) Smooth-Transition Correlation (STC) GARCH model to estimate the patterns and capture the structural shift where the rate of change of the transitional variable can be abrupt. One of the key limitations of this work is in sampling the correlation to strictly follow two states, which examines only dominant long term trends. Overcoming this limitation allows us to examine the non-monotonic comovements, which are prevalent especially during periods of economic recession.

Next, I discuss the general factor model, which is predominantly used to link SB returns to structural factors.

2.3.1 Dynamic Factor Model

The dynamic factor model is the most common method used to link asset return co-movements. For example, Baele et al. (2010) examine the stock-bond return comovement using dynamic factor model. To illustrate the dynamic factor model, let us consider an example of examine the factors that influence stock-bond return comovements. The model is represented as:

$$r_t = E[r_{t-1}] + \beta_t F_t + \varepsilon_t \tag{2-1}$$

where r_t denotes excess equity and bond return matrix $r_t = (r_{s,t}, r_{b,t})$, $E[r_{t-1}]$ is the stock-bond vector of expected stock-bond returns, β_t represents the sensitivity to structural factor, F_t and ε_t is the vector of sock-bond return shocks.

In order to capture the time varying sensitivity of the structural factor, *'beta'*, i.e. $\beta_t = (\beta_{s,t}, \beta_{b,t})$, can be modelled as a function of an information set, I_t and V_t, which are discrete variables that follows the Markov process. These variables can thus be used to capture unexpected regime changes. *'Beta'* can be characterised as:

$$\beta_t = \beta(I_{t-1}, V_t) \tag{2-2}$$

The dynamic factor model assumes that the structural factors matrix (F_t) are normally distributed across a zero mean and its conditional variance (C_t), which represents a diagonal matrix.

$$F_t \sim N(0, C_t) \tag{2-3}$$

In particular, the conditional matrix is also influenced by V_t in the Equation (2-2). The off-diagonal elements of C_t is zero, imposing the diagonal matrix to be orthogonal. The null hypothesis of the Equation (2-1) considers the residual stock-bond returns covariance matrix to be homoskedastic. The major drawback of using dynamic factor model is that it fails to capture the volatility clustering and asymmetric nature of asset return, which are the realistic features of asset returns.

The Equation (2-1) implies that common economic factors affect stock-bond return co-movements. If, v_t denotes the realised instances of V_t, then the conditional variance of r_t can be represented as:

$$\mathrm{cov}_t(r_t) = \sum \beta_s'(I_{t-1}, v_t) C(v_t | I_{t-1}) \beta_b'(I_{t-1}, v_t) P[v_t | I_{t-1}] \tag{2-4}$$

If the stock-bond return covariance is independent of regime shifts, then (2-4) simplifies to

$$\mathrm{cov}_t(r_t) = \beta_{s,t}' C_t \beta_{b,t} \tag{2-5}$$

In equations (2-4) and (2-5) the orthogonal variances matrix C is conditioned on the information set I_{t-1}. To estimate the conditional correlation between stock-bond return co-movements, Baele et al. (2010) divides the covariance of the returns influenced by the state factors by the stock and bond return volatilities, i.e. $\sqrt{\beta_{s,t}' C_t \beta_{s,t} + e_s}$ and $\sqrt{\beta_{b,t}' C_t \beta_{b,t} + e_b}$ respectively, where e_s and e_b signifies residual stock-bond returns of the model (2-1). The resulting stock-bond conditional correlation equation is:

$$\rho_t(r_t) = \frac{\beta_{s,t}^1 \beta_{b,t}^1 \,\mathrm{var}_t(F_t^1)}{\sqrt{\beta_{s,t}' C_t \beta_{s,t} + e_s}\sqrt{\beta_{b,t}' C_t \beta_{b,t} + e_b}} + \ldots + \frac{\beta_{s,t}^n \beta_{b,t}^n \,\mathrm{var}_t(F_t^n)}{\sqrt{\beta_{s,t}' C_t \beta_{s,t} + e_s}\sqrt{\beta_{b,t}' C_t \beta_{b,t} + e_b}} \tag{2-6}$$

Equation (2-6) reveals three stylized facts of the dynamic factor modelling of estimating asset return comovement. First, variances of state factors have a significant effect on asset return comovement. Second, the impact of factor variance can be arbitrarily large on the correlation estimate, especially in case of an unexpected abnormal increase of variances. Third, the betas determine the direction of the asset return comovement. For example, if the betas for stock-bond have the same sign, then increase in factor variances will generate substantial comovement variation. Likewise, for reverse co-movement, one of the betas must be negative and it should have a high relative covariance with the state factors. These characteristics of the dynamic factor model also highlight the major limitations of using such models. It is observed that significant dependence of the factors can lead to unreliable correlation estimates. Further, large deviations in the variance structure of the factors especially during periods of economic decline can make the model unstable leading to inefficient analysis of asset return comovements. Finally, these models heavily depend on the modelling of the structural factors. Presence of structural breaks in the factors observed during financial crisis can lead to undesirable and spurious results.

Over the years researchers have used various other methods to account for asset return correlation. One of such methods that has received wide acceptance relates to affine asset pricing models (d'Addona and Kind, 2006), which I discuss next.

2.3.2 Affine Asset Pricing Models

The fair price of a financial asset is calculated as the product of expected future pay-offs and the pricing kernel, which is the stochastic discount factor. This ensures that there are no arbitrage opportunities in the economy. Below I provide an example of modelling stock-bond return correlation underpinning affine asset pricing framework. In discrete form it can be written as:

$$P_t^* = E_t[C_{t+1}^*, K_{t+1}^*] \qquad \textbf{(2-7)}$$

where C represents the future expected cash flows and D represents the stochastic discount factor. The asterisk sign represents that the variables in the equation are considered as nominal rather than real. Drawing on Harrison and Kreps (1979), Campbell et al. (1997) derived the conditional logarithmic form of kernel. The general form is represented as:

$$-k_{t+1}^{*} = \delta + r_t^{*} + \varepsilon_{t+1}^{m*} \tag{2-8}$$

where $\varepsilon_{t+1}^{m*} \sim N(0, \sigma_{k*}^2)$ stands for *i.i.d.* nominal pricing shocks, $\delta = \frac{1}{2}\sigma_k^2$ and r_t^{*} represents the nominal risk-free interest rate. Vasicek's (1977) model captures the mean-reverting nature of real short rate in discrete time. Considering $\bar{r}$ and σ_r are the conditional mean and volatility respectively, the equation can be represented as:

$$r_{t+1} = \bar{r} + \alpha_r (r_t - \bar{r}) + \sigma_r \varepsilon_{t+1}^{r} \tag{2-9}$$

where $\varepsilon_{t+1}^{r} \sim N(0, \sigma_{k*}^2)$ is an *i.i.d.* Similarly, an analogous process for inflation rate is:

$$i_{t+1} = \bar{i} + \alpha_i (i_t - \bar{i}) + \sigma_i \varepsilon_{t+1}^{i} \tag{2-10}$$

Based on (2-9) and (2-10), the interaction between real interest rate and inflation is derived as:

$$\sigma_i \varepsilon_{t+1}^{i} = \rho_{i,r} \sigma_r \varepsilon_{t+1}^{r} + \sigma_\phi \varepsilon_{t+1}^{\phi} \tag{2-11}$$

where $\rho_{i,r}$ captures the co-movement between real interest rate and inflation and $\varepsilon_{t+1}^{\phi} \sim N(0,1), i.i.d.$ represents the inflation uncertainty orthogonal to r_t.

Campbell et al. (1997) extend the standard affine model by introducing $\rho_{i,r}$. Further d'Addona and Kind (2006) allows inflation to be correlated with stochastic interest rate to price inflation risk. Under this new correlation structure the pricing kernel is represented as:

$$\varepsilon_{t+1}^{m*} = \beta_{m,r}\sigma_r\varepsilon_{t+1}^{r} + \beta_{m,i}\sigma_i\varepsilon_{t+1}^{i} + \sigma_{\varphi}\varepsilon_{t+1}^{\varphi} \qquad \textbf{(2-12)}$$

where β estimates the shocks between the discount rate, interest and inflation. The error term $\varepsilon_{t+1}^{\varphi} \sim N(0,1), i.i.d.$ represents the orthogonal fluctuations of the pricing kernel and the exogenous variables. Since, the error term only affects the mean rather than the slope of term structure, d'Addona and Kind (2006) derive the logarithmic pricing kernel as:

$$m_{t+1}^{*} = -\delta - r_t^{*} - \beta_{m,r}\sigma_r\varepsilon_{t+1}^{r} - \beta_{m,i}\sigma_i\varepsilon_{t+1}^{i} \qquad \textbf{(2-13)}$$

For a bond with maturity *n*, the fair value is determined by the variables interest rate and inflation, which affects the nominal discount rate. The affine price model for a bond at time *t* can be represented as:

$$-B_t^{n*} = X_n + Y_n r_t + Z_n i_t \qquad \textbf{(2-14)}$$

Based on the roots of (2-14), which follow a recursive form (d'Addona and Kind, 2006), the unit period logarithmic bond return is:

$$BR_{t+1}^{n-1*} = -X_{n-1} - Y_{n-1}r_{t+1} - Z_{n-1}i_{t+1} + X_n + Y_n r_t + Z_n i_t \qquad \textbf{(2-15)}$$

In contrast to bonds, stocks do not have a pre-determined cash-flow stream. It can be derived as a present value of infinite stream of expected dividend pay-offs.

$$S_t = E_t[S_{t+1}\exp(d_{t+1}), K_{t+1}] \qquad \textbf{(2-16)}$$

Considering D_t as the real dividend at time *t*, the dividend yield is $d_t = \ln\left(1 + \frac{D_t}{S_t}\right)$.

Based on Campbell and Shiller (1998) and Lewellen (2004), d_t is modelled as a mean-reverting stochastic process.

$$d_{t+1} = \bar{d} + \alpha_d\left(d_t - \bar{d}\right) + \sigma_d \varepsilon^d_{t+1} \qquad \textbf{(2-17)}$$

d'Addona and Kind (2006) account for the interaction of interest rate and dividend yield, i.e.

$$\sigma_d \varepsilon^d_{t+1} = \beta_d \sigma_r \varepsilon^r_{t+1} + \sigma_\eta \varepsilon^\eta_{t+1} \qquad \textbf{(2-18)}$$

where β_d represents the interaction term between interest rate and dividend yield and ε^η_{t+1} is the orthogonal error term.

The affine-pricing model for stocks determined by the state variable interest rate can be formulated as:

$$S_t = \lim_{n \to \infty}\left(X_n + Y_n r_t + Z_n d_t\right) \qquad \textbf{(2-19)}$$

Unlike fixed income securities which have a finite maturity period, the roots of the affine-model for stocks follow an infinite recursive process. Including realised inflation, the logarithmic stock return for a unit period can be defined as:

$$SR^*_{t+1} = X_{n-1} - X_n + Y\left(r_{t+1} - r_t\right) + Z\left(d_{t+1} - d_t\right) + d_{t+1} + i_{t+1} \qquad \textbf{(2-20)}$$

Equation (2-20) models stock returns as a function of the dividend-yield process. In similar studies Bekaert et al. (2000) model the equity returns based on dividend growth. Their equation accommodates the price-dividend ratio. The studies show that modelling in terms of dividend yield allows capturing the influence of uncertainty in interest rate and dividend-yield risk on stock premium.

2.3.3 SB Return Correlation in Affine Pricing Model

The theoretical expression for SB return correlation is obtained by employing the expectation properties of linear functions to equations (2-15) and (2-20). The correlation equation obtained is:

$$\rho_{sb} = \frac{-Y^s F\sigma_r - G\sigma_i - \beta_i \sigma_r^2 \left(Y_{n-1}^b + Y^s Z_{n-1}^b\right) - Y_{n-1}^b H - \beta_i Z_{n-1}^b H}{\sqrt{F^2 + G^2 + 2FZ_{n-1}^b \beta_i \sigma_r}\sqrt{{Y^s}^2 \sigma_r^2 + \sigma_i^2 + \left(1 + Z^s\right)\sigma_d^2 + 2Y^s H + 2\beta_i (Y^s \sigma_r^2 + H)}} \quad \textbf{(2-21)}$$

where $F = Y_{n-1}^b \sigma_r$, $G = Z_{n-1}^b \sigma_i$ and $H = \left(1 + Z^s\right)\beta_d \sigma_r^2$.

Equation (2-21) reveals that the means of the three state variables, $\bar{r}$, $\bar{i}$ and $\bar{d}$, do not have any impact on the stock-bond return correlation, ρ_{sb}. However, in reality it is less likely that the economic state variable will have no impact on the asset return correlation. Therefore, it is important to have a deeper insight of the factors influencing the asset return co-movements. While the linear dependence structure is simple to use, it fails to accurately characterize the non-normal distributions of the asset returns (Jondeau and Rockinger, 2006).

2.4 Alternative Approaches to Modelling Co-variances

In the recent years multivariate GARCH models have been widely employed by authors to model time-varying co-movements. Among them the most commonly used ones are Bollerslev et al.'s (1988) VECH (Vectorised Heteroskedastic) model, Bollerslev's (1990) Constant Correlation Model (CCM), Engle et al.'s (1990) Factor Auto-Regressive Conditional Heteroskedastic (FARCH) model and Engle and Kroner's (1995) BEKK (Baba, Engle, Kraft and Kroner) model. To review these models, I adopt the following notations: R_{it} is the rate of return of an asset *i* at time *t*, μ_{it} is the expected rate of return of the asset under the information set at time *(t-1)*, e_{it} is the unexpected return of the asset at time *t*, v_{it} is the conditional variance of R_{it} under the information set at time *(t-1)*, v_{ijt} is the conditional covariance of asset return *i* and *j* under the information set at time *(t-1)* and V_t is the conditional covariance matrix $(V_t = [v_{ijt}])$

2.4.1 The VECH Model

The VECH model is represented as:

$$v_{ijt} = \alpha_{ij} + \beta_{ij} v_{ijt-1} + \gamma_{ij} e_{it-1} e_{jt-1} \tag{2-22}$$

where $\alpha_{ij}, \beta_{ij}, \gamma_{ij}$ are parameters for all $i, j = 1, ..., N$. The VECH model is an auto-regressive moving average (ARMA) model for the unexpected asset returns. Thus, the key advantage of this model lies in its simplicity to estimate the conditional asset covariance. Considering the coefficient of the conditional lag variance to lie between zero and one, i.e. $\beta_{ij} \in (0,1)$ for all assets, Equation (2-22) can be estimated as

$$v_{ijt} = \varphi_t + \gamma_{ij} \sum\nolimits_{t=1,t} \beta_{ij}^{\ \tau-1} e_{it-1} e_{jt-1} \tag{2-23}$$

where $\varphi_t = \beta^t v_0 + \alpha_{ij} \varphi_{t=0,t-1} \beta_{ij}^{\tau}$. This adjustment term ensures that the expectations of vi_j is the conditional asset covariance. Therefore, the model estimates the asset return co-movements as the geometrically weighted average of the past co-variances of expected returns. It gives lower weights to older observations.

The VECH model undermines two practical limitations. First, the number of parameters it generates is exceptionally large. For example, for a 10 (N)-asset model it generates $\frac{3}{2}N(N+1)$, i.e. 165 parameters. Second, the model only gives a definite covariance matrix if restrictions are imposed to the weights of the older observations (Engle and Kroner, 1995). Without these nonlinear restrictions, the off-diagonal terms take values that are too large relative to the diagonal variances which force the VECH model to yield non-positive definite covariance estimates. This issue is overcome by the BEKK model, which I illustrate next.

2.4.2 The BEKK Model

The BEKK model is characterised as

$$V_t = \Omega + B'V_{t-1}B + A'e_{t-1}e'_{t-1}A \tag{2-24}$$

where Ω, A, B are $N \times N$ matrix. The matrix Ω represents the positive-definite symmetric covariance estimate. In terms of asset covariance BEKK can be written as

$$v_{ijt} = \alpha_{ij} + \text{cov}_{t-1}(e_{rt}, e_{st}) + (e_{pt-1}, e_{qt-1}) \qquad \textbf{(2-25)}$$

where e_p, e_q, e_r, e_s are the unexpected returns of the portfolios p, q, r, s and α_{ij} is the *ijth* element of the positive-definite matrix. The portfolios *p* and *q* derive their weights from the *ijth* columns of matrix *A* and the weights of *r* and *s* comes from the matrix *B*. If Equation (2-25) is restricted to $B = kA$, where *k* is a scalar constant, then the model estimates conditional covariance for N-portfolios or assets.

While this model overcomes the positive-definite covariance limitation of the VECH model, it still estimates $(\frac{5}{2}N^2 + \frac{N}{2})$ parameters that restrict its practical usability. The FARCH model overcomes this issue of large scale estimation, which is presented next.

2.4.3 The FARCH Model

The model is represented as

$$V_t = \Omega + \lambda\lambda'[\beta\delta' V_{t-1}\delta + \gamma(\delta' e_{t-1})^2] \qquad \textbf{(2-26)}$$

where β, γ are scalars, λ, δ are $(N \times 1)$ vectors and Ω represents the positive-definite symmetric covariance $N \times N$ matrix. The FARCH model is a special case of the BEKK model. In particular the latter becomes FARCH when $A = \sqrt{\gamma}\delta\lambda'$ and $B = \sqrt{\beta}\delta\lambda'$. The number of parameters estimated by this model $\left(\frac{1}{2}N^2 + \frac{5}{2}N + 2\right)$ is considerably less than the VECH and BEKK models.

Using conditional covariance and unexpected return of the assets/portfolios, the FARCH model can be characterised as

$$v_{ijt} = \alpha_{ij} + \lambda_i \lambda_j v_{pt} \qquad \textbf{(2-27)}$$

$$v_{pt} = \alpha_p + \beta V_{pt-1} + \gamma e_{pt-1}^2 \qquad \textbf{(2-28)}$$

where $R_{pt} = \delta' R_t, v_{pt} = \delta' V_t \delta, e_{pt-1} = \delta' e_{t-1}$ and $\alpha_p = \delta' \Omega \delta, \sigma_{ij} = \Omega_{ij} - \lambda_i \lambda_j \alpha_p$

The FARCH model assumes that the assets' variances and co-variances contribute to the variance of a single portfolio, which follows a GARCH process. In case on a single factor model, the market return is considered to be R_{pt}. Thus, for a single factor model the variance-covariance asset return matrix is driven by the market portfolio.

The number of factors *(N)* that drive the conditional matrix Ω differentiates the use of the FARCH and the BEKK model. If there are multiple factors the BEKK model is used, whereas for a unit factor the single factor FARCH model is employed.

2.4.4 The Constant Correlation Model

In this model the conditional correlation of the asset returns are assumed as time-invariant. The restriction on the conditional variance is weighted proportional to the asset risk. The constant correlation model is represented as

$$v_{iit} = \alpha_{ii} + \beta_{ii} v_{iit-1} + \gamma_{ii} e_{it-1}^2 \qquad \textbf{(2-29)}$$

$$v_{ijt} = \rho_{ij} \left(\sqrt{v_{iit}} \sqrt{v_{jjt}} \right) \qquad \textbf{(2-30)}$$

Equation (2-29) is for all $i =,..., N$ and Equation (2-30) is for all $i \neq j$. Yet, CCM yield positive definite estimate only if the correlation matrix $[\rho_{ij}]$ is non-negative and definite.

2.4.5 Properties of the GARCH Models

The four models discussed above belong to the family of multivariate GARCH models. Each of them imposes a different set of restrictions to estimate the variance-covariance processes of the asset/portfolio returns. To analyse the properties of each of the four models, I rely on Kroner and Ng ‘s (1998) estimations of portfolio returns on small and big firms (corporate bonds are considered only in this sub-section of the thesis to present the limitations of GARCH models, rest of the study considers government bonds). The data consists of 1371 weekly observations from July 1962 to December 1988 for US market. The mean return is modelled using a 10-lag VAR process, which is characterised as

$$R_{it} = \Delta_{i0} + \sum_{j=1,2} \sum_{\tau=1,10} \left[\Delta_{j\tau} R_{jt-\tau} + d_{jt} \max(-R_{jt-\tau}, 0) \right] + e_{it} \qquad \textbf{(2-31)}$$

where *i* takes the value ‘*1’* and ‘*2’* for small firms and large firms-portfolio respectively. The q0-lag threshold terms ensure that the variance-covariance asymmetric effects do not impose misspecification in the estimation of the mean.

Table 2-1 shows the summary statistics of the different variance and covariance estimates of the four different MGARCH models.

Table 2-1: Estimated Variance and Covariance Series

Model	Variable	Mean	SD	Minimum	Maximum
Small-firm variance					
	ε_{1t}^2	7.43	28.97	0.00	825.45
VECH	h_{11t}	7.73	6.31	3.82	104.98
CCORR	h_{11t}	7.91	7.08	3.54	117.60
FARCH	h_{11t}	7.51	4.14	2.87	33.24
BEKK	h_{11t}	7.53	4.91	2.64	50.67
Large-firm variance					
	ε_{2t}^2	3.93	8.12	0.00	147.87
VECH	h_{22t}	3.89	2.58	1.10	21.53
CCORR	h_{22t}	3.96	2.78	0.98	23.49
FARCH	h_{22t}	4.12	3.18	0.74	27.08
BEKK	h_{22t}	4.16	3.20	0.76	26.15
Covariance					
	$\varepsilon_{1t}\varepsilon_{2t}$	2.61	8.59	−45.44	167.55
VECH	h_{12t}	2.33	1.49	0.30	17.59
CCORR	h_{12t}	2.47	1.48	0.91	15.60
FARCH	h_{12t}	2.79	2.42	0.30	21.71
BEKK	h_{12t}	2.77	2.66	0.25	30.71

The table reports the summary statistics of the four GARCH models. The results are computed on the same data set. *'e'* denotes the unexpected return shocks and *'h'* denotes the estimated variance-covariance of the portfolios.
[a] Source: Adopted from Kroner and Ng (1998)

It is evident that the co-variance estimates of FARCH and BEKK models are higher and more volatile than the VECH and constant correlation (CCORR) model. In particular, the BEKK models produce a greater range of estimates as compared to the remainder. Focusing on variance estimates, the volatility of FARCH and BEKK model estimates are higher for large-firms in contrast to the high volatility estimates of VECH and CCOR models for small firms.

In order to further justify my claims that the different models generate a different and varied range of estimates, I report the correlation of these covariance and variance estimate in Table 2-2.

Table 2-2: Correlation of MGARCH Model Estimates

Panel 1: Small-firm portfolio variance series

	VECH	CCORR	FARCH	BEKK
VECH	1.000			
CCORR	0.999	1.000		
FARCH	0.367	0.365	1.000	
BEKK	0.642	0.640	0.834	1.000

Panel 2: Large-firm portfolio variance series

	VECH	CCORR	FARCH	BEKK
VECH	1.000			
CCORR	0.999	1.000		
FARCH	0.999	0.999	1.000	
BEKK	0.954	0.954	0.955	1.000

Panel 3: Covariance series

	VECH	CCORR	FARCH	BEKK
VECH	1.000			
CCORR	0.876	1.000		
FARCH	0.748	0.785	1.000	
BEKK	0.752	0.719	0.885	1.000

The small firm correlation of variance estimates are presented in panel-1, the large firm correlation of variance estimates are presented in panel-2 and anel-3 reports the correlation of the covariance estimates.

[a] Source: Adopted from Kroner and Ng (1998)

The correlations of the variance of large-firm estimates in panel-2 exceed 0.999. This suggests that all models yield similar results; hence model selection is relatively unimportant. Yet, similar conclusions do not hold well for panel two and three. Judging from these findings, it is pertinent that model selection plays a vital role in estimating covariance of asset/portfolio returns. Consequently, the selection of models will invariantly affect asset pricing, estimation of assert return correlation and portfolio management applications. Drawing on this conclusion, it is fair to say that the multivariate GARCH models provide inconclusive outputs. Based on this analysis, in the next chapter I report the copula approach that is used in this study as an effective alternative methodology that overcomes the limitations of the linear approaches in examining asset return comovements.

In the next section I highlight the distinctive aspects of the asset return comovements corroborating the gaps in the extant literature. In particular, I investigate the stock and government bond return association for the U.S. capital market for the period 1991 to 2011. In this study the US government bond index is used instead of corporate bonds. Government bonds have a lower level of risk. Thus, they provide more diversification benefits during periods of economic distress. Drawing on this analysis and on the overall review of the existing literature, I will next provide an account for future research avenues and research gaps that I have explored in this work. The primary purpose of this examination is to make robust claims related to the extant literature. Further, the empirical findings considerably aid in i) analysing potential research gaps and in ii) proposing future areas of research, as elaborated in the following sections.

2.5 Empirical Analysis of US Stock-Bond Return Comovement

2.5.1 Data and Methodology

The empirical analysis examines quarterly data of U.S. SB returns. The U.S. market is considered for the analysis because i) it represents the largest financial market in the word and ii) it is generally viewed as the most important economy. The sample period spans from January 1991 to December 2011. Table 2-3 reports the description of the exogenous variables and data used for the empirical analysis.

Table 2-3: Description of Variables

Variable Category	Variable	Data Source
Endogenous Variable	i) Daily MSCI Stock Market Returns	DataStream
(quarterly correlation estimates are constructed from daily data)	ii) Government Bond Indices (10 years)	
Exogenous Variables:	Economic output gap (Eog), Real interest (Ri) and Expected inflation (Ei)	DataStream
Economic output gap (Eog)	Gross Domestic Product (GDP) is the measure of output. The gap is the percentage difference between the output and its quadratic trend.	
Real Interest (Ri)	Difference between annualized 3-month Treasury Bill middle rate annualized returns converted to quarterly returns (*(ln(1+R))/4*) and short-term expected inflation	
Expected Inflation (Ei)	One month forecast of monthly inflation, consumer price index, employing a Bayesian Vector Auto-regression model.	

Note: the exogenous and the endogenous variables for the empirical investigation are reported in this table. The table reports the various variables used and data source are reported.

To examine the impact of macroeconomic state variables on stock-bond return correlation, I formulate Equation (2-32). A potential challenge in regressing is that the correlation coefficient varies from positive one to negative one, i.e. [+1 to -1]. In contrast, the right hand side of the equation is unrestricted, thus to make the endogenous variable unrestricted, I employ Fisher's transformation using Equation (2-32). This transforms the correlation coefficient values from [-1, 1] to $(-\infty,\infty)$.

$$Corr = \frac{1}{2}\ln\left(\frac{1+\rho}{1-\rho}\right) \tag{2-32}$$

$$Corr_t = \alpha + \beta_0 Ri_t + \beta_1 Eog_t + \beta_0 Ei_t + \beta_0 Corr_{t-1} \tag{2-33}$$

where ρ is stock-bond return correlation, *Eog* is the economic output gap, *Ri* is the real interest rate, *Ei* is the expected inflation.

2.5.2 Results and Analysis

The descriptive statistics of the SB return correlation are reported in Table 2-4. The SB return correlation estimate for the period observes a negative mean of 0.032. The overall range of the estimate varies from negative 1.045 to 1.038.

Table 2-4: Descriptive Statistics of SB Return Correlation

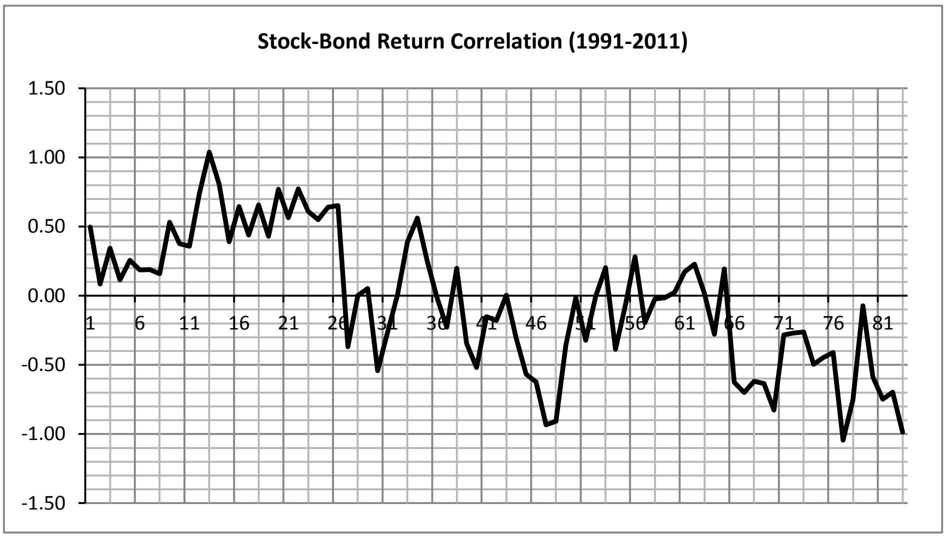
	Mean	Median	Std. Dev.	Kurtosis	Skewness	Minimum	Maximum
Corr.	-0.032	-0.006	0.490	-0.779	-0.059	-1.045	1.038

Note: The table reports the summary statistics of the return correlation of stock-bond returns.

The quarterly rolling correlation is plotted in Figure 2-2. Although the correlation is negative on average, it is apparent that the time-varying relationship of SB returns is unstable and has observed sustained variations over time. Moreover, the figures reveal that the co-movement can vary substantially over a short-period of time. For example, in the year 1997 the correlation changed from 0.48 to negative 0.16 for the period October – November. These unexpected changes in the correlation impose challenges for risk management measures and asset allocation. Thus, commonly employed risk monitoring techniques that assume time-invariant stock-bond return correlation will yield spurious results and may adversely affect investment strategies. For U.S. the co-movement remained positive until November 1997. After that it dipped below the neutral mark and hovered in the negative region until 2011. Yet, for a short period, i.e. March 1999 to June

2000, the correlation yielded a positive return. This can be attributed to the excessive economic growth during this period.

Figure 2-2: Quarterly Stock-Bond Return Correlation



Note: The figure shows the quarterly rolling correlation for the period 199-2011. The average stock-bond correlation is negative over the sample period.

The regression results of the dynamic model are reported in Table 2-5. The estimation results reveal that expected inflation is positively related to the SB return correlation. Arguing that bond prices are negatively related to expected inflation, my findings confirm that higher inflation expectations have a greater impact on discount rates than on expected equity dividends. This causes inflation to vary negatively with stock prices and thereby poses a positive relation with SB return co-movements. The positive significant impact of real interest rate is not surprising as increase in real interest rate has detrimental effect on both stock and bond returns. The result also shows a trend in the time-varying phenomenon with a positive coefficient of a single period SB return correlation lag. Finally, it can be noted that the estimated coefficients of expected economic output is statistically not significant.

Table 2-5: Impact of Macroeconomic Variables on SB Return Correlation

Estimation Results	Explanatory Variables				
	α	Ri_t	Eog_t	Ei_t	$Corr_{t-1}$
Coefficient	-0.023	0.119**	0.004	0.165**	0.423**
Standard Error	(0.032)	(0.045)	(0.035)	(0.045)	(0.116)
R-squared	0.672				
Durbin-Watson statistic	1.821				
BG Serial Correlation	1.022				
LM-test statistic	(0.365)				
Breusch-Pagan-Godfrey	1.239				
Heteroscedasticity test	(0.302)				

Note: The table reports the coefficient estimates of the model that identifies the impact of macroeconomic variables on stock-bond return correlation. The macroeconomic variables considered are real interest rate, economic output and inflation. The model is characterized as $Corr_t = \alpha + \beta_0 Ri_t + \beta_1 Eog_t + \beta_0 Ei_t + \beta_0 Corr_{t-1}$, where $Corr_t$ represents the contemporaneous stock-bond return correlation, *Ri* is the real interest rate, *Eog* is the economic output gap and *Ei* is the expected inflation. Stock-bond correlations are computed using daily returns over quarterly period. The results indicate that real interest rate and inflation have significant impact on the return correlation. The standard errors of the coefficients are reported in parenthesis and are corrected for serial correlation and heteroscedasticity. The serial correlation and the heteroscedasticity test suggest that the model does not suffer from residual serial correlation and heteroskedastic issues. The p-value of these test statistics are provided in the parenthesis. ** denotes significance at 0.01 percent level

The findings, therefore state that expected inflation and real interest rate play a dominant role in defining stock-bond return comovements. However, the impact of other economic state variables such as changes in output gap is insignificant in determining the return comovement. These results confirms several studies, including Baele et al. (2010), Bekaert and Engstrom (2010), Downing et al. (2009) amongst many other as discussed in the previous section. It, further, brings to concern the necessity to examine this phenomenon by considering factors other than generic economic state variables, which I carry out in this work. Further, it should be noted that such an examinations fails to capture the true dynamics of the return comovements as linear correlation fails to accommodate the asymmetric nature of the non-normal return distributions.

2.5.3 Research Gaps

Corroborating with the extant literature, the findings in the previous section reveal a wide range of promising directions for future research, which address the research gaps in the current literature. First, researchers fail to acknowledge that non-macroeconomic state variables such as illiquidity factors influence the asset return covariances more than the macroeconomic variables. Hence, much more scope lies in analysing the dynamic illiquidity effects. Specifically, the impact of liquidity on stock-bond return co-movement depends on how liquidity shocks vary across markets. Second, there is an interesting debate concerning the volatility dynamics of stocks and bonds. While the bond volatility depends on economic state variables, the non-economic variables such as liquidity factors and variance premiums drive the stock and commodity volatilities more significantly. These differences create complications in building an equilibrium model, which can jointly account for multi-asset pricing. Studies in this area have failed to account for a significant equilibrium model (Bekaert et al., 2009). Third, even though researchers in the past have exclusively focused on standard economic variables, more intricate models would likely yield superior results. These models may probably incorporate variables that have been neglected in the present literature. For example, 'depth of recession'[7] that serves as leading indicator of economic activity might provide more insight on asset pricing mechanism, even of developed economics like the U.S.

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[7] This measure allows the estimate to have values for both recession and expansion of the economy's business cycle. A negative value indicates an economic expansion period. The higher the value, the greater is the economy's recovery in process. In contrast, a positive value of this measure relates to a recessionary period.

Importantly, it is evident that stock-bond return co-movement has been an area of interest for a long time, whereas multi-asset return co-relationship has mostly been neglected. Few studies have tried to examine the return relationship of equity markets and commodities, the results remain inconclusive (cf. Section 2.2.1). Without a proper assessment of the characteristics of the time-varying phenomena generated by the models, judgments remain inconclusive and premature. For instance, the literature has made many claims about the negative stock-bond return correlation for the years. Yet, in recent times the real economy and inflation processes in developed and emerging economies have witnessed substantial changes. In particular, the volatility of the output growth, i.e. change in gross domestic product, and inflation has decreased significantly in the U.S. and other developed economies since 1985. This triggered large negative spikes in realized correlation in asset returns and a steep decrease in equity payoffs. Further, with the global economic crisis scare of 2003, investors started looking into the potential diversification benefits of multi-asset portfolios, containing non-conventional financial assets such as commodities and real estate securities. Yet, the diversification benefits were questioned after the financial crisis of 2007. Consequently, if different financial assets have similar exposure to these economic state variables, their return correlation should also decrease. It is equally pertinent that changes in these fundamental variables have affected the risk aversion, which influences various financial instruments in dissimilar ways. While extant literature shows that it is difficult to figure out specific economic state variables that influence multi-asset return correlation, it remains worthy to quantify the magnitude of the influence of these economic variables on the time-varying dynamics of multi-asset return comovements that constitute an investor's portfolio. This is what I aim to establish in my doctoral thesis, i.e. *the dynamics of asset* *return comovements*, employing an alternative approach, which is illustrated in the next section.

2.6 Summary

My review of the existing literature has illustrated the importance of multi-asset return correlation which has not been fully demystified and far less fully operationalised. The extant literature is still unsettled regarding the effect of certain macroeconomic factors like inflation volatility on multi-asset co-movements. Thus, the debate on how asset return comovements vary to changing macroeconomic conditions is open to further research and analysis.

This work incorporates both sufficient level of empirical analysis and economic rigor to reconcile time-varying multi-asset return comovement. To this end, I specify four boundaries, informed by the current literature that has characterized this study.

i. Theoretical Boundary: the analysis of multi-asset return correlation from an asset allocation perspective focuses on examining the interactions of various economic and non-economic state variables.

ii. Disciplinary Boundary: considering the inter-disciplinary nature of the topic, studies have been drawn from social sciences (financial economics) and applied sciences (applied mathematics).

iii. Application Boundary: to all intents and purposes, applications are social constructions. To draw this more clearly, the findings of this study have profound implications for investors and policy makers.

iv. Contextual Boundary: to explore the dynamics of multi-asset return co-movements in the US financial market, this hosts the world's leading economy by incremental gross domestic product measure (cf. IMF, 2012).

In sum, the non-linear relationship between real estate markets, commodities and conventional financial markets may reveal important insights pertaining to extreme market conditions, which may have significant implications for portfolio allocation. Surprisingly, the literature fails to provide a clear understanding of the dynamic nature of multi-asset return comovements.

In the next chapter I define my research questions that address the gaps in the literature described in this chapter.

CHAPTER 3

Research Objectives

3.1 Introduction

In this chapter I present the research questions that are addressed in this study. The research objectives are derived from the existing literature gaps as highlighted in the previous chapter. The examination of the extant literature yielded three main areas warranting further research: i) the distributional characteristics of the asset return, ii) the determinants of the bivariate asset return comovements and iii) the determinants of joint asset return comovements.

In the following sub-sections I document each of these areas and state the research objectives of this study.

3.2 Research Objectives

3.2.1 Distributional characteristics of the asset returns

The first area relates to the distributional characteristics of the asset returns. Research widely acknowledges that return distributions of financial assets are non-normal. When the joint distributions of the asset returns follow a non-elliptical structure, linear correlation fails to provide sufficient information of their dependence structure. In particular two issues arise from this existing empirical evidence. The first is to propose a more reliable alternative density specification for a higher-dimensional case. The second is to formulate a measure of the variables' dependence structure which is more instructive than linear correlation. Against this backdrop, in this work I aim to overcome the issues related to the modeling of the non-normal asset return in examine the return comovements between three different asset classes: financial assets, commodities and real estate in the US market.

3.2.2 Determinants of the bivariate asset return comovements

It is well known that asset return comovements are not time-invariant but tend to be rather dynamic in nature. Investors, therefore, require information about conditional distribution of the asset returns to implement dynamic asset allocation strategies. Information whether the returns of two or more assets are positively related in certain circumstances but negatively related in others may have key implications in portfolio diversification and asset allocation strategies. Thus, understanding asset return correlation, i.e. dependence structure, is a key aspect of asset allocation and portfolio optimization strategy. For the last decade, several studies have examined the stock and bond return comovements (Wainscott, 1990; Shiller and Beltratti, 1992; Connolly et al., 2007; Baele et al., 2010). But, far fewer studies have tried to examine the factors that drive the bivariate asset return comovements, i.e. combination of two different asset returns, especially for different asset classes. This research gap in the extant literature is addressed in this work. In particular, I examine the macroeconmic and non-macroeconomic factors that influence the asset return comovement of three different asset classes during periods of economic expansion and economic contraction regime. However, in this study I do not explicitly constrain the the expectations of the macroeconomic and the non-macroeconomic variables. This allows me to have an unbiased examination of the impact of the the various factors that drive the asset return comovements, especially during the various phases of the economy.

3.2.3 The determinants of joint asset return comovements

In the wake of the economic downturn during 2007-08, returns of different asset classes have shown evidence of strong linkages. This has led to a renewed interest amongst academics and practitioners in examining asset allocation strategies for effective diversification of risk during turbulent economic conditions. However, asset allocation strategies can be properly executed only if the nature of return comovements of various asset returns is well understood. Guidolin and Timmermann (2007) show that since asset return comovements are time varying and dynamic in nature, investors require information about conditional distribution of the asset returns for implementing dynamic asset allocation strategies. Further, asset return comovements change due to changes in economic conditions and/or changes in non-macroeconomic factors. For example, Piplack and Straetmans (2010) show that asset return comovements change during periods of market stress. Thus, in constructing an optimal portfolio, it is critical to identify the economic circumstances and understand the impact of macro and non-macro factors on asset return comovements.

It is fair to say that investors no longer invest in only conventional financial assets such as equities and bonds, but in a wide range of alternative financial assets including commodities and real estate. Fewer studies have dealt with a combination of bivariate asset return dynamics; however, research on the joint dependence structure of a portfolio of different asset classes, which I refer as multi-assets, is non-existent. This research is important because this study presents the first empirical evidence, examining the factors that drive the joint return distribution of different asset classes. Moreover, as stated earlier, in this study I do not explicitly constrain the the expectations of the macroeconomic and the non-macroeconomic variables. This allows me to conduct an unbiased examination of the impact of the the various factors that drive the asset return comovements during the various phases of the economy

3.3 Summary

This chapter presents the objectives of the study that aim to fill the gaps in the existing literature on asset return comovements. This work focuses on the research gap in three key areas relating to the distributional characteristics of the asset returns, the macroeconomic and the non-macro factors that influence the bivariate asset return comovements and the sources that impact the joint return comovements during periods of economic expansion and economic contraction.

In specific this study examines the determinants of the dependence structure of the comovements of two conventional financial assets, i.e. Standard & Poor's (S&P) 500 index (E) and US 10 year Government bond return index (B), two commodities, i.e. S&P GSCI Gold index (G) and West Texas Intermediate – WTI Cushing crude oil spot prices per barrel (O) and S&P Case-Shiller Composite-10 home price index (RE) for real estate for the period fourth quarter 1987 to the fourth quarter 2012 (1^{st} August 1987 to 1^{st} September 2012).

In sum, the key objectives of this work are as follows:

- To model the bivariate and the joint dependence structures accommodating the non-normal distributional characteristics of the asset returns.
- To examine the bivariate dependence structure of the asset return comovements.
    - Examine the regime switching behaviour of the 10 dependence structures corresponding to various asset return pairs.

  - Examine the differential impact of the macroeconomic and non-macroeconomic factors during periods of economic expansion and economic contraction regimes on the bivariate dependence structures.

- To examine the Joint Dependence Structure (JDS) of the multi-asset return comovements.
  - Examine the regime switching behaviour of the joint dependence structure.
  - Examine the differential impact of the macroeconomic and non-macroeconomic factors during periods of economic expansion and economic contraction regimes on the JDS.

In addition to the above research objectives, this study extends the work in examining international equity market linkages. It is widely acknowledged that India is playing an ever increasing role in driving the world economic growth. India with its large and educated human capital, access to natural resources and growing markets for goods and services offers an attractive destination for the international investors. Aloui et al. (2011) report that among the BRIC (Brazil, Russia, India and China) nations, India's well established trade links with the world is next only to China. Thus, there is little doubt that amongst the emerging economies, India is going to play an increasingly important role in shaping the world's economy in coming years. An understanding of the causes of comovements during the periods of economic expansion and contraction will therefore provide greater insights to both Indian policy makers and international investors. This study aims to achieve this by investigating the economic sources of stock return comovements of the emerging Indian equity market and the developed equity markets of US, UK, Germany, France, and Canada for the period April 1997 to March 2013.

CHAPTER 4

Modelling the Dependence Structures

4.1 Introduction

In the recent years, copulas have received considerable acceptance in modelling time-varying dependence (Patton, 2006). Yet, majority of the studies in the extant literature examine the comovement of different financial assets over time using linear correlation even though past research shows significant asymmetric dependence between the various financial assets.

Overall, the literature on the relationship of various financial asset returns explores small subsets of financial instruments. Some authors examine the stock and bond return comovements, while others investigate the relationship between equity markets and certain commodities or real estate assets. In particular, previous research fails to explore the asset linkages during the extreme market conditions that correspond to the upper and the lower tails of the return distribution. Some authors provide evidence of stock market contagion during periods of financial crisis among various nations (see King and Wadhwani, 1990; Sander and Kleimeier, 2003; Rodriguez, 2007). Yet, asset return linkages across various asset classes during periods of financial crisis remain unexplained. Thus, apart from examining the general dependence structure, I also focus on the tail asymmetries using our proposed dynamic conditional copula models.

Against this backdrop, the purpose of this chapter is three fold: First, I propose an alternative approach to model the dependence structures of the bivariate comovement of the asset return dynamics in the US market. Second, I model the joint dependence structure combining all the asset classes. Third, I provide the estimation process of the proposed models.

The rest of the chapter unfolds as follows: Section 4.2 discusses our proposed approach to model the joint dependence structure of the multi-asset returns. Section 4.3 provides the model specifications and Section 4.4 concludes the chapter.

4.2 Proposed Approach

The method, I implement in this study, is based on the theory of copula. The application of this theory in the field of finance has seen rapid growth over the years. Since the seminal work of Embrechts et al.'s (2002), authors have explored the use of copulas in financial economics. Nelsen (1998) provides a detailed note on copulas that includes statistical and mathematical foundations, while Cherubini et al. (2004) focuses on usage of copula functions approach in the field of mathematical finance.

In this work, I specifically focus on copula applications related to financial time series data, which relates to our work. Patton (2006) specifies the dependence parameter of the time-varying conditional copula that follows an autoregressive moving average type model. Rodriguez (2007) and Okimoto (2008) use regime switching copulas to account for asymmetric correlation structure in equity markets and financial contagion respectively, while Chen and Fan (2006) build on Panchenko (2005) to construct a conditional copula with a correlation matrix, which follows Engle's (2002) dynamic conditional correlation specifications. In a similar vein Lee and Long (2009) employ copula to capture the dynamic dependence of the uncorrelated standardized residuals to construct a copula based multivariate GARCH model. Based on previous studies, I next provide a concise description of the theory of copula, which elaborates its key advantages.

4.2.1 Theory of Copula

Nelsen (2006) describes copula, C, as a function that couples multiple distribution functions of random variables (RV) to their unit-dimensional distribution function. Application of the this cumulative distribution function (CDF) is derived from Sklar Theorem (Sklar, 1959). The theorem states that for a joint distribution function $H_{X,Y}(x,y)$ for all x, y, a function, copula $C(u,v)$, can be characterized in $\overline{R} \in (-\infty, \infty)$ such that $H_{XY}(x,y) = C(F_X(x), F_Y(y))$, where $F_X(x)$ and $F_Y(y)$ are the marginal distribution functions.

Alternatively, the concept of copula can be viewed as a function, which is expressed as a joint CDF, $H_{X,Y}(x,y)$ in [0, 1], which corresponds to a point, $(F_X(x), F_Y(y))$ in a unit square $[0,1] \times [0,1]$, where $F_X(x)$ and $F_Y(y)$ are the marginal distribution functions (Nelsen, 2006). Here, it is of interest to note that the joint CDF, $H_{X,Y}(x,y)$, is independent of the marginal distributions of the RV. This contributes to the growing popularity of copula functions in many research fields related to distribution fitting.

I use copula in this study because of its property in examining the scale-free dependence structure while preserving the dependence during simulation. I use Kendall's tau (τ) in this paper as an estimate of the scale-free measure of association. It is difference between the probability of concordance and discordance as detailed in the following section. Previous studies frequently use the Pearson's product moment correlation estimate (ρ)

to study the co-movement between various asset returns. Yet, it is important to note that this estimate, (ρ), is a measure of linear association which is time-variant and changes under nonlinear transformation of RV. Thus, a scale-free estimate produces a more reliable picture of the time-varying asset return correlation.

The Kendall's tau (τ) is characterized in terms of copula, C, as (Nelsen, 2006)

$$\tau = 4\int C(u,v)dC(u,v) - 1 \tag{4-1}$$

The above expression can be reduced to a much simpler computable expressions for Archimedean copula as compared to other classes of copula, namely Elliptical and Farlie – Gumbel - Morgenstern. The former, i.e. Archimedean copula, is most frequently used in research because of its unique mathematical properties, which I discuss next.

An Archimedean copula is characterized as

$$C(u,v) = \varphi^{[-1]}(\varphi(u) + \varphi(v)) \tag{4-2}$$

where $\varphi(\cdot)$ is the generator of the copula function and $\varphi^{[-1]}(\cdot)$ is the pseudo inverse, which takes the value $\varphi^{-1}(t)$ for $0 \le t \le \varphi(0)$ and 0 for $\varphi(0) \le t \le \infty$. The popular copulas belonging to Archimedean class are Frank (1979), Clayton (1978), Gumbel (1960) and Hougaard (1986). While Clayton and Gumble - Hougaard (GH) are asymmetric Archimedean copulas, Frank copula is a symmetric Archimedean copula. With X and Y as two RV, Kendall's tau (τ) for an Archimedean copula, C, can be represented in the form of its generator (φ) as (Nelsen, 2006)

$$\tau = 1 + 4\int_0^1 \frac{\varphi_\theta(t)}{\varphi'_\theta(t)} dt \qquad \textbf{(4-3)}$$

Equation (4-3) is the reduced form of equation (4-1), where θ is the dependence parameter. It is estimated from the sample estimate of Kendall's tau $(\hat{\tau})$. Considering Clayton copula as an example for which $\varphi_\theta(t) = \frac{1}{\theta}(t^{-\theta} - 1)$, we have $\frac{\varphi_\theta(t)}{\varphi'_\theta(t)} = \frac{t^{\theta+1} - t}{\theta}$ for $\theta \neq 0$ and $\frac{\varphi_\theta(t)}{\varphi'_\theta(t)} = t \ln t$ for $\theta = 0$. Next, putting the values in equation (4-3) I get

$$\tau = 1 + 4\int_0^1 \frac{\varphi_\theta(t)}{\varphi'_\theta(t)} dt = 1 + \frac{4}{\theta}\left(\frac{1}{\theta+2} - \frac{1}{2}\right) = \frac{\theta}{\theta+2} \qquad \textbf{(4-4)}$$

In case of Clayton copula we achieve a closed form estimate as shown in equation (4-4). Nelsen (2006) provides the details for all the copulas of the Archimedean class. A summary of the relationships are provided in Panel A of the table below. Panel B provides a summary of all the copulas.

Table 4-1: Summary of Different Copulas

Panel A: Relationship between the Archimedean Copulas

Copula	$C_\theta(u,v)$	$\varphi_\theta(t)$	τ	$\theta \in$
Clayton	$[\max(u^{-\theta} + v^{-\theta} - 1, 0)]^{-1/\theta}$	$(1/\theta)(t^{-\theta} - 1)$	$\theta/(\theta+2)$	$[1, \infty], not 0$
Frank	$(-1/\theta)\ln(1 + (k^u - 1)(k^v - 1)/(k-1))^a$	$-\ln[(k^t - 1)/(k-1)]$	$1 - 4/\theta[D_1(-\theta) - 1]^b$	$(-\infty, \infty), not 0$
Gumble-Hougaard	$\exp(-1[(-\ln u)^\theta + (-\ln v)^\theta]^{1/\theta})$	$(-\ln t)^\theta$	$(\theta - 1)/\theta$	$[-1, \infty)$

Panel A: Summary of the types of Copulas and tail dependence

Copula	**Type of Copula**	**Upper Tail**	**Lower Tail**
Clayton	Archimedean (non-elliptical)	non-existent	existent

Frank	Archimedean (non-elliptical)	non-existent	non-existent
Gumble-Hougaard	Archimedean (non-elliptical)	Existent (Gumble)	Existent (Hougaard)
Student - t	Elliptical	existent	existent

Panel A reports the relationship between the various Archimedean copulas. Panel B of the table shows the summary of the various copulas discussed highlights their type and tail dependence.

[a] $k = e^{-\theta}$; [b] $D_1(\theta) = (1/x)\int_o^\theta [t/(e^t - 1)]dt \forall \theta > 0; D_1(-\theta) = D_1(\theta) + (\theta/2)$, where D_1 is first-order Debye function (Zhang and Singh, 2006; Maity and Kumar, 2008).

4.2.2 Conditional Copula

Here I provide an account of conditional copula modelling. Like the unconditional case I consider two random variables (RV), i.e. X and Y, and introduce a conditioning vector K. Let the conditional CDF of the RV be $H_{XY|K}(x, y | K)$ and the marginal distributions be $F_{X|K}(x | K)$ and $F_{Y|K}(y | K)$ given K. Then there exists a copula C, such that

$$H_{XY|K}(x, y | k) = C((F_{X|K}(x | k), F_{Y|K}(y | k)) = C(u, v) \quad \textbf{(4-5)}$$

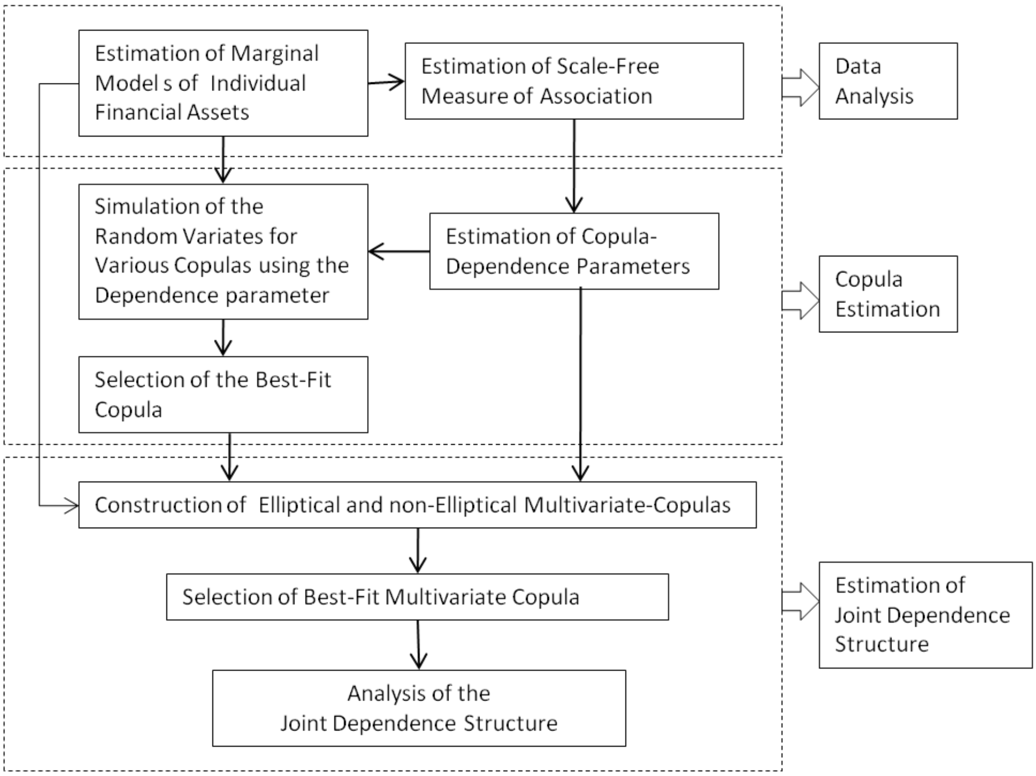
where, $(x, y | K) = k$ and υ is the support of k for all $k \in \upsilon$ and $(x, y) \in \overline{R} \times \overline{R}$. In equation (4-5), u and v are the realizations of $U \equiv F_{X|K}(x | k)$ and $V \equiv F_{Y|K}(y | k)$ given $K = k$. U and V are the conditional probability integrals of the RV, X and Y (Sklar, 1959). The properties of the conditional copulas are same as the unconditional copulas (Patton, 2006). Next, I discuss the model specifications for the analysis of the copula models.

4.3 Model Specifications

Before I present the estimation models, it is worthwhile to report the estimation strategy. It is well established that financial returns in general fail to follow a normal distribution and rather adhere to Student's t-distribution (Hu, 2010). Building on this, I model each marginal distribution of the asset returns employing an AR (p)-EGARCH (1, 1)-t model. Next, I estimate the scale-free measure of dependence, which preserves the dependence structure during the simulation of the RV.

The flowchart below summarizes the key steps that enable a sequential understanding of my proposed methodology. As reported below, there are three major steps: i) data analysis, ii) copula estimation and iii) estimation of joint dependence structure, which I next focus on.

Figure 4-1: Flowchart Summarizing the Proposed Method



4.3.1 Data Analysis and Estimation Procedure

4.3.1.1 Marginal Models

The model I employ for marginal distributions is presented below. I assume that the distributions of the asset returns follow an Autoregressive Moving Average ARMA (p,q)-EGARCH (1, 1)-t process (Nelson, 1991). The model is characterized as:

$$X_{i,t} = \theta_i + \sum_{j=1}^{p} \beta_j X_{i,t-j} + \sum_{k=i}^{q} \alpha_k \varepsilon_{t-k} + \varepsilon_{i,t} \tag{4-6}$$

$$\log(\sigma_t^2) = a_0 + \sum_{j=1}^{p} a_{1i} \log(\sigma_{t-j}^2) + \sum_{i=1}^{q} a_{2j} \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{j=1}^{q} a_{3j} \left(\frac{\varepsilon_{t-j}}{\sigma_{t-j}} \right) \tag{4-7}$$

$$\sqrt{\frac{d}{\sigma_{i,t}^2 (d-2)}} \cdot \varepsilon_{i,t} \mid I_{t-1} \sim i.i.d.t_{di} \tag{4-8}$$

where $X_{i,t}$ is the asset return series, θ_i and $\varepsilon_{i,t-1}$ are the conditional mean and error term, which is the news relating to the volatility from one lag period. β_j is the autoregressive component and α_k is the moving average parameter. The noise process ε_t represented in Equation (4-8) follows a skewed Student-t distribution with (d) degrees of freedom and σ_t^2 conditional variance. σ_{t-j}^2 is the GARCH component and the leverage effect is captured by a_3. The information contained about the volatility of the lagged period is captured by ε_{t-1} which represents the ARCH component. The information set is considered as the condition vector ‘k’ in the equation (4-5). The order of the ARMA term ‘p’ is determined using Akaike Information Criteria (AIC).

It is of prime importance to have precise marginal models since the joint CDF using copula is a function of the marginal distributions. Thus, mis-specification of the marginal models can lead to mis-specified copulas. Consequently, in order to check the empirical validly of the marginal models, I carry out mis-specification tests following Diebold et al. (1998), which are discussed in the next chapter.

4.3.1.2 Estimation of Scale-Free Measure of Association

For the scale-free measure I consider paired samples of the RV, (x_i, y_i) for $i = 1,...n$. The pairs (x_i, y_i) and (x_j, y_j) are concordant, provided the product of the difference of the consecutive RV is greater than zero, i.e. $(x_i - x_j)(y_i - y_j) > 0$, else it is discordant. Kendall's tau (τ) of the sample as a measure of scale-free association is calculated as the probability of concordance less the probability of discordance.

$$\hat{\tau} = P[(X_i - X_j)(X_i - Y_j) > 0] - P[(X_i - X_j)(X_i - Y_j) < 0] = \frac{con}{\binom{n}{2}} - \frac{dis}{\binom{n}{2}} = \frac{con - dis}{\binom{n}{2}}$$

(4-9)

where $\binom{n}{2}$ are the different combinations of selecting pairs from n variables, con represents the number of concordant pairs and dis presents the number of discordant pairs.

The tail dependence measure is another property of the copula that is very useful in analysing the joint tail dependence of bivariate distributions. Tail dependence estimates the probability of the RV in lower or upper joint tails. Intuitively, this measures the tendency of the asset returns to co-move up and down together.

$$\tau^U = Lt_{u\to 1} P\left[X \geq F_X^{-1}(u) / Y \geq F_Y^{-1}(u)\right] = Lt_{u\to 1} \frac{1-2u+C(u,u)}{1-u} \tag{4-10}$$

$$\tau^L = Lt_{u\to 0} P\left[X \geq F_X^{-1}(u) / Y \leq F_Y^{-1}(u)\right] = Lt_{u\to 0} \frac{C(u,u)}{u} \tag{4-11}$$

where $\tau^U, \tau^L \in [0,1]$ and F_X^{-1} and F_Y^{-1} are the marginal density functions of the RV series. If the tail dependence measures are positive then upper or lower tail dependence exists, i.e. $\tau^U(\tau^L)$ measures the probability of the RV-X is above (below) a high (low) quantile, given that the RV-Y is above (below) a high (low) quantile.

Next, I allow for the tail dependence estimate to follow an evolution process that captures the level changes. We define the evolution process as

$$\tau_t^{U/L} = \Theta\left(\beta_0^{U/L} + \beta_1^{U/L}\tau_{t-1}^{U/L} + \beta_2^{U/L}\frac{1}{q}\sum_{i=1}^{q}\left|u_{t-i} - v_{t-i}\right| + \beta_3^{U/L}D\right) \tag{4-12}$$

To restrict $\tau_t^{U/L} \in (-1.1)$, I conduct a logistic transformation on equation, i.e. $\Theta(h) = \left(\frac{1-e^{-h}}{1+e^{-h}}\right)$. The dependence parameter is assumed to follow an ARMA (p, q) determined by AIC values, characterized by β_1, the autoregressive term, and β_2, the forcing variable. While the former term accounts for the persistence effect, the latter term captures the variation effect of the dependence parameter. I, further, add a dummy variable term $\beta_3 D$ to allow for level variation in the dependence. The dummy variable takes the value ‘0’ prior to the subprime crisis, July 2007, and thereafter takes the value ‘1’.

4.3.2 Copula Estimation

4.3.2.1 Estimation of Dependence Parameter

I obtain the dependence parameter of the Archimedean copulas (θ) using the sample estimate of Kendall's tau $(\hat{\tau})$ in equation (4-3). For Gaussian, Student's-t and modified Joe-Clayton (MJC), I estimate the dependence parameter using maximum likelihood (ML) method.

Referring to equation (4-5) I have $C(u,v;\delta)=C((F_{X|K}(x\,|\,k;\theta_1),F_{Y|K}(y\,|\,k;\theta_2);\delta)$, where θ_1 and θ_2 are the coefficients of the conditioning vector k. Therefore, the joint density of an instance (x_t, y_t) is

$$c(x_t, y_t;\delta)=\frac{\partial^2 C(u_t, v_t;\delta)}{\partial u_t \partial v_t}\cdot\frac{\partial u_t}{\partial x_t}\cdot\frac{\partial v_t}{\partial y_t} \tag{4-13}$$
$$\Rightarrow c(x_t, y_t;\delta)=c(u_t, v_t;\delta).f_{X\,|k}(x_t\,|\,k;\theta_1).f_{Y\,|k}(y_t\,|\,k;\theta_2)$$

From the above equation, I write the log-likelihood of the sample $(x_{1,t}, y_{1,t})$ as

$$L(\Phi)=\sum_{t=1}^{T}\ln\left[c(u_t, v_t;\delta).f_{X\,|k}(x_t\,|\,k;\theta_1).f_{Y\,|k}(y_t\,|\,k;\theta_2)\right]$$
$$\Rightarrow L(\Phi)=\sum_{t=1}^{T}\ln\left[c\left(F_{X|k}(x_t\,|\,k;\theta_1\delta)\times F_{Y|k}(y_t\,|\,k;\theta_2\delta)\right).f_{X\,|k}(x_t\,|\,k;\theta_1).f_{Y\,|k}(y_t\,|\,k;\theta_2)\right]$$
$$\Rightarrow L(\Phi)=L_C+L_X+L_Y \tag{4-14}$$

As noted by Jondeau and Rockinger (2006), the ML estimation may be difficult to compute if the number of unknown parameters is large, in which case only numerical gradients can be computed instead of having an analytical expression of the likelihood gradients. This leads to considerable slowing down of the numerical estimation. I, therefore, compute the ML estimation using Inverse Function of Margins (Joe and Xu, 1996). This is a two-step estimation process. First, the marginal distribution parameters are estimated employing an AR (p)-EGARCH (1, 1)-t process as discussed above. I also capture the time variation of the dependence structure which further increases the number of unknown parameters to be estimated. The following estimation equation is used to compute the values of $\hat{\theta}_1$ and $\hat{\theta}_2$.

$$\hat{\theta}_K = arg \max_{\theta} L_{XY}(x_i, y_i; \theta_1, \theta_2); for\ k = 1,2 \tag{4-15}$$

Next, I estimate the copula parameter $(\hat{\delta})$ using the following equation.

$$\hat{\delta} = \arg \underset{\delta}{Max}\, L_C\left(x_t, y_t; \delta, \hat{\theta}_1, \hat{\theta}_2\right) \tag{4-16}$$

In this second step the marginal densities do not influence the copula estimation parameter as the marginal parameters are computed using equation (4-15). Therefore, the second equation remains unchanged and computes asymptotically efficient and normal estimates of the copula parameter (Joe, 1997; Cherubini et al., 2004).

4.3.2.2 Simulation of the Random Variates using Copula Models

In this study I employ several copula functions which capture the tail dependence patterns. The copulas are estimated using the inversion method by substituting the marginal densities of the RV in equation (4-5).

$$C(u,v) = H_{XY}\left(F_X^{-1}(u), F_Y^{-1}(v)\right) \tag{4-17}$$

where F_X^{-1} and F_Y^{-1} are the marginal density functions and u and v are the probabilities, i.e. realizations of $U \equiv F_{X|K}(x \mid k)$ and $V \equiv F_{Y|K}(y \mid k)$ given $K = k$, where U and V are the conditional probability integrals of the RV.

The Gaussian copula (G) for bivariate RV is characterized as $C_G(u, v; \rho) = \varphi\left(\varphi^{-1}(u), \varphi^{-1}(v)\right)$, where φ is the standard normal CDF with ρ as the dependence parameter and φ^{-1} the corresponding quantile function. Under normality conditions we have $\tau = \frac{2}{\pi} \arcsin \rho$. The copula density (c) is given as

$$c(u, v) = \frac{\partial^2 C}{\partial F_X(u) \partial F_Y(v)} \tag{4-18}$$

Considering $\tau^U = \tau^L = o$, i.e. zero tail dependence, for Gausian copula, equation (4-18) is reduced to

$$c(u, v) = \frac{1}{|R|^{\frac{1}{2}}} \exp\left\{ -\frac{1}{2} \begin{pmatrix} \varphi^{-1}(u) \\ \varphi^{-1}(v) \end{pmatrix}^T \times \left(R^{-1} - I\right) \times \begin{pmatrix} \varphi^{-1}(u) \\ \varphi^{-1}(v) \end{pmatrix} \right\} \tag{4-19}$$

where R and I are the correlation matrix and identity matrix respectively. In a similar vein, Student's –t copula is characterized as $C_t(u, v; \rho, d) = T\left(t^{-1}(u), t^{-1}(v)\right)$, where d denotes degrees of freedom and t and t^{-1} represents Student-t CDF and their corresponding quantile functions. Unlike the Gaussian copula Student's-t copula allows symmetric non-zero tail dependence, i.e. $\tau^U = \tau^L > o$. Thus, both the positive and negative realizations bear the same probability.

To accommodate likely asymmetric tail dependence, I compute Frank, Clayton, Gumbel - Hougaard copulas. Now I present the algorithm that I have employed to simulate these Archimedean copulas: i) for a specific Archimedean copula I obtain the values of $\varphi^{[-1]}(\cdot), \varphi'(\cdot), \varphi'^{-1}(\cdot)$ using equation (4-2), where $\varphi_\theta(\cdot)$ is the copula generator function with dependence parameter θ. $\varphi'(\cdot)$ is the derivative of $\varphi(\cdot)$ with respect to $(\cdot)$. ii) Next, I generate two uniformly distributed random variables u and l such that $(u,l) \sim U(0,1)$. iii) I obtain two new variables, $m = \frac{\varphi'(u)}{l}$ and $n = \varphi'^{-1}(m)$. iv) Next I estimate $v = \varphi^{[-1]}(\varphi(n) - \varphi(u))$. The variables u and v are in the range $[0,1]$. v) These simulated variables, u and v, which preserve the dependence structure are then back transformed, replacing their values by the corresponding cumulative density to obtain the simulated RV in the original scale. I repeat these steps for each of the Archimedean copulas.

Finally, I consider a MJC (Modified Joe – Clayton) copula that allows upper and lower tail dependence (Patton, 2006). Under symmetric dependence I have $\tau^U = \tau^L$. The copula is characterized as

$$C_{MJC}(u,v;\tau^U,\tau^L) = \frac{1}{2}\left(C_{JC}(u,v;\tau^U,\tau^L) + C_{JC}(1-u,1-v;\tau^U,\tau^L) + u + v - 1\right) \tag{4-20}$$

where the C_{JC} , the Joe-Clayton copula, is formulated as (Joe, 1997)

$$C_{JC}(u,v;\tau^U,\tau^L) = 1 - \left(1 - \left\{\left[1-(1-u)^k\right]^{-\gamma} + \left[1-(1-v)^k\right]^{-\gamma} - 1\right\}^{-\frac{1}{\gamma}}\right)^{\frac{1}{k}} \tag{4-21}$$

where $k = \dfrac{1}{\log_2(2-\tau^U)}$, $\gamma = \dfrac{1}{\log_2(\tau^L)}$ and $\tau^U, \tau^L \in (0,1)$. Alternatively, the JC copula is the Laplace transformation of the Clayton copula.

The copulas defined above allow the dependent structure to vary in different ways, yet it is assumed to be time-invariant. To accommodate for potential time-varying dependence structure corresponding to conditional copulas, I allow the dependence parameter to vary according to an evolution process. I specify the dependence parameter (ρ_t) of the Gaussian and Student's-t copulas to follow an auto-regressive moving-average ARMA $(1,q)$ process.

$$\rho_t = \Theta\left(\beta_0 + \beta_1\rho_{t-1} + \beta_2\frac{1}{q}\sum_{i=1}^{q}\varphi^{-1}(u_{t-i}).\varphi^{-1}(v_{t-i}) + \beta_3 D\right) \tag{4-22}$$

To restrict $\rho_t \in (-1.1)$, we conduct a logistic transformation on equation (4-22), i.e. $\Theta(h) = \left(\dfrac{1-e^{-h}}{1+e^{-h}}\right)$. The ARMA specification of the dependence structure is obtained based on AIC values. In the above equation β_1 is the autoregressive term, and β_2 is the average of the sum-product of the transformed variables u and v. The term $\beta_1\rho_{t-1}$ accounts for the persistence effect while the term $\beta_2\frac{1}{q}\sum_{i=1}^{q}\varphi^{-1}(u_{t-i}).\varphi^{-1}(v_{t-i})$ captures the variation effect of the dependence parameter. To allow for level variation in the dependence structure, I add a dummy variable term $\beta_3 D$. This enables me to examine how the co-movement of the multi-assets returns has evolved over an extended time period from 1987 to 2012 in the US markets. The dummy variable takes the value '0' prior to the subprime crisis, July 2007, and thereafter takes the value '1'.

I examine the performance of the various copula models based on Akaike information criterion (AIC), Bayesian information criterion (BIC) and log-likelihood test. The former is adjusted for small sample bias (Rodriguez, 2007) and the latter is a goodness-of-fit test for the copula models to compare the different dependence structures.

4.3.3 Estimation of Multivariate Copulas Models

4.3.3.1 Non-elliptical Copula

To estimate multivariate dependence structure, I focus on both non-elliptical and elliptical copula models. Considering the former first, I formulate a hierarchical Archimedean copula model. Based on Savu and Trede (2010) I consider K hierarchy levels, which are indexed by k, i.e. $k=1,...,K$. At each k there are m_k different objects, i.e. $n=1,...,m_k$. Therefore, at $k=1$, I have m_1 grouped $u_1,....,u_p$ multivariate Archimedean copulas $C_{1,n}$ taking the form:

$$C_{i,n}\left(u_{1,n}\right)=\varphi_{1,n}^{-1}\left(\sum_{u_{1,n}}\varphi_{1,n}(u_{1,n})\right), n=1,...,m_k \quad \textbf{(4-23)}$$

where $u_{1,n}$ represents the set of elements of $C_{1,n}$ with copula generator $\varphi_{1,n}$. The copulas at the first level are grouped to construct the copulas $C_{2,n}$ at $k=2$. Thus, hierarchical construction of Archimedean copula allows partial-exchangeable dependence structure at every successive level, consisting copulas from previous stage. It is characterized as

$$C_{2,n}\left(C_{2,n}^{1}\right)=\varphi_{2,n}^{-1}\left(\sum_{C_{2,n}}\varphi_{2,n}(C_{2,n}^{1})\right) \quad \textbf{(4-24)}$$

where $\varphi_{2,n}$ is the generator of $C_{2,n}$ and $C^{1}_{2,n}$ denotes the set of copulas at the first level that enters the second stage. I continue this process until I attain $C_{K,1}$. In order to achieve reliable $C_{K,1}$ I ensure that $\varphi_{k,n} \in \zeta_{\infty}$.

This states that φ^{-1} is completely monotonic on R with $\zeta_K \equiv \{\varphi : R \to [0,1] | \varphi(0)=1, \varphi(\infty)=0, (-1)^k \varphi^k(t) \geq 0, k=1,...K\}$ and $C_{k,n} \in C_{k+1,i}$. The hierarchical Archimedean copula density is given as.

$$\frac{\partial^p C_{K,1}}{\partial u_1,...u_p} = \sum \frac{\partial^{p-i} C_{K,1}}{\partial C^{b_m}_{K-1,1} ... \partial C^{b_m,K-1}_{K-1,m_{K-1}}} \times \prod_{t=1}^{m_{K-1}} \sum_{u=\upsilon_1,...\upsilon_t} \frac{\partial^{|\upsilon_1|} C_{K-1,t}}{\partial \upsilon_1}, ..., \frac{\partial^{|\upsilon_1 t|} C_{K-1,t}}{\partial \upsilon_t} \quad \textbf{(4-25)}$$

where the outer sums all the integers $b_1,...,b_{m,K-1} \in \mathrm{N}$ such that $\max_n b_n \leq p_{K-1,n}$ and $\sum_{n=1}^{m_{K-1}} b_n = p - i, \forall i = 0,..., p - m_{K-1}$. These terms represent the outer derivative of m_{K-1} copulas at $K-1$ level. The second part of the equation (4-25) represents the inner derivatives at $K-1$ level with respect to their corresponding arguments $u_{K-1,n}$.

Next, I discuss the construction of multivariate elliptical copulas.

4.3.3.2 Multivariate Elliptical Copulas

Apart from the non-elliptical copulas, I examine the dependence structure using two elliptical copulas, multivariate Gaussian copula and Student t-copula. I use the results of these elliptical copulas as a benchmark for comparing the estimates from non-elliptical copula as discussed above. A p-variate Gaussian copula of $X = (X_1,...,X_p) \sim N_p(0,R)$ is characterized as:

$$C_G(u_1,...,u_p) = \varphi_R(\varphi^{-1}(u_1),...,\varphi^{-1}(u_p)) \quad \textbf{(4-26)}$$

where φ_R represents the p-variate standard normal CDF, φ denotes the marginal normal CDF, R is the correlation matrix and $u_i = F_i(x_i)$. The log likelihood function of the corresponding p-variate Gaussian copula is defined as

$$L_G(R;u_t) = -\frac{1}{2}\sum_{t=1}^{T}\left(\log|R| + \mathrm{H}_t^T \times (R^{-1} - I) \times \mathrm{H}_t\right) \quad \textbf{(4-27)}$$

where $\mathrm{H}_t = (\varphi^{-1}(u_{1,t},...,u_{p,t})$ and I is an identity matrix. φ^{-1} is the inverse univariate standard distribution and R is the correlation matrix.

In a similar vein a p-dimensional t-copula is characterized as:

$$C_t(u_1,...,u_p) = t_R(t^{-1}(u_1),...,t^{-1}(u_p)) \quad \textbf{(4-28)}$$

where t_R represents the joint distribution of the vector $X \sim t(0,R)$, t denotes the CDF of a standard t-distribution and R is the correlation matrix. The corresponding log likelihood function is:

$$L_t(R,d;u_t) = -T\log\frac{\Gamma\left(\frac{d+p}{2}\right)}{\Gamma\left(\frac{d}{2}\right)} - pT\log\frac{\Gamma\left(\frac{d+1}{2}\right)}{\Gamma\left(\frac{d}{2}\right)} - \left(\frac{d+p}{2}\right)\sum_{t=1}^{T}\left(\log(1 + \frac{\mathrm{H}_t^T \times R^{-1} \times \mathrm{H}_t}{d}\right)$$

$$-\sum_{t=1}^{T}\log|R|+\left(\frac{d+1}{2}\right)\sum_{t=1}^{T}\sum_{i=1}^{p}\log\left(1+\frac{\mathrm{H}_{it}^{2}}{d}\right) \quad \textbf{(4-29)}$$

For t-copula I have $\mathrm{H}_t = \left(t_t^{-1}(u_{1,t},...,u_{p,t}\right)$, which is the vector of transformed standardized residuals, where t^{-1} represents inverse of Student's t-distribution, d is the degrees of freedom and R is the correlation matrix.

4.4 Summary

Dependence measure has prime importance in analysing asset market linkages and financial contagion. Studies in the past have dealt this issue considering linear correlation as an estimate of the comovement between two random variables. Though this measure of association is easy and convenient to calibrate, it might yield highly biased results in case of non-normal distribution of the sample data. In particular, the linear correlation measure fails to provide an appropriate estimate of the dependence structure when dealing with multivariate distributions exhibiting complex dynamic characteristics. In addition, literature confirms the presence of asymmetric dependence among various asset returns (Barsky, 1989; Baele et al., 2010; Chan et al., 2011; Reboredo, 2011).

Further, when the joint distributions of the asset returns follow a non-elliptical structure, linear correlation fails to provide sufficient information of their dependence structure. In particular two issues arise from this existing empirical evidence. The first is to propose a more reliable alternative density specification for a higher-dimensional case. The second is to formulate a measure of the variables' dependence structure which is more instructive than linear correlation. In this chapter I employ an alternative method to estimate the dependence structure of the asset return comovements based on the theory of copula. The prime motivation to employ copula is that it enables to examine scale-free dependence structure, which is preserved during simulation. Further, there is no restriction on the distribution of the data set, unlike other parametric methods.

Using these time-varying conditional multivariate elliptical and non-elliptical copulas, in the next chapter I examine the return comovements between three different asset classes: financial assets, commodities and real estate in the US market. Also, the proposed approach enables me to examine the asset return comovements during the extremes, i.e. tail dependencies. Analysing the tail dependence structures provide novel insights which have significant implications for the portfolio diversification and asset return comovement literature.

CHAPTER 5

Examination of Bi-variate and Joint Dependence Structures

5.1 Introduction

In this chapter I use time-varying conditional multivariate elliptical and non-elliptical copulas to examine the return comovements between three different asset classes: financial assets, commodities and real estate in the US market. In this regard, I report several key sights on asset return comovements.

The purpose of this chapter is three fold: First, I examine the bivariate comovement of the asset return dynamics in the US market. Second, I statistically test the performance of elliptical and non-elliptical copula models for both the constant and the dynamic dependence structures. Third, I present and analysis of the joint dependence structure combining all the three asset classes, i.e. conventional assets, commodities and real estate.

As stated in the previous chapter I adopt an alternative approach to overcome the limitations of simple linear correlations to examine the dependence structure of the multi-asset return comovements. My proposed approach models the dependence structure of the returns across three different asset classes using dynamic conditional copula models. In my sample, all the five asset returns follow a non-normal distribution. I analyse both the general and the tail dependence structures of the bivariate asset pairs and the joint comovement of the multi-asset returns. The empirical findings contribute to the literature along several dimensions. First, the dataset contains a wider range of assets rather than the conventional financial assets. I analyse the multi-asset return comovements for common financial assets, (equities and bonds), commodities (oil and gold) and real estate. The period of analysis is from 1987 to 2012 (1^{st} August 1987 to 1^{st} September 2012), which allows me to capture the changing dependence during the periods of financial turmoil.

Second, I examine the dynamics of the general and the tail dependence structures for the ten bivariate combinations of asset pairs. It is, to my knowledge, the first study that comprehensively examines the combinations of the dependence structure of the multi-asset return comovements. Further, I extend the modelling of dependence structure to capture the time-varying evolutionary effect of the return comovements especially during the crisis period.

Third, I compare and statistically test the performance of various elliptical and non-elliptical copula models. This enables proper selection of a superior model to understand more complex return dynamics, especially during periods of financial turbulences.

Fourth, I examine the joint dependence structure by combining all the asset classes. With the ever rising uncertainty in the financial markets, investors do not solely invest in only one or two assets but in a portfolio of assets. To the best of my knowledge this is the first study, which attempts to examine the joint return distribution of a multi-asset portfolio. Therefore, this examination of the joint dependence structure of the multi-asset return comovement yields important information for portfolio diversification and asset allocation.

This chapter has five key empirical findings: First, the time-varying copula models provide superior dependence structure measures compared to the static copula models. This illustrates that asset allocation based on simple static covariance of asset returns will result in underperforming portfolios. Second, findings show that lower tail dependence is much higher than upper tail dependence. This suggests that there is high probability of extreme comovements in economic contractionary period. The higher dependence measure implies that some of the diversification benefits are lost during the contraction periods, which are characterized by increased risk. The only exception is the comovement between real estate and bond. Third, the empirical findings reveal an increase in the dependence measure of multi-asset return comovements post the August 2007 U.S. subprime crisis. An important implication of high dependence measure is that otherwise-diversified portfolios, which combine safe assets such as bond and gold, show a decline in diversification benefits during periods of economic contraction. Fourth, results show that despite the volatility in financial markets caused by credit crisis, the Student t-distribution still plays a dominant role in defining the distribution fitting.

The rest of the chapter unfolds as follows: Section 5.2 provides the data description. Section 5.3 discusses the empirical findings on dynamics of the bivariate asset return comovements. Section 5.4 reports the empirical findings on dynamics of the multivariate (combination of all the asset classes) asset return comovements and Section 5.4 concludes the chapter.

5.2 Data Description

I examine the joint dependence structure of five financial assets including conventional financial securities, commodities and real estate security for the US market. My sample includes i) Standard & Poor's (S&P) 500 index (E), ii) US 10 year Government bond return index (B), iii) S&P Case-Shiller Composite-10 home price index (RE), iv) S&P GSCI Gold index (G) and v) West Texas Intermediate -WTI Cushing crude oil spot prices per barrel (O). The monthly returns are obtained from DataStream. The sample period is from the fourth quarter 1987 to the fourth quarter 2012 (1st August 1987 to 1st September 2012). Table 5-2 provides the summary statistics of all the financial asset returns. The returns are compute on a continuous compounding basis, calculated as 100 times the logarithmic difference of the index/price values.

Previous studies show that changing business conditions reflect on asset returns, which are largely common across various asset classes (Fama and French, 1989; Balvers et al., 1990). Consequently, we examine the monthly returns in relation to the phases of the business cycle. Every month is classified as either a business expansion or a business contraction month. This is based on the turning point, i.e. trough to peak dates, as specified by the NBER's Business cycle Dating Committee[8]. Thus, we create two sub-samples, the business expansion (E) phase and the business contraction (C) phase.

Table 5-1: Turning Points in the Business Cycle

Turning Point	Date	Expansion (E)/Contraction (C)	Months in Phase
0	8/1987	E1	35
1	7/1990	C1	8
2	3/1991	E2	120
3	3/2001	C2	8
4	11/2001	E3	73
5	12/2007	C3	18
6	6/2009	E4	40

Notes: The turning points of the business cycle are based on the NBER-official dates of troughs and peaks (NBER, 2012). The sample period is from the fourth quarter of 1987 to the fourth quarter of 2012, yielding 302 monthly observations. Each month in the sample is divided into

[8] The NBER considers recession, i.e. contraction phase, as a significant decline in economic activities spread over several months. The various economic activities include real GDP, real income, whole-retail sales and industrial production. An expansionary phase marks the end of a contraction phase and beginning of the recovery phase in the business cycle (NBER, 2012).

either an expansionary phase or a contractionary phase based on the turning point. The expansionary period has 268 months and the contractionary period has 34 months.

Table 5-1 shows the turning points in the business cycle. Over the sample period there are four expansionary and three contractionary periods. Of the 302 months in the full sample, 268 months, i.e. 89 percent, are in expansionary phase and 34 months, i.e. 11 percent, are in contractionary phase. The average duration of the expansionary phases is 66.5 months and the average duration of the contractionary phases is 11.3 months.

Table 5-2 presents the summary statistics of the asset returns. In Panel (A) of Table 5-2 the annualized mean return of oil (6.33 percent) is higher than any other assets followed by equity and bond returns of 6.27 and 5.52 percent, respectively. The standard deviation is highest for oil returns (33 percent) followed by equity returns (16.42 percent). Except for gold returns, the asset returns are negatively skewed. All the asset returns show excess kurtosis, indicating that the distributions have a fatter tail and the probability of extreme variance is more likely as compared to a normal distribution. The Jarque-Bera test statistics in Panel (B) of Table 5-2 confirm that the unconditional distributions of the asset returns are not normal. Thus, it is less likely that multivariate Gaussian distribution will provide the best-fit for the dependence structure. The Lagrangian Multiplier (LM) test examines the presence of serial correlation of the squared return up to lag 10. The significant LM statistics confirm the presence of autoregressive conditional heteroskedastic (ARCH) effects. The Ljung-Box test also reports that most of the asset returns are serially correlated for at least one of the lag orders. The autocorrelation test is performed with correction for heteroskedasticity at lag orders 1, 5 and 10.

Panel C of Table 5-2 provides the linear correlation matrix for the expansion and the contraction periods. The correlation coefficients provide insights of the asset return comovements. Overall, results indicate that the asset return correlation during the contraction phase is substantially higher than the correlation during the expansion phase except for the Bond-Oil pair. This potentially indicates that bond provides good hedge for oil during economic contraction phase. In line with Jensen and Mercer (2003), a marked decrease is observed in the correlation of the equity-paired assets in the expansion phase. For example, the equity-bond correlation in the contraction phase is 0.044, whereas in the expansion phase it is negative 0.133. The higher dependence measure implies that some of the diversification benefits are lost during the contraction periods, which are characterized by increased risk. Brocato and Steed (2005) show that asset allocation changes keyed to business cycle turning points yield improved results over a long-term buy and hold strategy. This exemplifies the importance of a more informative and dependable estimate of the dependence structure, which would lead to enhanced portfolio performance. Understanding the dynamics of asset return comovements in extreme economic conditions, particularly in the contraction phase, will provide critical information for better asset allocation and optimized risk diversification.

Table 5-2: Summary Statistics

	Equity (E)	Bond (B)	Real Estate (RE)	Gold (G)	Oil (O)
Panel A: Descriptive Statistics [a]					
Mean (%)	6.274	5.524	3.394	5.438	6.331
Standard Deviation (%)	16.428	1.293	2.730	15.449	33.000
Kurtosis	3.854	0.138	0.611	1.986	1.687
Skewness	-1.114	-0.165	-0.726	0.064	-0.357
Panel B: Diagnostics (1987-2012) [b]					
Jarque-Bera statistics	208.3** (0.000)	7.7** (0.020)	31.5** (0.000)	45.7** (0.000)	48.4** (0.000)
ARCH LM statistic (1)	31.586** (0.000)	17.737** (0.000)	1741.764** (0.000)	4.586** (0.033)	13.676** (0.000)
ARCH LM statistic (5)	17.489** (0.000)	8.571** (0.000)	371.920** (0.000)	3.003** (0.016)	4.563** (0.000)
ARCH LM statistic (10)	12.804** (0.000)	4.903** (0.000)	190.231** (0.000)	1.927** (0.041)	2.913** (0.001)
Ljung-Box statistic (1)	3.293 (0.0705)	9649.404** (0.000)	4232.160** (0.000)	4.433** (0.036)	5.757** (0.017)
Ljung-Box statistic (5)	1.254 (0.282)	1932.252** (0.000)	914.690** (0.000)	3.005** (0.011)	3.223** (0.007)
Ljung-Box statistic (10)	0.869 (0.562)	971.691** (0.000)	452.606** (0.000)	1.619 (0.100)	2.156** (0.022)

Panel C: Linear Correlations [c]					
Expansion Phase					
Equity (E)	1.000				
Bond (B)	-0.133**	1.000			
	(0.030)				
Real Estate (RE)	-0.098	-0.074	1.000		
	(0.108)	(0.227)			
Gold (G)	-0.058	0.022	-0.057	1.000	
	(0.345)	(0.716)	(0.353)		
Oil (0)	0.071	-0.144**	0.027	0.206***	1.000
	(0.246)	(0.018)	(0.660)	(0.001)	
Contraction Phase					
Equity (E)	1.000				
Bond (B)	0.044***	1.000			
	(0.006)				
Real Estate (RE)	0.029	-0.074	1.000		
	(0.872)	(0.676)			
Gold (G)	0.010	0.229	-0.016	1.000	
	(0.956)	(0.193)	(0.929)		
Oil (O)	0.349**	-0.293*	0.085	0.335**	1.000
	(0.043)	(0.093)	(0.632)	(0.035)	

Note: Panel A represents the descriptive statistics of the asset returns. The sample period is from the fourth quarter of 1987 to the fourth quarter of 2012, yielding 302 observations. The return figures are annualized from the monthly observations. Annualized return = [(1+monthly mean return)^{12} - 1], Annualized standard deviation = [monthly standard deviation$\times 12^{1/2}$]. Panel B provides the diagnostic test results. Under the normality null hypothesis, Jarque-Bera test statistic follows a Chi-square distribution with fixed (2) degrees of freedom. The null hypothesis of the ARCH-LM test is: there is no evidence of ARCH effect. We conduct the test at lags 1, 5 and 10 with corresponding 1, 5, 10 degrees of freedom. Tests using other lags yield the same results. We conduct the Ljung-Box test for serial correlation, corrected for heteroskedasticity at lags 1, 5 and 10. The p-values are reported in the parentheses.

** signifies rejection of the null hypothesis at 5 percent level.

The commonly used measure of covariance structure, i.e. the linear correlation is one among the many ways to measure the degree of dependence. For the most appropriate use of this measure, two assumptions must be satisfied. First, the data in both the pairs must be generated from a Gaussian distribution. Second, the data should be in the same frequency. But, in this study the first assumption is clearly violated (see Panel B of Table 5-2). Thus, I confirm that the use of serial correlation will most likely not lead to an appropriate estimate of the asset return dependence structure. I, therefore, focus in the use of the Kendall's τ measure as an alternative method to predict a more reliable dependence structure of the asset returns. The use of copula as discussed in the previous chapter computes the dependence parameter based on this alternative measure of association.

Thus far, the evidence reported clearly show that correlation, i.e. the dependence structure of the asset returns, is influenced by expansion and contraction phases. Therefore, it is of key interest to examine the asset returns covariance during the business cycle phases. Such an analysis in performed in the following section.

5.3 Estimation of Marginal Models

To estimate the bivariate distributions, I first need to generate the univariate marginal distribution of each asset returns. In this study, I estimate ARMA (p, q) – EGARCH (1, 1) model for each of the financial return time-series. The appropriate lag orders for each of the return series are selected based on the Akaike information criteria (AIC), observing the conditional variance equation as EGARCH (1, 1)-t process. The estimates of the marginal models are reported in Table 5-3. The mean equations of equity, bond, real estate, gold and oils follow ARMA (2, 2), ARMA (5, 5), ARMA (7, 7), ARMA (6, 6) and

ARMA (7, 6), respectively. Table 5-3 also shows that the marginal models are free from autocorrelation and heteroskedastic effects.

Table 5-3: Parameter Estimates of the Marginal Models

	Equity (E)	Bond (B)	Real Estate (RE)	Gold (G)	Oil (O)
Mean Equation					
θ_1	0.006***	0.005***	0.002	0.002	0.006
	(0.002)	(0.000)	(0.420)	(0.493)	(0.102)
β_1	0.69***	1.003***	-0.140	-0.035	0.143
	(0.000)	(0.000)	(0.414)	(0.769)	(0.581)
β_2	-0.736***	-0.310**	0.812***	0.520***	1.382***
	(0.000)	(0.0422)	(0.000)	(0.000)	(0.000)
β_3	-	0.182	-0.126	-0.477***	-0.420
		(0.1832)	(0.507)	(0.000)	(0.119)
β_4	-	-0.692***	-0.326*	0.510***	-1.010***
		(0.000)	(0.067)	(0.000)	(0.002)
β_5	-	0.561***	-0.047	0.664***	0.123
		(0.001)	(0.736)	(0.000)	(0.525)
β_6	-	-	0.331***	-0.353***	0.346**
			(0.002)	(0.005)	(0.044)
β_7	-	-	0.363***	-	0.117
			(0.001)		(0.199)
α_1	-0.739***	-0.942***	1.157***	-0.199*	-0.060
	(0.000)	(0.000)	(0.000)	(0.061)	(0.820)
α_2	0.811***	0.114	0.545**	-0.616***	-1.627***
	(0.000)	(0.373)	(0.021)	(0.000)	(0.000)
α_3	-	-0.015	0.608***	0.573***	0.397
		(0.894)	(0.002)	(0.000)	(0.212)
α_4	-	0.671***	0.600***	-0.645***	1.333***
		(0.000)	(0.007)	(0.000)	(0.000)
α_5	-	-0.729***	0.694***	-0.623***	-0.282
		(0.000)	(0.000)	(0.000)	(0.260)

α_6	-	-	0.420***	0.671***	-0.515***
			(0.005)	(0.000)	(0.001)
α_7	-	-	-0.015	-	-
			(0.835)		
Variance Equation					
a_0	-1.106***	-1.137*	-0.285	-1.454**	-0.825**
	(0.001)	(0.063)	(0.127)	(0.027)	(0.022)
a_1	0.350***	-0.161**	0.120**	0.301**	0.353***
	(0.007)	(0.040)	(0.044)	(0.029)	(0.002)
a_2	-0.207**	0.167**	-0.026	0.175*	0.044
	(0.006)	(0.021)	(0.518)	(0.062)	(0.358)
a_3	0.874***	0.839***	0.983***	0.810***	0.888***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log likelihood	536.521	742.140	742.830	533.587	302.396
AIC	-1057.042	-1462.279	-1465.6593	-1053.173	-580.791
ARCH LM (1)	-0.050	0.041	0.014	-0.033	0.017
	(0.399)	(0.496)	(0.164)	(0.584)	(0.776)
ARCH LM (5)	-0.051	0.013	-0.022	-0.022	-0.013
	(0.415)	(0.825)	(0.719)	(0.713)	(0.827)
ARCH LM (10)	0.025	0.013	0.005	-0.001	-0.097
	(0.676)	(0.829)	(0.954)	(0.978)	(0.129)
Ljung-Box Statistic (20)	1.101	1.476	1.386	1.29	1.525
	(0.438)	(0.088)	(0.127)	(0.179)	(0.071)

Notes: The table reports the parameter estimates and the corresponding p-values in the parentheses. All the assets are estimated using ARMA (p, q)-EGARCH (1, 1)-t model. The lags of the corresponding models are determined using AIC values. The mean equations of equity, bond, real estate, gold and oils follow ARMA (2, 2), ARMA (5, 5), ARMA (7, 7), ARMA (6, 6) and ARMA (7, 6), respectively. The ARCH LM test at lags 1, 5 and 10 tests for the presence of the ARCH effect in the residuals. Ljung-Box test statistic test for the presence of serial correlation, computed at lag 20. The p-values are reported in the parentheses.

***, ** and * signifies rejection of the null hypothesis at 1, 5 and 10 percent levels, respectively.

To evaluate the adequacy of the marginal estimations, misspecification tests are conducted following Diebold et al. (1998). I examine the correlograms of $(\hat{u}_t - \bar{u})^l$ and $(\hat{v}_t - \bar{v})^l$ for '*l*' ranging from one to four. The values *u* and *v* are the probability integral transformations of the estimates of the marginal models. Table 5-4 reports the tests for each of the models. The correlograms show no presence of serial correlation in the first four moments. This indicates that the marginal distribution models for the different asset returns are correctly specified. This ensures that the copula models can correctly estimate the dependence structure of the asset return comovements.

Table 5-4: Test of Marginal Distribution Models

	Equity (E)	Bond (B)	Real Estate (RE)	Gold (G)	Oil (O)
First moment	0.327	0.991	0.417	0.854	0.160
Second moment	0.586	0.934	0.352	0.522	0.892
Third moment	0.236	0.623	0.357	0.295	0.889
Fourth moment	0.104	0.603	0.124	0.488	0.482

Notes: This table reports the p-values for the LM statistics for the null of no serial correlation. The results are reported for the first four moments of the variables u_t and v_t from the marginal distribution models, ARMA (p, q)-EGARCH (1, 1)-t process. The test statistic follows a Chi-squared distribution under the null. Reported p-values below 0.05 indicated rejection of the null hypothesis which states that the model is well specified.

5.4 The Dynamics of the Bivariate Asset Return Comovements

5.4.1 Parameter Estimates of the Bivariate Dependence Structures

In this study I use MATLAB (Matrix Laboratory) software in estimating the copula parameters. MATLAB is a high-level language that provides an enhanced interactive environment to test algorithms immediately without recompilations. The key reasons for using MATLAB in estimating the copula parameters are i) it allows for immediate execution of a command without compiling the whole programme/set of instructions, ii) allows for working independently with the data, keeping a track of the variables generated and the files produced, and iii) the ability to call external libraries with associated codes (aids in enhancing computing performance). These features of MATLAB greatly facilitate in developing algorithms that meet the desired requirements.

Table 5-5 reports the equity-related copula parameter estimates for static and time-varying Clayton, MJC and Student t-copula models. Panel A of Table 5-5 summarizes the time-invariant copula models. The constant dependence parameters of all the copulas are significantly different from the linear correlations (c.f. Table 5-2). To evaluate the goodness-of-fit for the different time-invariant copulas I calibrate the AIC, BIC measures. The findings suggest that Student t-copula is a more appropriate fit for the dependence measure.

Panel A of Table 5-5 reports the static dependence measure of the different equity based asset return pairs. Based on the AIC and BIC measures I find that the Student-t copula outperforms the rest. Also, the lower and the upper tail probability parameter estimates $\left(\tau_U, \tau_L\right)$ of MJC copula are significant. It is important to note that the lower tail dependence probability of E/B, i.e. 0.0433, is higher than the upper tail dependence measure (0.0139). This indicates that the likelihood of extreme equity-bond return comovement (degree of association between equity and bond returns) is higher in the contraction phase than in the expansion phase. An important implication of this finding is that some of the diversification benefits of investing in fixed income assets are lost during periods of economic decline. Likewise the probability of the lower tail measure of E/O (0.0804) signifies that during the periods of economic contraction the equity and oil prices are more closely associated than in the expansion period. Thus, investments in these two assets classes might lead in considerable losses in the recessionary phases of the economy.

In Panel B of Table 5-5 I capture the persistence and variation effects in the dependence structure of the asset return comovements. The degrees of freedom for the Student t-copula (d), ranges from 6.64 to 19.9, which indicate that there is evidence of considerable comovements and tail dependence of the various asset returns. Observing the estimates of the MJC copula, which allows us to examine the asymmetric upper and lower tail dependence measures; I find evidence for asymmetric tail dependence of asset return comovements, which is less likely to be captured by the linear correlation measure of return comovements. Results show that the lower tail dependence measure (τ_L) of E/B and E/O is higher than the upper tail dependence measure (τ_U). Thus, there is evidence of higher probability of comovement among equity and bond returns and equity and oil returns in the economic contraction regime than in the economic expansion regime.

Of course, similar results are obtained in static dependence measure (see Panel A of Table 5-5). Yet, it is interesting to note that the probability of static tail dependence measures are overestimated in case of upper tail (by 44.44 percent) and underestimated in case of lower tail (by 15.68 percent for E/B pair and 13.54 percent for E/O pair). This bears considerable implications for dynamic asset management strategies.

Since, the static case is a restricted approximation of the time-varying evolution of dependence parameters; Likelihood Ratio (LR) test is conducted to claim my acceptance of the most appropriate copula models that defines the dependence structure. The null hypothesis of the test is that there is no significant difference when one moves from the restricted to the unrestricted time-varying model. The LR test statistics reported in the Panel B of Table 5-5 rejects the null for all the copula pairs. This suggests that the dynamics of the dependence structure is well captured by the evolutionary process parameters of the time-varying copula models.

Table 5-5: Estimates of Equity-Paired Copula Models

	E/B	**E/RE**	**E/G**	**E/O**
Panel A: Time-invariant having constant dependence parameter				
Student t-copula				
ρ	0.11 (0.004)**	0.07 (0.004)**	-0.04(0.006)**	0.10 (0.004)**
AIC	-12.0	-3.23	-3.25	-32.29
BIC	-12.0	-3.19	-3.22	-32.25
Log Likelihood	-6.03	-1.62	-1.64	-16.16
Clayton copula				
δ	0.013 (0.045)**	0.0395(0.30)**	0.011(0.04)**	0.081 (0.03)**
AIC	-5.86	-0.65	-0.06	-9.04
BIC	-5.84	-0.64	-0.05	-9.03
Log Likelihood	-2.93	-0.32	-0.03	-4.52
Modified Joe-Clayton Copula				
τ_U	0.013 (0.095)**	0.000 (0.000)**	0.000 (0.000)**	0.000 (0.000)**
τ_L	0.0433 (0.076)**	0.000 (0.000)**	0.000 (0.000)**	0.080 (0.9)**
AIC	-11.3	-0.27	0.55	-11.67
BIC	-11.3	-0.24	0.57	-11.64
Log Likelihood	-5.68	-0.14	0.27	-5.841

Panel B: Time-varying with time dummy				
Student t-copula				
d	9.158 (6.323)	19.9 (6.78)	6.644 (4.702)	13.81 (2.48)
β_1	0.186 (0.086)**	0.057 (0.12)**	0.021 (0.019)**	0.098 (0.02)**
β_2	0.000 (0.072)***	0.000 (2.12)	0.97 (0.016)**	0.899 (0.031)
β_3	0.134 (0.169)	0.013 (1.2)	0.489 (0.72)	0.004 (1.34)
AIC	-31.5	-0.51	-31.5	-37.6
BIC	-31.3	-0.49	-31.4	-37.6
Log Likelihood	5.7	5.26	5.7	8.8
LR (3) statistics (p-value)	11.984***	11.45***	10.2***	7.871***
	(0.000)	(0.000)	(0.000)	(0.000)
Clayton Copula				
β_o^L	-0.775 (.098)**	-3.48 (1.09)**	-4.03 (2.19)	-3.70 (0.75)**
β_1^L	-3.913 (4.01))	-4.8441 (1.96)	-4.771 (3.12)	0.137 (0.469)
β_2^L	0.088 (.295)**	-0.678 (0.143)	-0.65 (0.12)**	-0.891 (0.048)
β_3^L	-0.002 (1.000)	-0.001 (2.12)	0.000 (.018)	-0.001 (0.19)
AIC	-17.0	-1.79	-7.22	-25.19
BIC	-16.8	-1.75	-7.18	-25.15
Log Likelihood	8.52	6.90	5.61	8.60
LR (3) statistics (p-value)	15.784***	13.754***	10.762***	10.181***
	(0.000)	(0.000)	(0.000)	(0.000)
Modified Joe-Clayton Copula				
β_o^L	-1.688 (1.000)**	-9.572 (2.81)**	-9.99 (7.53)**	-5.71 (0.46)**
β_1^L	-4.620 (4.13)	7.913 (0.17)	9.91 (2.13)	9.99 (7.172)
β_2^L	-0.918 (0.048)	9.600 (2.786)	8.67 (5.55)	5.27 (0.610)**

β_3^L	0.001 (2.32)	-0.001 (.012)	0.000 (2.12)	0.000 (2.17)
β_0^U	0.0271 (1.408)**	-9.583 (3.46)**	-9.8 (2.12)**	-1.09 (1.43)**
β_1^U	-9.999 (5.127)	5.598 (7.49)	-3.573 (3.80)	-9.995 (2.78)
β_2^U	-0.056 (3.15)	9.817 (1.47)	0.420 (3.45)	-0.921 (1.42)
β_3^U	-0.002 (2.68)	-0.001 (1.45)	0.001 (1.13)	0.001 (1.13)
AIC	-13.8	0.65	2.04	-23.15
BIC	-13.7	0.72	2.11	-23.08
Log Likelihood	7.94	6.31	7.00	11.59
LR (6) statistics (p-value)	12.734***	11.464***	14.891***	21.911***
	(0.000)	(0.000)	(0.000)	(0.000)
τ_U	0.009 (0.931)**	0.000 (0.902)**	0.000 (0.952)**	0.000 (1.782)**
τ_L	0.051 (1.311)**	0.000 (0.872)**	0.000 (1.276)**	0.093 (0.972)**

Notes: The table reports the copula estimates of different equity-paired copula models. Panel A reports the time-invariant copula estimates, while Panel B presents the time-varying copula estimates. Goodness of fit AIC, BIC and log-likelihood statistics is presented for each of the copula models. The LR (d) test statistics test the null hypothesis that the time-invariant copula model is not rejected as one move from time-invariant to time-varying copula models, where (d) is the degrees of freedom of the LR test. The standard errors of the copula estimates and p-values of the LR tests are reported in the parentheses. The MA processes of E/B, E/Re, E/G, and E/O are 1, 2, 2 and 2, respectively.

*** and ** signifies rejection of the null hypothesis at 1 and 5 percent levels, respectively.

Likewise, we estimate the dependence parameters for all the possible ten copula pairs from the three different asset classes**.** The results are provided in the chapter Appendix.

The findings of the goodness of fit test of each of the copula pairs are provided in Table 5-6. Panel A provides the performance statistics of the time-invariant copulas, including Student-t, Clayton, Frank, Gumble - Hougaard and MJC copula. The test statistics show that static Student t-copula provides the best fit for the dependence measure of the asset return comovements based on AIC measures. Panel B reports the test statistics of the time-varying copula estimates, which includes Student t-copula, Clayton and MJC copulas. Since, the Clayton and MJC perform next best to Student t-copula they are included in my time-varying model. The results show that on the basis of information criteria the time-varying Student t-copula best fits the data for the asset return comovements.

Further, the Likelihood Ratio (LR) test statistics reported in Panel B of Table 5-6 rejects the null for all the copula pairs. Thus, the dynamics of the dependence structure are well captured by the evolutionary process parameters of the time-varying copula models.

Table 5-6: Performance Analysis of All Copula Models

	B/RE	B/G	B/O	RE/G	RE/O	G/O	E/B	E/RE	E/G	E/O
Panel A: Time-invariant having constant dependence parameter										
Student t-copula										
AIC	-4.91	-5.95	-0.12	-2.29	-0.98	-20.5	-12.0	-3.23	-3.25	-32.3
BIC	-4.87	-5.92	-0.08	-2.26	-0.94	-20.4	-12.0	-3.19	-3.22	-32.2
Log Likelihood	-2.46	-2.98	-0.07	-1.15	0.45	-10.3	-6.03	-1.62	-1.64	-16.1
Clayton copula										
AIC	-0.84	-3.11	-3.20	0.01	0.01	-17.6	-5.86	-0.65	-0.06	-9.04
BIC	-0.83	-3.10	-3.19	0.02	0.02	-17.6	-5.84	-0.64	-0.05	-9.03
Log Likelihood	-0.42	-1.56	-1.60	0.00	0.00	-8.80	-2.93	-0.32	-0.03	-4.52
Frank Copula										
AIC	-2.06	-0.06	0.00	0.00	0.01	-10.1	-6.21	-0.96	0.01	-2.40
BIC	-2.05	-0.04	0.01	0.01	0.01	-10.1	-6.20	-0.95	0.02	-2.39
Log Likelihood	-1.03	-0.03	0.00	0.00	0.00	-5.07	-3.11	-0.48	0.00	-1.25

Gumble - Hougaard (GH) copula										
AIC	-0.02	2.39	5.32	15.7	6.63	-6.36	-7.29	4.32	11.2	-3.88
BIC	-0.03	2.40	5.33	15.7	6.64	-6.35	-7.28	4.34	11.3	-3.86
Log Likelihood	-0.02	1.19	2.65	7.85	3.31	-3.18	-3.65	2.16	5.61	-1.94
Modified Joe – Clayton copula										
AIC	-3.37	-5.26	-5.25	3.10	0.91	-18.8	-11.3	-0.27	0.55	-11.6
BIC	-3.34	-5.24	-5.23	3.12	0.94	-18.8	-11.3	-0.24	0.57	-11.4
Log Likelihood	-1.69	-2.64	-2.63	1.54	0.45	-9.45	-5.68	-0.14	0.27	-5.84
Panel B: Time varying with time dummy										
Time-varying Student t-copula										
AIC	-13.46	-29.7	-31.3	-23.3	-22.4	-44.1	-31.5	-0.51	-31.5	-37.6
BIC	-13.44	-29.7	-31.2	-23.2	-22.4	-44.0	-31.3	-0.49	-31.4	-37.6
Log Likelihood	5.74	14.9	15.6	11.6	11.2	22.2	15.7	7.26	15.7	18.8
LR (3) statistics (p-value)	14.2*** (0.000)	31.4*** (0.000)	30.2*** (0.000)	24.8*** (0.000)	23.2*** (0.00)	41.3*** (0.000)	41.9*** (0.00)	16.72*** (0.000)	31.2*** (0.000)	47.8*** (0.000)
Time-varying Clayton copula										
AIC	-3.82	-12.0	-16.8	-0.76	-0.05	-23.0	-17.0	-1.79	-7.22	-25.1
BIC	-3.78	-12.0	-16.8	-0.72	-0.02	-22.8	-16.8	-1.75	-7.18	-25.1
Log Likelihood	5.92	6.03	6.43	5.39	5.04	6.4	8.52	7.90	5.61	6.6
LR (3) statistics (p-value)	13*** (0.000)	11.7*** (0.000)	10.7*** (0.000)	10.1*** (0.000)	9.7** (0.045)	11.82*** (0.000)	15.7*** (0.000)	13.7*** (0.000)	10.7*** (0.000)	10.18*** (0.000)
Time-varying Modified Joe – Clayton copula										
AIC	-3.54	-8.85	-6.46	6.64	2.72	-21.1	-13.8	0.65	2.04	-23.1
BIC	-3.47	-8.77	-6.39	6.71	2.79	-21.0	-13.7	0.72	2.11	-23.0
Log Likelihood	5.79	8.44	4.25	4.30	3.34	5.6	6.94	6.31	4.00	4.5

LR (6) statistics (p-value)	10.7*** (0.000)	19.4*** (0.000)	8.3** (0.048)	9.7** (0.045)	7.9** (0.045)	11.8*** (0.000)	12.7*** (0.000)	11.4*** (0.000)	7.8** (0.049)	8.9** (0.048)

Notes: The table reports the goodness of fit AIC, BIC and log-likelihood statistics for each of the paired- copula models. Panel A reports the time-invariant copula estimates, while Panel B presents the time-varying copula estimates. The LR (d) test statistics test the null hypothesis that the time-invariant copula model is not rejected as one move from time-invariant to time-varying copula models, where (d) is the degrees of freedom of the LR test. The standard errors of the copula estimates and p-values of the LR tests are reported in the parentheses.
*, ** and *** signifies rejection of the null hypothesis at 10, 5 and 1 percent levels, respectively.

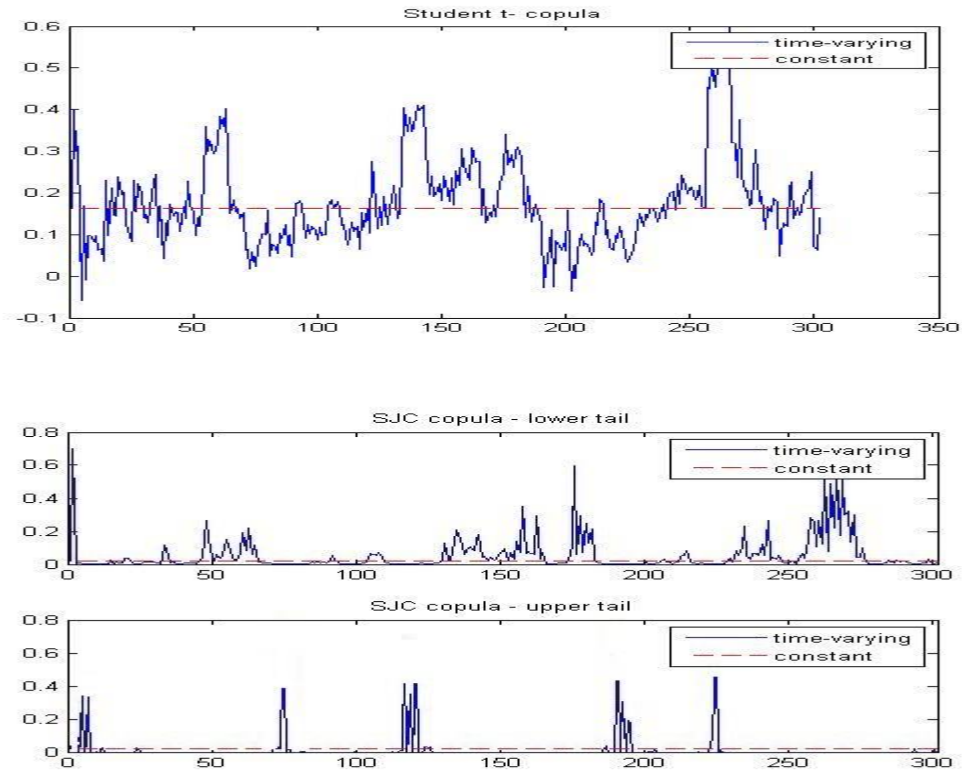
5.4.2 Time-path of the Dependence Structures

Figure 5-1 presents the time path of the dependence structure of the ten combinations of the bivariate copula pairs. It shows the probability of lower and the upper tail dependence structures along with the time path of the time-varying Student-t copula models for each of the pairs. In all the cases it can be seen that the dependence structure significantly differs from white noise and reveals useful information. It is observed that the probability of extreme comovement of the lower tail is higher than the upper tail for the entire set of asset pairs (see note of Figure 5-1). For example, the probability of extreme comovement of E/B pair in the expansion phase is 0.103 as compared to 0.192 in the contraction phase. Therefore, findings show that the covariance structure of the asset returns in the business expansion phase is substantially lower than in the business contraction phase. This indicates that there is a higher probability of extreme comovements in bear market as compared to bull market. An important implication of the high measure of dependence structure is that the diversified portfolios lose some diversification benefits during economic recession. Importantly, it is observed that for all the real estate-paired copulas and for the E/G pair the probability of joint extreme comovements in either of the phases is less likely.

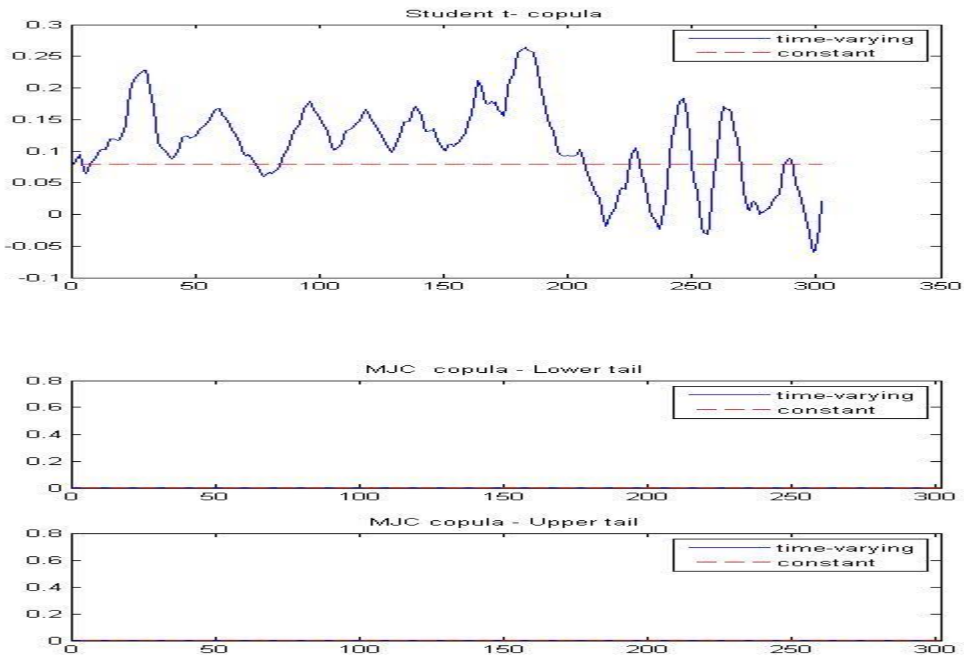
Part A: For equity-paired copulas the dependence measure is highest for the E/B pair (0.113). This is no surprise as we expect the equities and bonds to show more return correlation than for the rest of the pairs. All the pairs show positive average dependence measure except for the E/G pair. This indicates that investment in gold can serve as a good hedging option as the pair also shows an average negative dependence measure of 0.046 and 0.047 in both the lower and upper tails, respectively (for values see note Figure 5-1). Further, there is no likelihood of extreme comovements in either of the economic phases. The variability of the dependence structure is highest for the E/O pair, ranging from negative 0.78 to positive 0.70 (for values see note Figure 5-1). The lower tail dependence also shows high volatility, indicating the high probability of extreme movements in the contraction phase. Part B: The constant dependence measure for the bond-paired copulas is lower than rest of the asset pairs. A key implication of the low covariance structure implies that investment in bonds leads to reduction in portfolio risk, especially during a crisis period. Intuitively, B/G pair shows a higher positive average dependence measure of 0.044 in the contraction phase than in the expansion phase (0.027) (see note of Figure 5-1). Hence, the lower tail dependence structure of the B/G pair is quite evident, confirming a high probability of extreme bond-gold return comovement during the bear market. Unlike the E/O pair, the B/O pair shows less variability, yet there is considerable evidence of extreme comovements during the crisis period as the dependence measure of both the O/E and O/B pairs are higher in the business contraction phase. But, it is of interest to note that O/B covariance structure is considerably low, indicating that investment in bonds facilitates risk diversification. Part C: The pair RE/G shows a negative average dependence measure of 0.091, which implies that gold is suitable for risk diversification. Though both the real estate pairs witness high volatility and increase in dependence measure post August 2007 subprime crisis, they do not show any indication of extreme comovements in either bear or bull markets. Part D: The pair G/O show positive dependence structure with an average value of 0.18 (see note of Figure 5-1). The pair shows high volatility in the lower tail. This indicates that the gold and oil returns have a high probability of extreme comovements in the crisis period.

In sum, the average dependence structure is highest for equity-paired copulas. Further, evidence shows that the probability of lower tail dependence measures for all the asset pairs is higher than the upper tail measures except for the B/O pair. An important implication of this is that there is a loss of diversification benefit due to financial contagion. Yet for the B/O pair, the average dependence measure is low (0.017), indicating that investment in bonds aid in risk reduction. Bond and gold pairs have a low or a negative dependence structure measure and hence these assets are best suited for risk diversification. Yet, the dependence measure of the B/G pair is considerably high (0.044) during the economic contractionary phase (see note of Figure 5-1). This implies a contagion effect of the bond and the gold market in the contraction period. Therefore considering the probability of the lower tail dependence structure of each of the bond and gold pairs separately, investment in gold is more favourable than to investment in bond for all asset pairs except for oil during the contraction period for maximizing portfolio diversification, though investment in bonds will lead to higher returns with reduced risk diversification benefits.

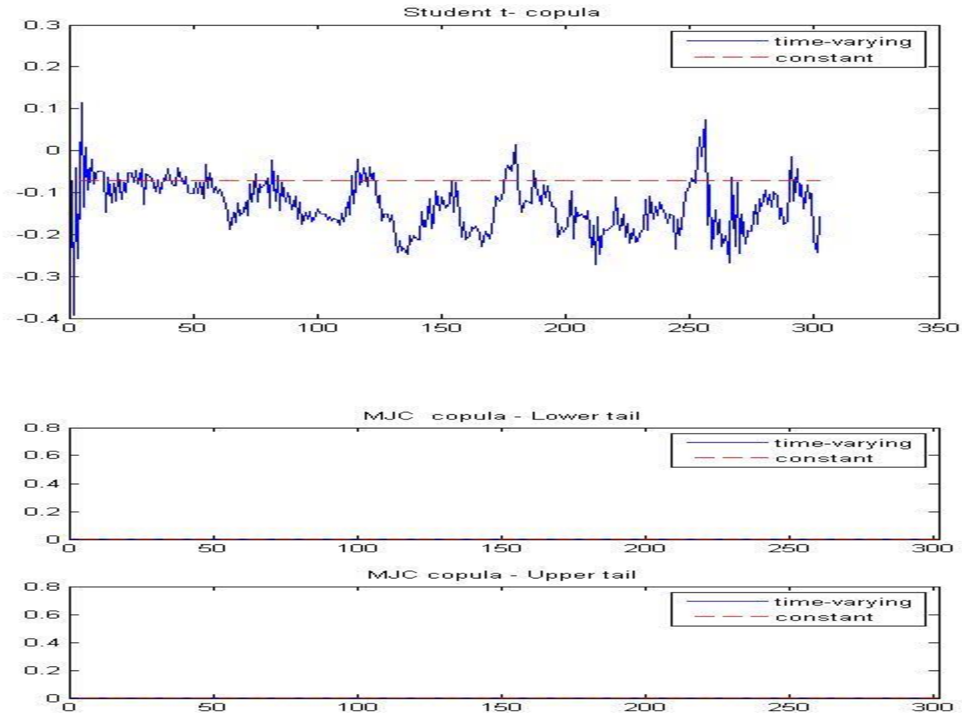
Figure 5-1: Time Path of Bivariate Copula Pairs



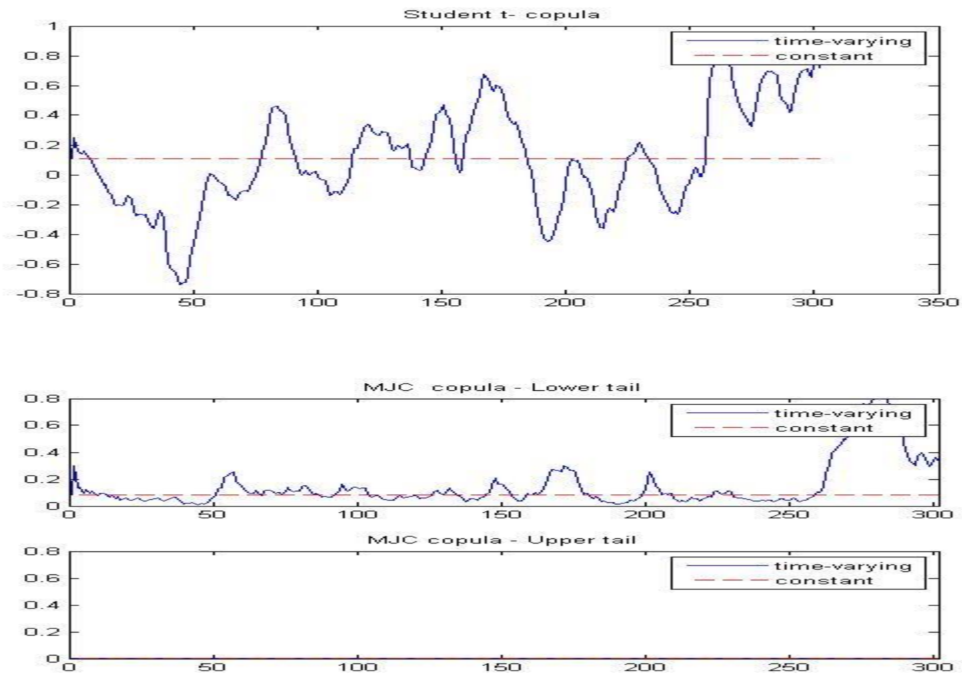
A (i): Dependence Structure of Equity-Bond Copula Pair



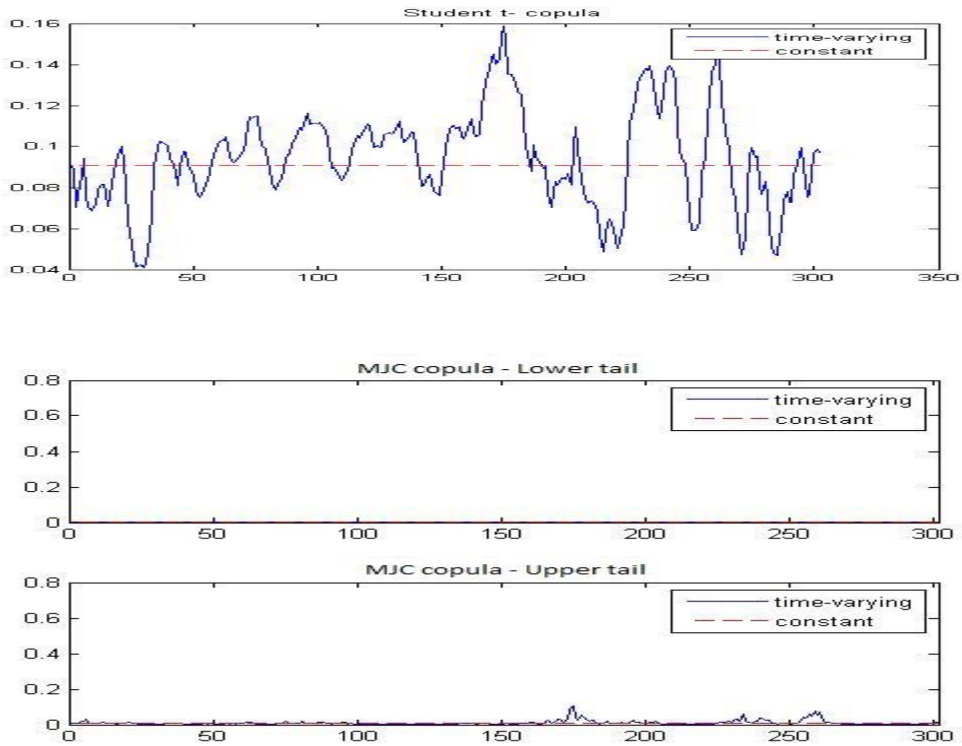
A (ii): Dependence Structure of Equity-Real Estate Copula Pair



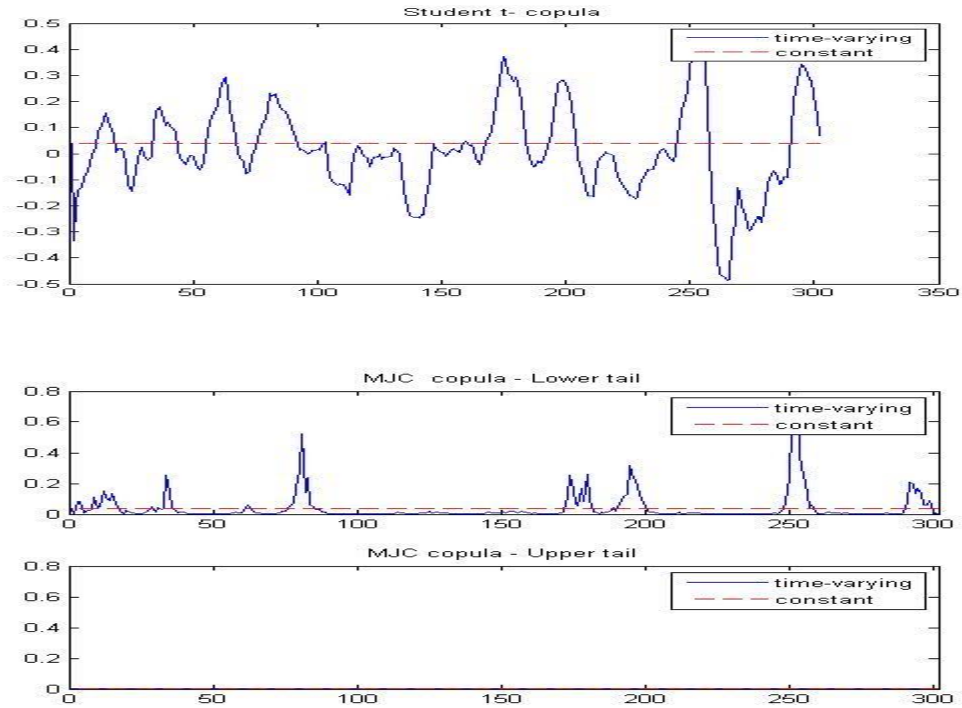
A (iii): Dependence Structure of Equity-Gold Copula Pair



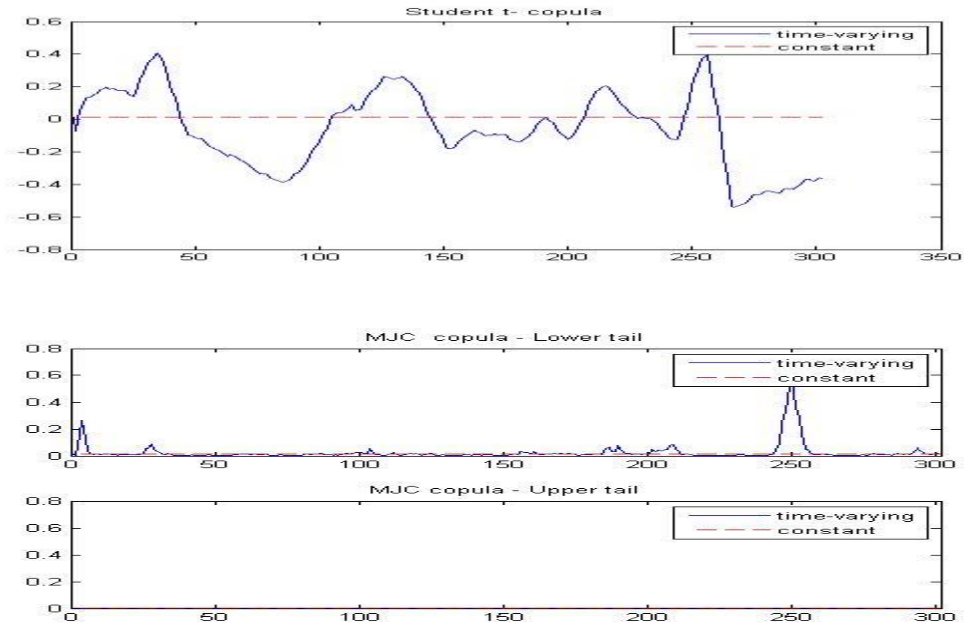
A (iv): Dependence Structure of Equity-Oil Copula Pair



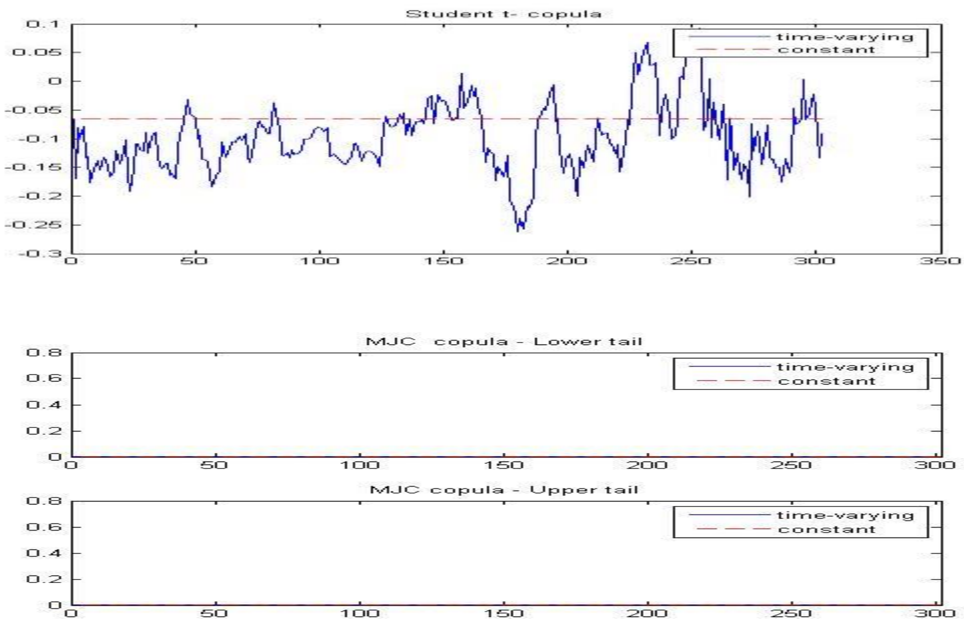
B (i): Dependence Structure of Bond-Real Estate Copula Pair



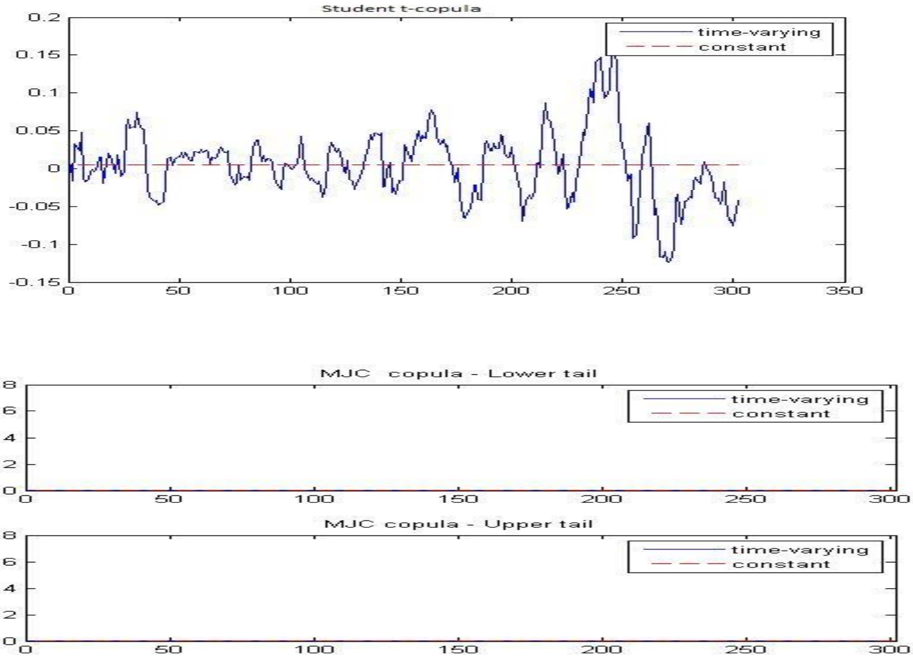
B (ii): Dependence Structure of Bond-Gold Copula Pair



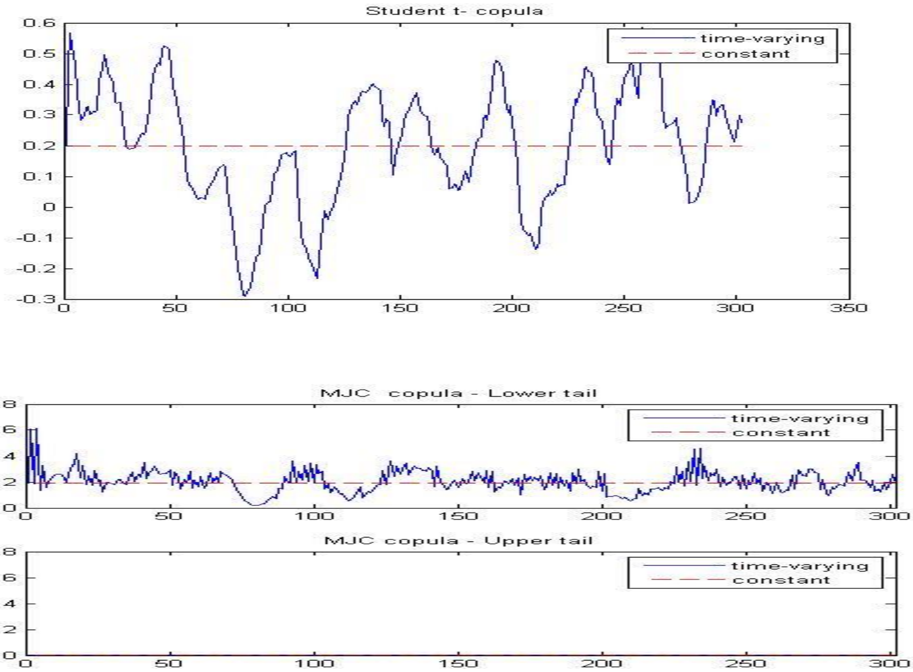
B (iii): Dependence Structure of Bond-Oil Copula Pair



C (i): Dependence Structure of Real Estate-Gold Copula Pair



C (ii): Dependence Structure of Real Estate-Oil Copula Pair



D: Dependence Structure of Gold-Oil Copula Pair

Notes: In the figure, Panel A to D shows the time path of the time-varying dependence structure of the 10 asset-pairs. The average dependence measures for the period 1987 to 2012 of the different asset pairs are: E/B = 0.113, E/RE = 0.078, E/G = -0.047, E/O = 0.103, B/RE = 0.112, B/G = 0.029, B/O = 0.017, RE/G = -0.091, RE/O = 0.005 and G/O = 0.180. The average dependence measures for the asset pairs during the expansion period are: E/B = 0.103, E/RE = 0.077, E/G = -0.047, E/O = 0.100, B/RE = 0.111, B/G = 0.027, B/O = 0.017, RE/G = -0.094, RE/O = 0.003 and G/O = 0.162. The average dependence measure for the asset pairs during the contraction period are: E/B = 0.192, E/RE = 0.084, E/G = -0.046, E/O = 0.124, B/RE = 0.121, B/G = 0.044, B/O = 0.013, RE/G = -0.069, RE/O = 0.017 and G/O = 0.321. The expansionary and the contractionary periods are based on the NBER cycles as discussed in Table 5-1. The lower tail corresponds to contractionary phase and the upper tail corresponds to expansionary phase.

5.5 The Dynamics of the Multivariate Asset Return Comovements

5.5.1 The parameters of the Multivariate Dependence Structures

After estimating the pair wise copula estimates, I next focus on constructing the multivariate copula models. In this analysis, I consider both elliptical and non-elliptical copulas of the Archimedean family. Table 5-7 provides the parameter estimates of both the classes of copulas. First, I focus on the non-elliptical class of copulas that include Clayton, Frank and HG copulas as a basis of the 5-dimensional hierarchical copulas computed in this study. The dependence parameter of the hierarchical (H) structure of all the copulas is significant. The value of the estimate is highest for the H-GH copula (1.312) and lowest for the H-Clayton copula (0.102). Thus, the dependence estimate measures of the non-elliptical H-copulas vary over a broad range, which leads to over estimation of the dependence structure. In particular, based on the information criteria measure of the goodness of fit test statistic, the best fit copula model is the H-Clayton copula.

Next, I consider the elliptical copulas for the Student-t and the Gaussian copula. The high ‘degrees of freedom’, i.e. 28, for Student t-copula confirms that there is a considerable evidence of significant comovements and tail dependence of the multivariate copula model. The findings report that all the estimation parameters are significant for both the copulas. Yet, the performance test statistics, i.e. AIC and BIC measures, show that the Student-t multivariate copula is a better fit of the observed data than the Gaussian copula.

Table 5-7: Parameter Estimates of Multivariate Elliptical Copulas

	Elliptical Copula		Hierarchical (H) Non-Elliptical Copula		
	Student t-copula	**Gaussian copula**	**H-Clayton copula**	**H-GH copula**	**H-Frank copula**
δ	-	-	0.102**	1.312**	0.557**
			(0.01)	(0.01)	(0.01)
d	28	-	-	-	-
β_1	0.019**	0.018**	-	-	-
	(0.009)	(0.01)			
β_2	0.921 **	0.920**	-	-	-
	(0.21)	(0.022)			
AIC	-33.645	-32.585	-3.778	0.451	-2.893
BIC	-22.514	-25.163	-3.766	0.463	-2.880
Log likelihood	19.823	18.293	-1.892	0.222	-1.450

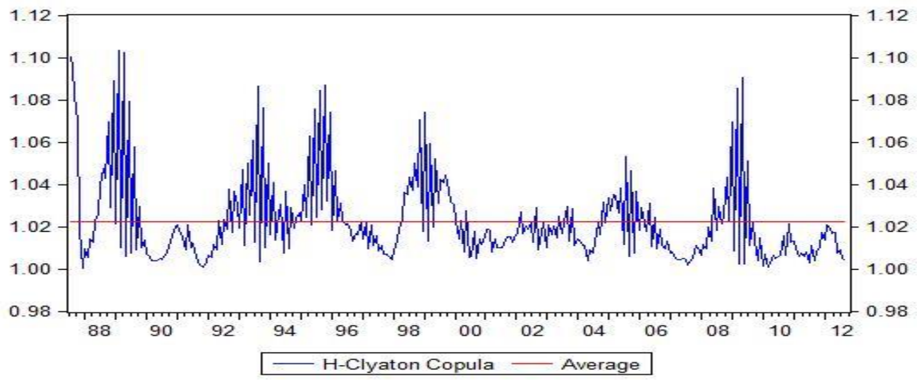
Notes: The table reports the copula estimates for the different multivariate elliptical and non-elliptical copula models. Goodness of fit AIC, BIC and log-likelihood statistics is presented for each of the copula models. The standard errors of the copula estimates are reported in the parentheses.

** signifies rejection of the null hypothesis at 5 percent level.

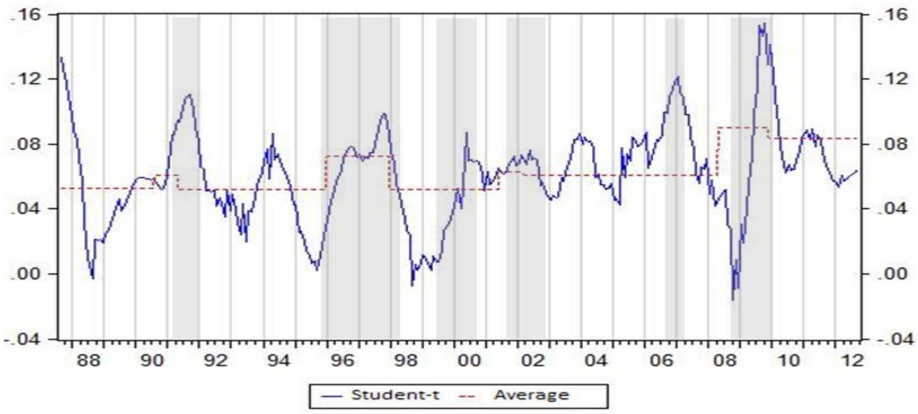
5.5.2 Time-path of the Multivariate Dependence Structures

Figure 5-2 shows the time path of the dependence parameter for both the multivariate copulas, namely and the H-Clayton copula (Part A) the Student-t copula (Part B). We notice that the time path projected by the H-Clayton copula is close to the white noise, while the Student t-copula seems to be informative. Thus, in my discussion I focus on Part B of Figure 5-2, i.e. the multivariate Student t-copula. The shaded region in the figure represents the contractionary periods. It is observed that the dependence measure reaches high peaks during these phases. Interestingly, the regimes of the JDS align closely with the economic expansionary and contractionary phases of the dating cycle committee as proposed by NBER (the dating cycles are reported in Table 5-1).

Figure 5-2: Dependence Structure of the Multivariate Copula



A: Time Path of Joint Dependence Structure of Hierarchical Clayton Copula



B: Time Path of Joint Dependence Structure of Multivariate Student–t Copula

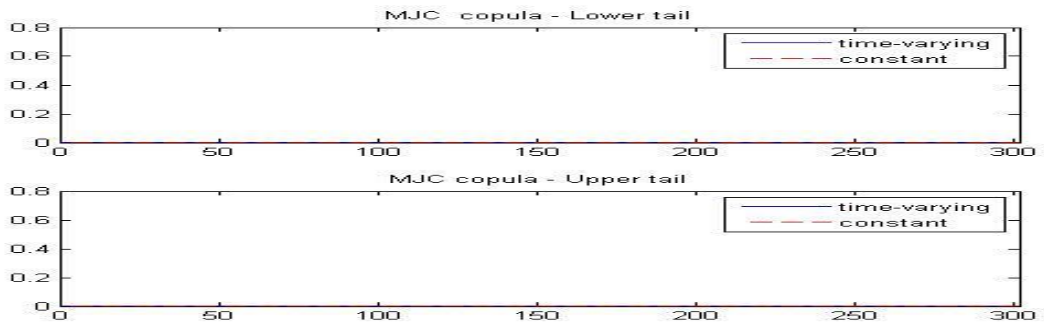
Note: The figure represents the time-path of the multivariate copulas. Part A corresponds to hierarchical Clayton copula while Part B represents the Student-t copula. The shaded regions in Part B corresponds to the contractionary periods. The period of analysis is from the fourth quarter 1987 to the fourth quarter 2012.

During the late 1980s, the Gross Domestic Product (GDP) rose from 3 percent in 1987 to 4.3 percent in 1988. Modest growth and low unemployment marked the expansionary phase in the economy, triggering a sharp fall in the dependence measure. By the early 1990s, signs of trouble began to emerge in the US economy. Investor sentiments about the inflation due to large US budget deficits pushed the economy into recession during July 1990 to March 1991. In this phase the dependence structure witnessed a sharp rise peaking to 0.097. The recession of 1991-1992 and the prolonged high unemployment rates gradually ended over the next couple of year as the economy stated to recover. Yet, the fiscal discipline during the 1990s which was extended to 1993 substantially reduced the scope for the US economy to introduce policy changes for future growth. Further, the failure of the Health and security Act in 1994 resulted in a mere contraction of the economy. Consequently, we observe a rise in the dependence structure during the years 1993-1994. In the following years, 1995 to 1997 the corporate profits declined. The economy entered into a sub-contractionary period with yet another rise in the dependence measure. But, even as the manufacturing profit rate fell significantly, the stock market witnessed a sharp rally during 1997-2000. The 'wealth effect' of the rising equity markets replaced the revival of the manufacturing profits. In 1998, the Wall Street witnessed the bailout of Long Term Capital Management (LTCM), triggering a reaction across the US financial markets. The dependence structure significantly rose during this period.

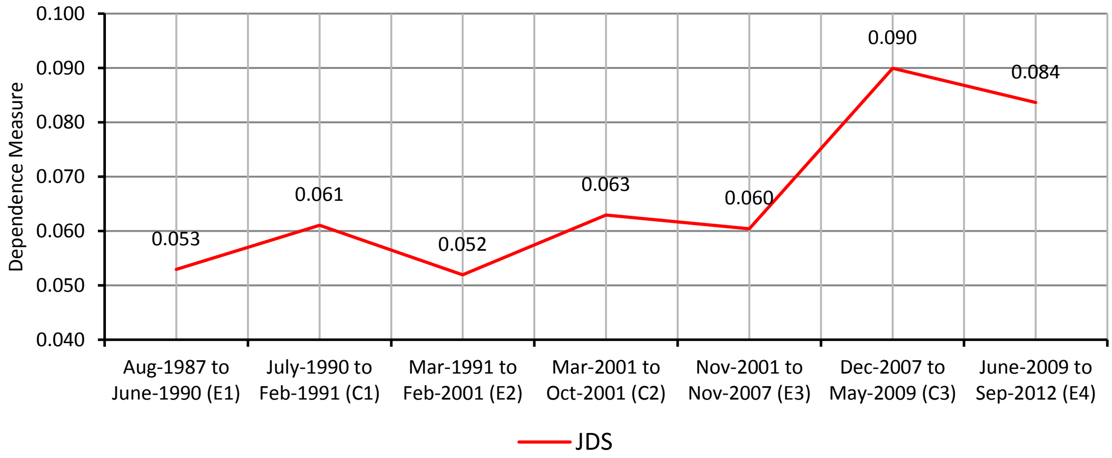
In the early 2000s, the US economy witnessed dot com bubble. This was created by the growing gap between the rising equity prices and the falling corporate profitability. The economy entered a contractionary phase following the dot com crisis. As the recession deepened, the US Federal Reserve brought down the interest rate. Consequently, the economy recovered as the investors increased their spending rate. Corporations restored their inventories. The US household debt exploded. This laid the foundation for the 2007-2009 subprime crises. During this contractionary phase the dependence measure reached a peak value of 0.154. Thereafter, the US economy witnessed a slow recovery. Yet, the average dependence remained high in the following years 2009-2012.

Panel A of Figure 5-3 shows the probability of extreme variations in the JDS. It is observed that neither the lower nor the upper tails are statistically significant. Hence, extreme events are less likely to happen and also there is no time variation in the tail dependence of the JDS. For economic significance, it implies that if certain asset returns experience extreme downturn or upturn, then it will not impact the joint dependence measure. In Panel B of Figure 5-3, I show the average joint dependence measure combining all the assets during the period August 1987 to September 2012. It is evident that the dependence measure during the economic contractionary period is higher than the economic expansionary period. Further, it shows evidence of increase in the dependence measure post August 2007 subprime crisis.

Figure 5-3: Joint-Dependence Structure



Panel A: Probability of Tail Dependence



Panel B: Average Joint-Dependence Structure

Note: The figure shows dependence structure of the joint return movements of the three different asset class. The period of analysis is from the fourth quarter 1987 to the fourth quarter 2012. The shaded portion in Panel A represents the upper and the lower tail dependence. It is evident that no significant variation is observed. Panel B presents the average dependence measure for the whole sample. It is evident that the dependence measure increases post sub-prime crisis. In panel B the various economic expansion (E) and economic contraction (C) corresponds to the economic cycles as dated by NBER. The periods are presented in Table 5-1.

5.6 Summary

In this chapter, I use copula models to examine the return comovement of five assets belonging to three different asset classes: financial assets (equities and bonds), real estate (housing) and commodities (gold and oil) for the US market. I examine the bivariate and the multivariate dependence structures using static and time-varying elliptical and non-elliptical copulas. First, I model the appropriate marginal distributions for each of the financial assets using the standard ARMA (p, q)-t-EGARCH (1, 1) model. Next, I carry out the misspecification test of the conditional distributions following Diebold et al. (1998) to verify the reliability of the models constructed. Thereafter, five copula models are constructed, namely Student-t, Clayton, Frank, GH and MJC to examine the bivariate dependence structure of the asset return pairs. Moreover, I allow the dependence structure to follow an evolution process to examine the time varying nature of the dependence measure. I report and analyse the goodness of fit statistics and the time path of the dependence structures of each of the bivariate copula pairs. Next, I construct two elliptical multivariate copulas, i.e. Student-t and Gaussian, and three hierarchical non-elliptical multivariate copulas, i.e. H-Clayton, H-Frank and HGH, to examine the dependence structure of the multi-asset return comovements. I report and analyse the goodness of fit statistics and time path of the dependence structure for each of the multivariate copula models. Based on my examination, the key findings are as follows:

First, the Student-t copula provides superior dependence measures for all the combinations of the asset pairs across the three different asset classes. Further, as we increase our sample size, Student-t copula should be most appropriate and preferred from an estimation purpose. Second, concerning the bivariate copula approach: i) the Student-t copulas dominate in both the static case with constant dependence structure and the time varying case with the dependence structure following an ARMA process, ii) in case of non-elliptical copulas the Clayton copulas show the best fit statistics followed by MJC. Yet, it should be noted that only in the case of B/RE and E/RE the time-varying Clayton copula dominates over Student t-copula. This is because of the asymptotic joint distribution of B/RE and E/RE. Third, the LR test statistics of the time-varying copulas rejects the null for all the copula pairs. This specifies that the dynamics of the dependence structure are well captured by the evolutionary process of the time-varying copula models. Consistent with this finding, I also observe that the static dependence measure overestimates the correlation of the asset returns during the expansion phase and underestimates the correlation measure in the contraction phase. Fourth, for the multivariate copula models, the Student-t copula dominates over the Gaussian copula. Likewise the H-Clayton copula dominates over the other non-elliptical Archimedean copulas. Focusing on the non-elliptical hierarchical copulas, I find that the goodness of fit statistic is considerably low and the corresponding dependence structure generated is close to white noise and provides less information. In contrast to the H-Clayton copula, the time path dependence structure generated by the Student t-copula provides substantial information regarding the comovement of the multi-asset returns. Results also show an increase in the dependence measure of the return comovements for the combination of all the assets since the August 2007 subprime crisis. This suggests that some diversification benefits are reduced due to high measure of return comovement. Further, it is observed that Student-t copula provides the best fit and its time-variant construction dominates over the other copula models. This indicates that Student –t distribution stages a dominant role in distribution fitting.

These findings have important implications for portfolio diversification and asset allocation. For instance, if the dependence structure of the asset returns comovements is sufficiently estimated, dynamic asset allocation techniques can be adopted to rebalance the multi-asset portfolio. Analysing the tails of the dependence structure reveals critical information for active portfolio management, specifically during extreme market conditions. In particular, the findings of the lower tails favour (i) investments in gold over bond during economic contraction phase to maximize risk diversification and (ii) show that investment in bonds provide superior hedge for oil.

Even if the dependence structure of the asset return comovements might not be perfectly predicted especially during periods of economic crisis, my findings still hold important implications for portfolio diversification and hedging. In phases of economic contraction, the primary concern of the investors is to minimize losses. Time path of the dependence structure reveal that there is evidence of financial contagion between all assets, yet the probability of joint extreme events is significantly less for the gold-paired copulas. This implies that in order to hedge financial risks when it is most needed, investors should hold a component of gold in their portfolio.

5.7 Appendix

The table below reports the copula parameter estimates for static and time-varying Clayton, MJC and Student t-copula models for bond, real estate a, oil and gold based pairs. Panel A of Table 5-A1 and Table 5-A2 summarizes the time-invariant copula models. The constant dependence parameters of all the copulas are significantly different from the linear correlations (linear correlations are reported in Table 5-2). To evaluate the goodness-of-fit for the different time-invariant copulas the AIC, BIC measures are reported. The findings suggest that Student t-copula is a more appropriate fit for the dependence measure.

Panel A of Table 5-A1 and Table 5-A1 reports the static dependence measure of the different asset return pairs. Based on the AIC and BIC measures it is evident that the Student-t copula outperforms the rest. Also, the lower and the upper tail probability parameter estimates (τ_U, τ_L) of MJC copula are significant. It is important to note that the probability of lower tail extreme comovement are higher than the upper tail. This indicates that the likelihood of extreme return comovement (degree of association between various asset return) is higher in the economic contraction phase than in the economic expansion phase. An important implication of this finding is that some of the diversification benefits of investing in fixed income assets are lost during periods of economic decline.

Panel B of Table 5-A1 and Table 5-A2 reports the persistence and variation effects in the dependence structure of the asset return comovements. The degrees of freedom for the Student t-copula (d), ranges from 7.478 to 19.955, which indicate that there is evidence of considerable comovements and tail dependence of the various asset returns. Observing the estimates of the MJC copula, which allows us to examine the asymmetric upper and lower tail dependence measures; evidence for asymmetric tail dependence of asset return comovements is observed, which is less likely to be captured by the linear correlation measure of return comovements. Results show that in general the lower tail dependence is higher than the upper tail dependence measure (τ_U). Thus, there is evidence of higher probability of comovement among asset returns in the economic contraction regime than in the economic expansion regime.

Similar results are obtained for static dependence measure (see Panel A of Table 5-A1 and Table 5-A2). However, it is interesting to note that the probability of static tail dependence measures are overestimated in case of upper tail and underestimated in case of lower tail. This bears considerable implications for dynamic asset management strategies. Since, the static case is a restricted approximation of the time-varying evolution of dependence parameters, Likelihood Ratio (LR) test is conducted to claim the acceptance of the most appropriate copula models that defines the dependence structure. The null hypothesis of the test is that there is no significant difference when one moves from the restricted to the unrestricted time-varying model. The LR test statistics reported in the Panel B of Table 5-A1 and Table 5-A2 rejects the null for all the copula pairs. This suggests that the dynamics of the dependence structure is well captured by the evolutionary process parameters of the time-varying copula models.

Table 5 (A-1): The Estimates of Copula Parameters

	B/G	**B/RE**	**B/O**
Panel A: Time-invariant having constant dependence parameter			
Student t-copula			
ρ	0.076 (0.037)**	-0.063 (0.044)**	-0.163(0.045)**
AIC	-12.0	-3.23	-3.25
BIC	-12.0	-3.19	-3.22
Log Likelihood	-6.03	-1.62	-1.64
Clayton copula			
δ	0.063 (0.045)**	-0.05(0.030)**	-0.140(0.040)**
AIC	-5.86	-0.65	-0.06
BIC	-5.84	-0.64	-0.05
Log Likelihood	-2.93	-0.32	-0.03
Modified Joe-Clayton Copula			
τ_U	0.000 (0.095)**	0.009 (0.000)**	0.000 (0.000)**
τ_L	0.340 (0.076)**	0.000 (0.000)**	0.041 (0.000)**
AIC	-11.3	-0.27	0.55
BIC	-11.3	-0.24	0.57
Log Likelihood	-5.68	-0.14	0.27
Panel B: Time-varying with time dummy			
Student t-copula			
d	7.869 (6.323)	19.564 (6.78)	7.478 (4.702)
β_1	0.010 (0.086)**	0.135 (0.12)**	0.044 (0.047)**
β_2	0.604 (0.072)***	0.403 (2.12)	0.841 (0.024)**
β_3	0.014 (0.169)	0.013 (1.2)	0.059 (0.290)
AIC	-31.5	-0.51	-31.5
BIC	-31.3	-0.49	-31.4
Log Likelihood	5.7	5.26	5.7
LR (3) statistics (p-value)	11.984***	11.45***	10.2***
	(0.000)	(0.000)	(0.000)

Clayton Copula			
β_o^L	-5.289 (.098)**	-2.051 (1.09)**	-1.043 (0.19)
β_1^L	3.007 (4.01))	-3.744 (1.96)	-3.091 (1.12)
β_2^L	-0.804 (.295)**	-0.091 (0.143)	-0.71 (0.19)**
β_3^L	0.002 (1.000)	-0.001 (2.12)	0.000 (.010)
AIC	-17.0	-1.79	-7.22
BIC	-16.8	-1.75	-7.18
Log Likelihood	8.52	6.90	5.61
LR (3) statistics (p-value)	15.784***	13.754***	10.762***
	(0.000)	(0.000)	(0.000)
Modified Joe-Clayton Copula			
β_o^L	-9.205 (1.000)**	-9.193 (2.81)**	-9.577 (7.530)**
β_1^L	-7.063 (4.13)	-7.914 (0.17)	9.996 (2.072)
β_2^L	0.408 (0.048)	-0.164 (2.786)	4.143 (3.338)
β_3^L	0.001 (2.32)	-0.001 (.012)	0.000 (2.720)
β_0^U	-9.991 (1.408)**	-9.992 (3.46)**	-9.992 (2.120)**
β_1^U	0.330 (5.127)	1.340 (7.49)	0.329 (3.800)
β_2^U	9.999 (3.15)	9.943 (1.47)	9.991 (3.450)
β_3^U	0.002 (2.68)	-0.001 (1.45)	0.001 (0.930)
AIC	-13.8	0.65	2.04
BIC	-13.7	0.72	2.11
Log Likelihood	7.94	6.31	7.00
LR (6) statistics (p-value)	12.734***	11.464***	14.891***
	(0.000)	(0.000)	(0.000)
τ_U	0.000 (0.095)**	0.010 (0.000)**	0.000 (0.000)**

τ_L	0.410 (0.076)**	0.000 (0.000)**	0.046 (0.000)**

Notes: The table reports the copula estimates of different bond-paired copula models. Panel A reports the time-invariant copula estimates, while Panel B presents the time-varying copula estimates. Goodness of fit AIC, BIC and log-likelihood statistics is presented for each of the copula models. The LR (d) test statistics test the null hypothesis that the time-invariant copula model is not rejected as one move from time-invariant to time-varying copula models, where (d) is the degrees of freedom of the LR test. The standard errors of the copula estimates and p-values of the LR tests are reported in the parentheses. The MA processes of B/G, B/Re, and B/O are 4, 1 and 2, respectively.

*** and ** signifies rejection of the null hypothesis at 1 and 5 percent levels, respectively.

Table 5 (A-2): The Estimates of Copula Parameters

	RE/G	**RE/O**	**G/O**
Panel A: Time-invariant having constant dependence parameter			
Student t-copula			
ρ	-0.051 (0.004)**	0.101 (0.004)**	0.340 (0.006)**
AIC	-12.0	-3.23	-3.25
BIC	-12.0	-3.19	-3.22
Log Likelihood	-6.03	-1.62	-1.64
Clayton copula			
δ	0.013 (0.045)**	0.039 (0.30)**	0.011 (0.04)**
AIC	-5.86	-0.65	-0.06
BIC	-5.84	-0.64	-0.05
Log Likelihood	-2.93	-0.32	-0.03
Modified Joe-Clayton Copula			
τ_U	0.000 (0.095)**	0.000 (0.000)**	0.000 (0.000)**
τ_L	0.000 (0.076)**	0.000 (0.000)**	0.557 (0.000)**
AIC	-11.3	-0.27	0.55
BIC	-11.3	-0.24	0.57
Log Likelihood	-5.68	-0.14	0.27

Panel B: Time-varying with time dummy			
Student t-copula			
d	8.754 (6.323)	19.955 (6.78)	9.558 (4.702)
β_1	0.001 (0.086)	0.000 (0.12)	0.099 (0.019)**
β_2	0.230 (0.072)***	0.389 (2.12)	0.899 (0.016)**
β_3	0.034 (0.169)	0.013 (1.2)	0.009 (0.72)
AIC	-31.5	-0.51	-31.5
BIC	-31.3	-0.49	-31.4
Log Likelihood	5.7	5.26	5.7
LR (3) statistics (p-value)	11.984***	11.45***	10.2***
	(0.000)	(0.000)	(0.000)
Clayton Copula			
β_o^L	-0.066 (.098)**	-6.727 (1.09)**	-5.047 (2.19)**
β_1^L	-0.009 (4.01)	0.579 (1.96)**	0.771 (3.12)**
β_2^L	0.088 (0.295)*	-0.970 (0.143)	-1.096 (0.12)**
β_3^L	0.002 (1.000)	-0.001 (2.12)	0.000 (.018)
AIC	-17.0	-1.79	-7.22
BIC	-16.8	-1.75	-7.18
Log Likelihood	8.52	6.90	5.61
LR (3) statistics (p-value)	15.784***	13.754***	10.762***
	(0.000)	(0.000)	(0.000)
Modified Joe-Clayton Copula			
β_o^L	-1.692 (1.000)**	-1.342 (2.81)**	-1.99 (7.53)**
β_1^L	4.339 (4.13)	-0.685 (0.17)	0.791 (2.13)
β_2^L	2.472 (0.048)	2.452(2.786)	1.467 (5.55)
β_3^L	0.001 (2.32)	-0.001 (.012)	0.000 (2.12)

β_0^U	-8.849 (1.408)**	-0.838 (3.46)**	-0.981 (2.12)**
β_1^U	1.586 (5.127)	-0.550 (7.49)	-0.573 (3.80)
β_2^U	9.102 (3.15)	1.746 (1.47)	0.721 (3.45)
β_3^U	-0.002 (2.68)	-0.001 (1.45)	0.001 (1.13)
AIC	-13.8	0.65	2.04
BIC	-13.7	0.72	2.11
Log Likelihood	7.94	6.31	7.00
LR (6) statistics (p-value)	12.734***	11.464***	14.891***
	(0.000)	(0.000)	(0.000)
τ_U	0.000 (0.095)**	0.000 (0.000)**	0.000 (0.000)**
τ_L	0.000 (0.076)**	0.000 (0.000)**	0.603 (0.000)**

Notes: The table reports the copula estimates of different real estate and gold-paired copula models. Panel A reports the time-invariant copula estimates, while Panel B presents the time-varying copula estimates. Goodness of fit AIC, BIC and log-likelihood statistics is presented for each of the copula models. The LR (d) test statistics test the null hypothesis that the time-invariant copula model is not rejected as one move from time-invariant to time-varying copula models, where (d) is the degrees of freedom of the LR test. The standard errors of the copula estimates and p-values of the LR tests are reported in the parentheses. The MA processes of Re/G, Re/O, and G/O are 2, 2 and 2, respectively.

*** and ** signifies rejection of the null hypothesis at 1 and 5 percent levels, respectively.

CHAPTER 6

Modelling the Dynamics of the Dependence Structure Models

6.1 Introduction

A model identifying variations in the asset market linkages and decomposing the effects of macroeconomic and non-macro factors influencing the dependence structure of different asset return comovements is critical for accurately estimating the portfolio risk. Further, identifying the determinants of asset return comovements across different asset classes has significant implications for policymakers and financial regulators. If different assets show positive comovements especially during periods of economic contraction (For example, the probability of extreme comovement of E/B pair in the expansion phase is 0.103 as compared to 0.192 in the contraction phase, see Figure 5.1), then an understanding of key determinants of their dependence structures will aid in implementation of appropriate interventions by the policy makers. Previous studies exist on stock-bond return comovement; however, research on the determinants of the linkages amongst other asset classes is relatively scarce. Thus, in spite of knowing the importance of such an examination the present body of literature fails to answer various questions as highlighted in the literature review. For instance, questions such as what are the determinants of the multi-asset return comovements? What are the differential impacts of these economic factors during the economic contraction and economic expansion? Are there any other non-macroeconomic factors that influence the return comovements of the conventional assets and the commodities and oil? These questions still remain unexplored in the existing studies.

To answer the above questions, two key issues need to be addressed. First, to model the dependence structure of the asset return comovements and second to link it with the factors that influences it. In the previous two chapters I have comprehensively addressed the former issue. I have examined the dependence structures and have identified and explored their stylised facts. Now, focusing on the latter issue, two prime concerns arise. First, to identify the state variables that is likely to influence the return comovements and second, to construct a structural model that adequately identifies and accommodates for the dynamics of the state variables, i.e. the determinants of the return comovements. In this chapter, I address these issues. In particular, the purpose of this chapter is twofold: First, to propose the state variables and second, to model the dynamic of the behaviour of these factors.

This work, in modelling the dynamics of the determinants of the return comovements, has a number of distinct features. First, I consider a wide range of macro and non-macro variables to explore the determinants of the dynamics of the dependence structures for the 11 combinations of asset pairs. The state variables include interest rates, output gap and inflation and also risk aversion. I also consider macroeconomic uncertainty measures to accommodate for economic uncertainties as shown by David (2008) and Bekaert et al. (2009a). Additionally, other non-macro variables are included such as liquidity for stock and bond markets, variance premium and depth of recession. This is, to the best of my knowledge, the first study that comprehensively examines the macro and non-macro determinants of the dependence structure for three different asset classes. Third, I propose two structural frameworks to examine the influence of the state variables on the dependence structures. First, I model a structural framework to examine the dynamics of the state variables. This structural framework has three key economic implications i) it allows the dynamics of the state variables to depend on the expectations of future values as is true in cases of macro-models ii) it captures the contemporaneous correlation between the fundamental state variables and iii) it captures the structural changes in the macro-economic relationships. These regime-switching models accommodate for heteroskedastic shocks in the state variables. Second, I impose structural restrictions inspired by New-Keynesian dynamics in identifying the macroeconomic variables.

Third, the estimated state variables are fed into a Markov Switching Stochastic Volatility (MSSV) model to examine the influence of the state variables on the return comovements.

The rest of the paper is organized as follows: Section 2 presents the Markov switching model in investigating the dependence structure. Section 3 discusses the selection and modelling of the dynamics of state variables and Section 4 Section 5 concludes the paper.

6.2 Modelling the Dynamics of the Dependence Structure

I employ a Markov switching (MS) model in investigating the dependence structures. Further, this study allows each state variable to follow an evolutionary process which is presented in the following section. Although autoregressive conditional heteroskedasticity (ARCH) models can be employed to tackle this issue (Bollerslev et al., 1988; Engle, 1982), the standard normally and independently distributed (NID) assumption of the error term is often violated in the practice. I, therefore, specify a model for the state variables that allows each of the vectors to follow an independent stochastic volatility (ISV) process. The stochastic volatility (SV) specification builds in a time-varying variance process for each of the elements of the structural factors, by allowing the variance to be a latent process.

7.2.1 The Markov Switching (MS) Model

I specify the MS model, which defines the dependence structure y_t as

$$y_t = \sum_{l=1}^{L} \varphi_l S_t x_{l,t}^{S} + \varepsilon_t \tag{6-1}$$

where L denotes the number of switching coefficients, $x_{l,t}$ represents the explanatory state variables and $\varepsilon_t \sim P\left(\phi_{S_t}\right)$ with $P(\phi)$ as the probability density function of the innovations, defined by the vector ϕ. Each of the independent state variables follows a Markov switching stochastic volatility (MSSV) process, which we discuss next.

6.2.2 The Stochastic Volatility (SV) Model

In contract to the ARCH-type models, I allow the log volatility of the state variables to evolve stochastically over time. Therefore, my main motive is to make the model parsimonious and yet flexible. Following the discrete type convention (Ball and Torous, 1999; Shephard, 1996), I characterize the SV model as an extension of the time-diffusion process

$$\Delta x_t = a + b x_{t-1} + \sigma_t x_{t-1}^{\gamma} \varepsilon_t \tag{6-2}$$

where γ represents the diffusion term, $\Delta x_t = x_t - x_{t-1}$ and ε_t is the standard normal random variable. The residual of the above equation is $e_t = \sigma_t x_{t-1}^{\gamma} \varepsilon_t$. The model allows the volatility (σ) to evolve stochastically, following a first-order autoregressive process

$$\log \sigma_t^2 = \omega + \varphi \log \sigma_{t-1}^2 + \eta_t \tag{6-3}$$

where $\eta_t \sim N\left(0, \sigma_\eta^2\right), i.i.d.$ represents the disturbance term. It makes the variance subjected to random shocks, making the process stochastic.

Harvey et al. (1994) provides a quasi-maximum likelihood estimation procedure for the SV models. The approach transforms the residuals in equation (6-2) to $e_t = \Delta x_t - a - b x_{t-1}$ and allows formulating a quasi-likelihood function by employing Kalman filter. The log of the squared residuals is

$$\log e_t^2 = \log \sigma_t^2 + 2\gamma \log x_{t-1} + \log \varepsilon_t^2 \qquad \textbf{(6-4)}$$

Considering $z_t = \log e_t^2$ and $g_t = \log \sigma_t^2$ equation (6-) reduces to

$$z_t = g_t + 2\gamma \log x_{t-1} + \log \varepsilon_t^2 \qquad \textbf{(6-5)}$$

where $g_t = \omega + \varphi g_{t-1} + \eta_t$. Next I discuss the MSSV model, which is employed to examine the dynamics of the dependence structure in equation (6-1).

6.2.3 The Markov Switching Stochastic Volatility (MSSV) model

This is a generalization of the SV and the MS model. This model allows the volatility to vary across different regimes. Assuming constant volatility in the regimes will yield in either underestimation or overestimation of the volatility. Thus, the motivation to use MSSV is that it allows different estimates of the elasticity of variance (γ). In this study the MSSV model is characterized as

$$\begin{aligned} z_t &= g_t + 2\gamma \log x_{t-1} + \log \varepsilon_t^2 \\ g_t &= \omega_m + \varphi g_{t-1} + \eta_t \end{aligned} \qquad \textbf{(6-6)}$$

In contrast to equation (6-5), the above equation defines $\omega_m = \log \sigma_m^2$, allowing me to capture the different regimes at a particular point in time. Duffee (1993) provides evidence for structural breaks with the monetarist experiment and shows that even the SV models lack in analysing these effects in the economy. With the regimes governing the dynamic behaviour of the estimated state variables, I can condition a particular regime and calibrate the density of the variable of interest. In this parameterization of the MS model, the transition probabilities from state *m* to state *n* in time t are defined as $p_{mn} = \Pr\left[S_t = m \middle| S_{t-1} = n\right]$. It should be noted that for

$m = 1,\ldots,M$, only $M(M-1)$ needs to be specified as $p_{mn} = \Pr\left[S_t = M \middle| S_{t-1} = n\right] = 1 - \sum_{m=1}^{M-1} \Pr\left[S_t = m \middle| S_{t-1} = n\right]$. In my model I allow the unconditional volatility to change between different states by allowing σ_i in equation (6-2) to take values $m \in \{1,\ldots,M\}$ at time t. The corresponding equation transforms to

$$\Delta x_t = a + bx_{t-1} + \sigma_m x_{t-1}^{\gamma} \varepsilon_t \qquad \textbf{(6-7)}$$

An important component of the structure of the Markov switching model is that the switching of the states follows a stochastic process. Thus, identifying states based on distributional characterise of the regime switching variable, such as $(\mu \pm \sigma)$, i.e. mean plus or minus standard deviation, would lead to restricted form of the switching model failing to capture the true dynamics of the dependence structure. However, weak regime classification will imply that the model is unable to successfully distinguish between the regimes from the behaviour of the data leading to misspecification. In order to address this issue, in this study I identify the regimes based on regime switching classification. An ideal switching model should classify the regimes sharply, i.e. the regime transition probabilities (p_{mn}) should be as close to 0 or 1. Based on Ang and Bakaert (2002) I construct the regime classification statistic (RCS) for M states as

$$RCS(M) = 100M^2 \frac{1}{T} \sum_{t=1}^{T} \left(\prod_{m=1}^{M} p_{mt} \right)$$

where $p_{mt} = Pr\ (S_t = m | I_T)$ indicate the regime transition probabilities and $100M^2$ serves as a normalizing constant to keep the statistic between 0 and 100. A value of 0 signifies perfect regime classification, whereas a value of 100 implies that the regimes are not capable of distinguishing the behaviour of the data, i.e. dependence structure, across the defined regimes and hence they are irrelevant.

I use Kalman filter of the estimation of the MSSV model. However, it should be noted that the above procedures makes our process exclusively path dependent. Hence, to remove the path dependence I compute the conditional expectation of the log-volatility forecast by taking the weighted average output of the previous iteration.

Next I discuss the filtering procedure used for the MSSV model based on Kalman filter mechanism for the SV models and Hamilton (1989) filter that allows estimation of the probability of the regimes at time t iteratively.

6.2.4 Estimation filter for the MSSV model

The Kalpan filter employed for projection is an iterative process. It forecasts the state variable at $'t+1'$ period and updates it when z_t is observable in the equation (6-6). For deriving the filtering equations I denote:

$$g_{t|t-1}^{(m,n)} = E\left[g_t \middle| S_t = m, S_{t-1} = n, \psi_{t-1}\right],\ p_{t|t-1}^{m,n} = E\left[(g_t - g_{t|t-1}^{m,n}) \middle| S_t = m, S_{t-1} = n, \psi_{t-1}\right],$$

$$g_{t|t-1}^{m} = E\left[g_t \middle| S_t = m, \psi_{t-1}\right] \text{and } p_{t|t-1}^{m} = E\left[(g_t - g_{t|t-1}^{m})^2 \middle| S_t = m, \psi_{t-1}\right].$$

Following Smith (2002), I first forecast log-volatility and then update the previous forecasted estimate. The sequential steps are:

Step 1: The log-volatility is forecast using:

$$g_{t|t-1}^{m,n} = \omega_m + \varphi_m g_{t-1|t-1}^{n} \qquad \textbf{(6-8)}$$

$$p_{t|t-1}^{m,n} = \varphi_m^2 p_{t-1|t-1}^{n} + \sigma_{\eta m}^2 \qquad \textbf{(6-9)}$$

Step 2: The forecasted estimate is updated using

$$g_{t|t}^{m.n} = g_{t|t-1}^{m.n} + p_{t|t-1}^{m,n}\left(p_{t|t-1}^{m,n} + \frac{\pi^2}{2}\right)^{-1}\left(z_t - z_{t|t-1}^{m,n}\right) \quad \textbf{(6-10)}$$

$$p_{t|t}^{m.n} = p_{t|t-1}^{m.n} - p_{t|t-1}^{m,n}\left(p_{t|t-1}^{m,n} + \frac{\pi^2}{2}\right)^{-1} p_{t|t-1}^{m,n} \quad \textbf{(6-11)}$$

The conditional densities are computed using the following equation

$$f\left(z_t \middle| S_t = m, S_{t-1} = n, \psi_{t-1}\right) = \frac{1}{\sqrt{2\pi\left(p_{t|t-1}^{m,n} + \frac{\pi^2}{2}\right)}} - \exp\left(\frac{-\left(z_t - z_{t|t-1}^{m,n}\right)^2}{2\left(p_{t|t-1}^{m,n} + \frac{\pi^2}{2}\right)}\right)^{-1} p_{t|t-1}^{m,n} \quad \textbf{(6-12)}$$

It can be noted that the above procedures makes the process exclusively path dependent. Hence, to remove the path dependence I rely on Kim (1994) as stated in Smith (2002). I compute the conditional expectation of the log-volatility forecast by taking the weighted average output of the previous iteration using the formulations stated below.

$$g_{t|t}^{m} = \frac{\sum_{n=1}^{N} \Pr\left[S_t = m, S_{t-1} = n \middle| \psi_t\right] g_{t|t}^{m,n}}{\Pr\left[S_t = m \middle| \psi_t\right]} \quad \textbf{(6-13)}$$

$$p_{t|t}^{m} = \frac{\sum_{n=1}^{N} \Pr\left[S_t = m, S_{t-1} = n \middle| \psi_t\right]\left(p_{t|t}^{m,n} + (g_{t|t}^{n} - g_{t|t}^{m,n})^2\right)}{\Pr\left[S_t = m \middle| \psi_t\right]} \quad \textbf{(6-14)}$$

I calculate the regime probabilities based on Smith's (2002) modification of Hamilton's (1989) filter. First, I estimate the regime probabilities using

$$\Pr\left[S_t = m, S_{t-1} = n \middle| \psi_{t-1}\right] = \Pr\left[S_t = m \middle| S_{t-1} = n\right] \times \Pr\left[S_{t-1} = m \middle| \psi_{t-1}\right] \quad \textbf{(6-15)}$$

The term $\Pr[S_{t-1} = m|\psi_{t-1}]$ in the equation (6-15) is the previous iteration filter output. Next I calibrate the joint density using

$$f(z_t, S_t = m, S_{t-1} = n|\psi_{t-1}) = f(z_t|S_t = m, S_{t-1} = n, \psi_{t-1}) \times \Pr[S_{t-1} = m|\psi_{t-1}] \tag{6-16}$$

where $f(z_t, S_t = m, S_{t-1} = n|\psi_{t-1})$ is defined previously in equation (6-12). In step three we integrate the regimes to calculate the unconditional density as given in equation (6-17) and then we update the probability of the regimes in state $'t'$ using equation (6-18).

$$f(z_t|\psi_{t-1}) = \sum_{m=1}^{M}\sum_{n=1}^{N} f(z_t|S_t = m, S_{t-1} = n, \psi_{t-1}) \tag{6-17}$$

$$\Pr[S_t = m, S_{t-1} = m|\psi_{t-1}] = \frac{f(z_t|S_t = m, S_{t-1} = n, \psi_{t-1})}{f(z_t, |\psi_{t-1})} \tag{6-18}$$

7.3 Estimating the State Variables

7.3.1 Selection of the State Variables

Here, I provide a discussion of macroeconomic and non-macroeconomic factors which we include in our analysis.

Macroeconomic Variables – The selection of our standard macroeconomic variables is based on the existing literature (d'Addona and Kind, 2006; Fama and Schwert,1977; Bekaert and Engstrom, 2010) . I include three macro-economic factors: inflation, the nominal risk-free rate and the output gap. These variables predominantly affect both cash flows and discount rates and hence affect asset values (d'Addona and Kind, 2006). However, it is not always easy to predict their precise impact on asset returns. For instance, since bonds have predetermined fixed cash flows, inflation influences stocks and bond returns differently. Analogously, if the output gap is associated with dividends, they should influence stock returns but not fixed income securities. Yet, both inflation and output gap drives the term structure of interest rates. Therefore, these two state variables have an influence on the asset prices. But, since equities are a claim on real assets, expected inflation should not influence the discount rate on stocks. Yet, a recurring finding by Fama and Schwert (1977) show that stock returns are negatively correlated with expected inflation. This also suggests that equities are inadequately hedged against inflation shocks. Campbell and Vuolteenaho (2004) interpret this as money illusion, whereas Bekaert and Engstrom (2010) argue that inflation and risk premiums are correlated. In this study, the sign of the exposure is left unconstrained. This allows the model to gain maximum power in explaining the variation in the data.

The interest rate affects most of the variations in the bond returns. I, therefore, include nominal risk-free rate as a factor in the model. Yet, for long-term bonds the appropriate determinant is the long-term interest rate, which can be decomposed into nominal risk-free rate, expected inflation and term premium. An increase in these components decrease the bond returns. In order to capture the effect of the term and the inflation premium I use a number of direct 'economic' risk proxies, which is discuss next.

Risk Premium Factors – In this study I use various measures of economic uncertainty and risk aversion to proxy asset risk premia. Bekaert et al. (2010b) show that stochastic risk aversion significantly influences positive stock-bond return correlation. Further, Wachter (2006) finds that risk aversion is positively related to equity and bond premiums, but its effect on interest rates is ambiguous. However because of the effects of consumption smoothing and precautionary savings, a rise in risk aversion may increase or decrease interest rates respectively. In summary, the effect of risk aversion on asset returns is not straight forward. Bekaert et al. (2009a) provide evidence for economic uncertainties, which impact risk-premiums and asset valuation. Through the precautionary savings effect an increase in economic uncertainty will lower the interest rates. Hence, it leads to an ambiguous effect on equity valuation that is often considered to be negatively affected with changing economic conditions. Therefore, economic uncertainty can drive asset returns in the opposite direction depending on the effects of term structure and risk-premium. In addition, David (2008) provides an alternative illustration for the use of uncertainty measures. He shows that higher economic uncertainty triggers investors to react more swiftly to information and therefore it has a profound effect on asset return covariance. In the paper, I use inflation and economic output as measures of uncertainty in identifying the determinants of dependence structures of return comovements.

In this study I use an empirical proxy for risk aversion based on Bekaert and Engstrom's (2010) model, which is created using Campbell and Cochrane's (1995) external habit specification. This risk aversion proxy is based on historical consumption growth data. Since it behaves counter cyclically it is unlikely to capture complete variations in equity risk-premium. Thus, I use an additional variable, i.e. the variance premium. Bollerslev et al. (2009) show that variance premium has predictive power for forecasting equity returns. Drechsler and Yaron (2011) include additional non-Gaussian components in the consumption growth model. Employing their extended model, they show that risk aversion and nonlinear components significantly influence variance premium. In contrast, Connolly et al. (2005) use the VIX implied volatility estimate as a proxy for stock market uncertainty. They report that stock-bond co-movements are inversely related to stock market uncertainty. This can be justified as 'flight to safety', where investors switch from risky assets to relatively less risky financial investment options. This study includes two additional variables, i.e. inflation uncertainty and output gap uncertainty, to account for economic uncertainty in our model.

Stock and Bond Liquidity Factors – Liquidity affects asset pricing in two central ways. First, in illiquid markets beta may fail to quickly respond to economic shocks. Second, economic shocks that increase liquidity may have a positive impact on asset returns. This corresponds to the liquidity price factor. Therefore, the impact of liquidity on asset return co-movements depends on how liquidity shocks vary across markets. For example in periods of economic crisis, investors may move from less liquid stocks to treasury bonds. Consequently, the resulting price pressure may trigger negative equity and safer assets, such as bonds and gold, returns co-movement. Monetary policy can affect liquidity in financial markets. It may increase borrowing constraints or trigger trading activity, influencing asset returns to covary. Existing studies by Chordia et al. (2005) and Goyenko et al. (2009) are rather inconclusive in accounting for these liquidity effects. To address this issue, we consider unconstrained proxies of liquidity shocks in our estimation model. To measure stock market illiquidity we use capitalization-based proportion of zero daily returns across all listed firms in the US market, i.e. Standard & Poor's (S&P) 500 index and for bond market illiquidity we use bid-ask spreads[9] across all securities, i.e. one month , three months, and one, two, three, five, seven, ten, twenty and thirty years of maturity.

Business Cycle Proxies – Plosser and Rouwenhorst (1994) and Estrella and Hardouvelis (2012) use the term spread as a leading indicator of economic activity. Yet, more recent evidence shows that the spread is not as informative as it has been in the past. In particular, Dotsey (1998) and Henry et al. (2004) show that the relationship between business cycles and economic output behave asymmetrically. Ocal (2006) provides evidence for asymmetric relations in economic outputs and growth. Therefore, the existence of a non-linear relationship between these variables is more likely than a linear one. Building on this, I use an alternative measure to capture the different regimes of the business cycle. My measure of modified depth of recession is based on Lee and Wang's (2012) estimate of business cycle proxy. This measure

[9] It should be noted that bond illiquidity can be measured using several proxies including systematic liquidity risk. However, for the purpose of this study we use bid-ask spread as a bond illiquidity factor.

allows the estimate to have values for both recession and expansion of the economy's business cycle. A negative value indicates an economic expansion period. The higher the value, the greater is the economy's recovery in process. In contrast, a positive value of this measure relates to a recessionary period.

In summary, my model includes the following economic state variables: the risk free rate (rf_t), output gap (o_t), inflation (i_t), risk aversion (ra_t), output uncertainty (ou_t), inflation uncertainty (iu_t), bond market illiquidity (ds_t), equity market illiquidity (lr_t), variance premium (vp_t), term spread (ts_t) and the depth of recession (dr_t). I collect these variables in a vector (K_t) to identify the explanatory structural factors (X_t). The chapter Appendix provides an account of the data used. Next, I focus on the modelling of the state variable dynamics.

7.3.2 Modelling of State Variable Dynamics

To estimate the structural factors (X_t), it is necessary to specify the dynamics of the state variables (K_t) that include the macro and non-macroeconomic factors. The three key reasons why I implement these structural framework are i) to allow the dynamics of the state variables to depend on the expectations of future values as is true in cases of macro-models ii) to capture the contemporaneous correlation between the fundamental state variables and iii) to capture the structural changes in the macro-economic relationships. To attain structural identification of the shocks in Equation (6-6), I split the state variables into two sets: i) "macro variables (mv)", $K_{t,mv} = [rf_t, o_t, i_t, ra_t]'$ and ii) "other variables (ov)", i.e. $K_{t,ov} = [ou_t, iu_t, ds_t, lr_t, vp_t, ts_t, dr_t]'$. The 'other variables' (ov) include the non-macroeconomic variables. For modelling $K_{t,mv}$ I employ a New Keynesian model, which is discussed in the following sub-section. To identify the $K_{t,ov}$ shocks I characterize a simple empirical model where the other variables are dependent on the macro variables. An alternative source of motivation for the structural equation comes from Goyenko et al. (2009) where they illustrate that inflation affects market illiquidity.

I characterize the structural model as:

$$K_{t,ov} = \alpha_{ov}(S_t) + \beta_{ov} K_{t-1,ov} + \Sigma_{ov}^{mv} K_{t,mv} + X_{t,ov} \qquad \textbf{(6-19)}$$

where S_t represents the set of regime variables that drive the coefficient matrices. $K_{t,ov}$ is modelled based on Hamilton's (1989) specifications. β_{ov} is a diagonal matrix, Σ_{ov}^{mv} is a 7×4 matrix, which appropriates contemporaneous covariance with the macro variables $K_{t,mv}$ and $X_{t,ov}$ is the vector of uncorrelated structural shocks of the "other variables". Employing Equation (6-19), the "other variable", i.e. non-macro, factors may partially exhibit autoregressive dynamics of the macro-state variables. Further, $X_{t,ov}$ should be interpreted as non-macro variable shocks eliminated from the macro-economic shocks. Finally, allowing the drifts to depend on the regime variable S_t enables me to model the structural changes in the liquidity parameters (Hasbrouck, 2009).

Structural Model for the Macro Variables

Based on Bekaert et al.'s (2010) New-Keynesian model I formulate the structural model for $X_{t,mv}$. The model comprises three equations i) the demand (IS) equation, ii) the aggregate supply (AS) equation and iii) the forward feeding monetary policy (MP) rule. This allows me to capture the time-varying risk aversion dynamics in the structural model.

$$rf_t = \alpha_{MP} + \tau rf_{t-1} + (1-\tau)\left[a\left(S_t^{MP}\right)E_t\left(i_{t+1}\right) + b\left(S_t^{MP}\right)o_t\right] + X_t^{rf} \tag{6-20}$$

$$o_t = \alpha_{IS} + \omega E_t\left(o_{t+1}\right) + (1-\omega)o_{t-1} + \theta ra_t - \varphi\left(rf_t - E_t\left(i_{t+1}\right)\right) + X_t^{o} \tag{6-21}$$

$$i_t = \alpha_{AS} + \lambda E_t\left(i_{t+1}\right) + (1-\lambda)i_{t-1} + \phi o_t + X_t^{i} \tag{6-22}$$

$$ra_t = \beta_{ra} + \gamma ra_{t-1} + X_t^{ra} \tag{6-23}$$

The parameter (τ) in the equation (6-20) represents the forward-looking monetary policy smoothing estimate. Cho and Moreno (2006) show that changes in monetary policy significantly influence macro dynamics and structural shocks. I, therefore, introduce a standard Markov-chain process to allow the monetary policy to vary across two regimes (S_t^{MP}) with constant transition probabilities.

The parameters ω and λ in the equations (6-21) and (6-22) represent the degree of IS and AS forward-looking behaviour respectively. The parameter (φ) estimates the impact of real interest rate on the output gap and (ϕ) the effect of output gap on inflation. A high positive value of φ and ϕ indicate that monetary transmission mechanism has a significant influence on economy's output and inflation. The state variable (ra_t) accommodates stochastic risk aversion to the demand equation of the New-Keynesian model that nests on Campbell and Cochrane's (1995) external habit model. In particular (ra_t) represents the local curvature of the utility function. The parameter (θ) measures counteracting effect of consumption-smoothing and precautionary-savings of risk aversion on the real economy. Though, the output shocks and risk aversion are negatively correlated, I do not give a definite sign to the estimate in the equation (6-21).

6.4 Specification Tests

In order to ensure that the state variable and the MSSV models are adequate in estimating the dynamics of the state variables and factor exposures, they must satisfy a number of requirements. To this end, this study performs a battery of specification tests on the residuals of the models. In particular, univariate tests and covariance tests are performed.

6.4.1 Univariate Test

Consider following equation defines that defines the reduced form model, encompassing both the state variable models and the MSSV models used to identify the structural factors and the factor exposure of the determinants of the return comovements.

$$y_t = \mu(R_s) + \beta K_{t-1} + \sigma(R_s)\varepsilon_t \qquad \textbf{(6-24)}$$

In this study, it suffices to state that R_s assumes two values which represents the regimes 1 and 2. Let the conditional probability for $R_s = 1$ be p_{t-1} and the corresponding conditional probability for $R_s = 2$ be $(1 - p_{t-1})$. Considering these conditional probability estimates the residual of the above model is defined as:

$$resid_t = y_t - \beta K_{t-1} - (p_{t-1}\mu_1 + (1 - p_{t-1})\mu_2) \qquad \textbf{(6-25)}$$

where $\mu_1$and μ_2 are the means of regime 1 and regime 2 respectively. The conditional variance $(CV_{resid,t-1})$ of $resid_t$ is:

$$CV_{resid,t-1} = p_{t-1}\sigma_1^2 + (1 - p_{t-1})\sigma_2^2 + p_{t-1}(1 - p_{t-1})(\mu_1 - \mu_2)^2 \qquad \textbf{(6-26)}$$

where σ_1^2 and σ_2^2 are the variances of regime 1 and regime 2 respectively. Based on Timmermann (2000), the conditional skewness ($CSk_{resid,t-1}$) and the conditional kurtosis ($CKr_{resid,t-1}$) is given by:

$$CSk_{resid,t-1} = \frac{p_{t-1}(1-p_{t-1})(\mu_1-\mu_2)(3(\sigma_1^2-\sigma_2^2)+(1-2p_{t-1})(\mu_1-\mu_2)^2}{[p_{t-1}\sigma_1^2+(1-p_{t-1})\sigma_2^2+p_{t-1}(1-p_{t-1})(\mu_1-\mu_2)^2]^{3/2}} \quad \textbf{(6-27)}$$

$$CKr_{resid,t-1} = \frac{p_{t-1}[3\sigma_1^2+(\mu_1-\mu)^4+6\sigma_1^2(\mu_1-\mu)^2]+(1-p_{t-1})[3\sigma_1^2+(\mu_1-\mu)^4+6\sigma_1^2(\mu_1-\mu)^2]}{[p_{t-1}\sigma_1^2+(1-p_{t-1})\sigma_2^2+p_{t-1}(1-p_{t-1})(\mu_1-\mu_2)^2]^{3/2}}$$

In the univariate specification tests, I test for zero mean, no higher order correlation for five lags, i.e. whether or not μ_0, l_1, l_2, l_3, l_4 and l_5 are zero in the following equations.

$$E[resid_t]-\mu_0=0$$

$$E[(resid_t-\mu_0)(resid_{t-1}-\mu_0)]-l_1=0$$

$$E[(resid_t-\mu_0)(resid_{t-2}-\mu_0)]-l_2=0$$

$$E[(resid_t-\mu_0)(resid_{t-3}-\mu_0)]-l_3=0$$

$$E[(resid_t-\mu_0)(resid_{t-4}-\mu_0)]-l_4=0$$

$$E[(resid_t-\mu_0)(resid_{t-5}-\mu_0)]-l_5=0$$

To test for excess skewness and kurtosis, we examine whether or not e_{sk} and e_{kr} are equal to zero in the following equations, respectively.

$$\frac{E[(resid_t-\mu_0)^3]}{E[(resid_t-\mu_0)^2]^{3/2}}-CSk_{resid}-e_{sk}=0$$

$$\frac{E[(resid_t - \mu_0)^4]}{E[(resid_t - \mu_0)^2]^2} - CSk_{resid} - e_{kr} = 0$$

The estimates of μ_0, l_1, l_2, l_3, l_4, l_5, e_{sk} and e_{kr} are obtained using general Methods of Moment (GMM) employing a Newey-West (1987) weighting matrix accommodating for 5 lags. The univariate test of zero means, unit variance, presence of zero excess skewness and kurtosis follows a chi-squared distribution with one degree of freedom. The test of no autocorrelation up to 5 lags follows a chi-squared distribution with degrees of freedom equal to the number of lags.

6.4.2 Covariance Test

The covariance test is carried out to ensure that the state variables adequately capture the covariance between the factor shocks. The following condition is tested:

$$E\left[resid_{i,t} resid_{j,t}\right] = 0, \; for \; i = 1, \dots, N \; ; \; j = 1, \dots, N \; ; \; i \neq j$$

where N denotes the number of state variables. The joint test follows a chi-squared distribution with degrees of freedom equals to $N(N-1)/2$. Further, I also test whether the shocks of each of the state variables have zero covariance with the factor shocks. This follows a chi-square distribution with 10 degrees of freedom.

Table 6-1: Specification Tests for the State Variables and the MSSV Models

Panel A: Specification Tests for State variable Models

State Variables	Univariate Test									Covariance Test
	mean	lag 1[a]	lag 2[a]	lag 3[a]	lag 4[a]	lag 5[a]	Excess Skewness	Excess Kurtosis	Variance	
rf	0.999	0.738	0.723	0.871	0.587	0.688	0.170	0.370	0.742	0.900
o	0.999	0.061	0.169	0.311	0.462	0.515	0.380	0.250	0.096	0.970
i	0.876	0.830	0.514	0.681	0.752	0.817	0.280	0.430	0.828	0.976
ra	0.999	0.553	0.621	0.667	0.714	0.726	0.270	0.400	0.530	0.999
ou	0.999	0.259	0.324	0.382	0.438	0.496	0.390	0.400	0.202	0.999
iu	0.149	0.981	0.988	0.995	0.442	0.195	0.180	0.220	0.535	0.936
lr	0.999	0.522	0.755	0.879	0.934	0.96	0.220	0.270	0.936	0.999
ds	0.282	0.907	0.981	0.105	0.512	0.323	0.340	0.260	0.929	0.982
ts	0.999	0.694	0.781	0.839	0.895	0.934	0.150	0.280	0.935	0.999
vp	0.999	0.927	0.877	0.353	0.501	0.639	0.310	0.220	0.198	0.999
dr	0.999	0.934	0.953	0.947	0.967	0.973	0.160	0.320	0.825	0.999

Panel B: Specification Tests for MSSV Models									
State	Univariate Test								
Variables	mean	lag 1[a]	lag 2[a]	lag 3[a]	lag 4[a]	lag 5[a]	Excess Skewness	Excess Kurtosis	Variance
eb	0.999	0.076	0.18	0.316	0.442	0.282	0.330	0.600	0.748
ere	0.999	0.124	0.176	0.076	0.114	0.181	0.130	0.470	0.939
eg	0.152	0.647	0.599	0.624	0.520	0.566	0.470	0.450	0.728
eo	0.999	0.461	0.526	0.516	0.516	0.584	0.230	0.120	0.981
bre	0.999	0.551	0.343	0.435	0.411	0.396	0.260	0.140	0.954
bg	0.999	0.835	0.913	0.349	0.346	0.442	0.330	0.190	0.953
bo	0.999	0.983	0.989	0.993	0.995	0.997	0.440	0.120	0.985
reg	0.999	0.965	0.944	0.951	0.955	0.972	0.400	0.120	0.727
reo	0.999	0.801	0.878	0.929	0.925	0.948	0.310	0.120	0.971
go	0.999	0.125	0.305	0.441	0.556	0.698	0.220	0.440	0.887

Note: The table reports the specification tests for the state variables and the MSSV models that examine the determinants of the asset return comovements. Panel A presents the Monte-Carlo p-value estimates of the univariate and covariance tests for the 11 state variables - the risk free rate *(rf_t)*, output gap *(o_t)*, inflation *(i_t)*, risk aversion *(ra_t)*, output uncertainty *(ou_t)*, inflation uncertainty *(iu_t)*, bond market illiquidity *(ds_t)*, equity market illiquidity *(lr_t)*, variance premium *(vp_t)*, term spread *(ts_t)* and the depth of recession *(dr_t)*. The p-values are reported for zero mean, serial correlation for up to five lags, zero excess Skewness, zero excess kurtosis, and constant variance. The covariance test reports the Monte-Carlo p-values of zero covariance of the factor shocks of one state variable with the factor shocks of the other state variables. Panel B Panel A presents the Monte-Carlo p-value estimates of the univariate and covariance tests for the 10 different pairs of asset return comovements – Equity-Bond (eb), Equity-Real Estate (ere), Equity-Gold (eg), Equity-Oil (eo). Bond-Real Estate (bre), Bond-Gold (bg), Bond-Oil (bo), Real Estate-Gold, Real Estate-Oil and Gold-Oil (go). The p-values are reported for zero mean, serial correlation for up to five lags, zero excess Skewness, zero excess kurtosis, and constant variance. The results of both the panels indicate that the state variable model and the MSSV models are correctly specified, providing consistent outcomes that adequately accommodate the dynamics of the state variables and the determinants of the return comovements.

6.5 Summary

A good understanding of the determinants of the asset return comovements and its influence on the return dependence structure is not only essential for designing efficient portfolios but also have key significance for researchers and policy makers. In order to accomplish this it is necessary to have sound structural models that can capture the dynamics of not only the dependence structure but also the state variables, i.e. the determinants of the return comovements.

Against this backdrop, in this chapter I present the modelling of the dynamics of the dependence structure and that of the state variables. Unlike majority of the existing studies, I follow a two structure framework. These models have several novel characteristics in capturing the time-varying nature of the variables. First, the structural model of the state variables has three key advantages. They are i) it allows the dynamics of the state variables to depend on the expectations of future values as is true in cases of macro-models ii) it captures the contemporaneous correlation between the fundamental state variables and iii) it accommodates the structural changes in the macro-economic relationships. Second, the macroeconomic variables are estimated following the New-Keynesian dynamics. Thus, it has three equations i) the demand equation, ii) the aggregate supply equation and iii) the forward feeding monetary policy rule. This allows my study to capture the time-varying risk aversion dynamics in our structural model.

This chapter also presents several significant modelling features that this study employs to examine how the macro and non-macroeconomic variables impact the asset return comovements during economic contraction and expansion regimes. First, unlike the autoregressive conditional heteroskedasticity (ARCH) models, the developed Markov switching stochastic volatility framework does not rely upon the unrealistic standard normally and independently distributed (NID) assumption of the error term, which is often violated in the practice. Second, in contrast to the ARCH-type models, my framework allows the log volatility of the estimated state variables to evolve stochastically over time. Therefore, it makes the model parsimonious and yet flexible. Third, my model (MSSV) overcomes the limitation of constant volatility in its regimes. Assuming constant volatility in the regimes will yield in either underestimation or overestimation of the volatility. However, the developed MSSV model allows different estimates of the elasticity of regime variance. Forth, my proposed approach chooses the regimes based of regime classification statistic. This ensures that our model identifies significant regime behaviours that are neither restricted of irrelevant. Fifth, the estimation process of my models is free from the limitations of being path dependent. This adds to the robustness of the MSSV model estimation process.

In sum, the dual structural framework assures sound examination of the determinants of the dependence structure which is discussed in the nest chapter.

6.6 Appendix

Table 6 (A-1): Data Description

Output Gap (o_t): Gross Domestic Product (GDP) is the measure of output. The gap is the percentage difference between the output and its expected output gap.

Expected Output Gap (g_e): It is estimated as

$$E_t[g_e] = E_t\left[\frac{GDP_t}{GDP_t}\left(\frac{GDP_{t+1}}{GDP_{t+1}^{qt}} - 1\right)\right] = GDP_t \frac{E_t\left[\frac{GDP_{t+1}}{GDP_t}\right]}{GDP_{t+1}^{qt}}$$

Where GDP_t is the level of real GDP at time *t* and GDP^{qt} is the quadratic trend value of real GDP. To measure $E_t\left[\frac{GDP_{t+1}}{GDP_t}\right]$, the median of the survey response from Survey of Professional Forecasters (SPF) is used when available.

Output Uncertainty (ou_t): Mean of SPF's real output volatility.

Inflation (i_t measured as (π)): Log difference of the Consumer Price Index (CPI) for all items for all urban consumers.

Inflation Uncertainty (iu_t measured as (π_u)): It will be estimated as the fractional uncertainty measure of inflation $\left[\frac{\pi_e - \pi}{\pi}\right]$.

Risk Aversion Factor (ra_t): The measure of the risk aversion factor is based on external habit specifications of Campbell and Cochrane (1995) taken from Baele et al. (2010). The values are considered from Bekaert and Engstrom (2009).

Nominal Risk-free Rate (R_f): Three-month Treasury bill rate

Stock Market Illiquidity (lr_t): Capitalization-based zero daily returns across all listed firms

Bond Market Illiquidity (ds_t): Bid-ask spreads across all securities, i.e. one month , three months, and one, two, three, five, seven, ten, twenty and thirty years of maturity.
Variance Premium (vp): The difference between ex-post realized variance and variance swap rate.
Term Spread (ts_t): Difference between ten-year and three-month Treasury bill yields. This will serve as a proxy for short term economic condition.
*Depth of recession (dr_t):*It is based on Lee and Wang's (2012) estimate of business cycle proxy.

Demand Equation with Stochastic Risk Aversion factor

In Campbell and Cochrane's external habit model the pricing kernel, i.e. the stochastic discount factor (sdf_t), is represented as:

$$sdf_{t+1} = -\varphi \Delta cg_{t+1} + \varphi ra_{t+1} \tag{A-1}$$

where Δcg is logarithmic value of consumption (C_t) growth and φ is the curvature parameter of the utility function represented as $U(C_t) = \left(\frac{C_t - Z_t}{1-\varphi}\right)^{1-\varphi}$. Z_t in the utility function corresponds to the habit (level of habit). The surplus consumption ratio (SCR) allows to capture the relation between consumption and habit, which relates to the history of consumption $SCR_t = \frac{C_t - Z_t}{C_t}$. In particular, the process of ra_t shows how habit responds to the history of consumption. We define ra_t as $log\left(\frac{1}{SCR_t}\right)$. The time-varying characteristics of ra_t is specified as:

$$ra_t = \mu_{ra} + \beta_{ra}^1 ra_{t-1} + \beta_{ra}^2 (ra_{t-1})^{1/2} \epsilon_t^{ra} \quad \textbf{(A-2)}$$

where ϵ_t^{ra} is a standard normal innovation process and $\mu_{ra}, \beta_{ra}^1\ and\ \beta_{ra}^2$ are the parameters that define the dynamics of the stochastic risk aversion process. ϵ_t^{ra} accommodates for the conditional uncertainty in the stochastic risk aversion process. The square root process in the equation (A-2) ensures that the conditional variance of the stochastic discount factor in Equation (A-1) is positively related to the inverse of the surplus consumption ratio. This suggests that risk aversion rises as *SCR* declines. The consumption process is characterised as:

$$\Delta cg_t = \mu_{\Delta cg} + \beta_{cg}^1 (ra_{t-1})^{1/2} \left[(1+\alpha^2)^{1/2} \epsilon_t^{cg} + \alpha \epsilon_t^{ra} \right] \quad \textbf{(A-3)}$$

where $\mu_{\Delta cg} = E_{t-1}[\Delta cg_t]$, β_{cg}^1 and α are parameters and ϵ_t^{cg} is a standard normal innovation specific to the consumption growth process. In the Equation (A-2) and (A-3) ϵ_t^{ra} and ϵ_t^{cg} are assumed to be jointly $N(0, I)$. Thus, the conditional covariance between risk aversion and consumption growth equates to $Cov_{t-1}(\Delta cg_t, ra_t) = \alpha \beta_{cg}^1 \beta_{ra}^2 ra_t$, where α represents the conditional correlation between Δcg_t and ra_t. The value of α is expected to be negative to have an intuitive counter-cyclical risk aversion.

The real interest rate (rir) in a jog-normal framework is characterised as:

$$rir_t = -E_t[sdf_{t+1}] - \frac{1}{2} Var_t[sdf_{t+1}] \quad \textbf{(A-4)}$$

From the Equation (A-1), (A-2) and (A-3), $Var_t[sdf_{t+1}]$equates to:

$$Var_t[sdf_{t+1}] = \varphi^2 ra_t \left[(\beta_{cg}^1)^2 + (\beta_{ra}^2)^2 - 2\alpha \beta_{cg}^1 \beta_{ra}^2 \right] \quad \textbf{(A-5)}$$

Substituting the value of $Var_t[sdf_{t+1}]$ from the Equation (A-5) in the Equation (A-4) and using (A-1), we have:

$$rir_t = \varphi E_t[\Delta cg_{t+1}] - \varphi\left[\mu_{\Delta cg} + (\beta_{ra}^1 - 1)ra_t\right]$$
$$-\frac{\varphi^2}{2}ra_t\left[(\beta_{cg}^1)^2 + (\beta_{ra}^2)^2 - 2\alpha\beta_{cg}^1\beta_{ra}^2\right]$$

$$\Rightarrow rir_t = -\varphi\mu_{\Delta cg} + \varphi E_t[\Delta cg_{t+1}] - \varphi\Delta cg_t + \overline{\omega}ra_t \quad \textbf{(A-6)}$$

where $\overline{\omega} = -\varphi(\beta_{ra}^1 - 1) - \frac{\varphi^2}{2}\left[(\beta_{cg}^1)^2 + (\beta_{ra}^2)^2 - 2\alpha\beta_{cg}^1\beta_{ra}^2\right]$. From the above equation, solving for cg_t we obtain:

$$cg_t = -\mu_{ra} + E_t[cg_{t+1}] - \frac{1}{\varphi}rir_t + \omega ra_t \quad \textbf{(A-7)}$$

where $\omega = \overline{\omega}/\varphi = (1 - \beta_{ra}^1) - \frac{\varphi}{2}\left[(\beta_{cg}^1)^2 + (\beta_{ra}^2)^2 - 2\alpha\beta_{cg}^1\beta_{ra}^2\right]$. To transform Equation (A-7) into a demand equation we use:

$$rir_t = rf_t - E_t[i_{t+1}] + i_{ji} \quad \textbf{(A-8)}$$

where rf is the nominal risk-free rate, i is the inflation and i_{ji} arises from Jensen's inequality. We, therefore, assume constant inflation risk premium. In order to equate consumption and output, we use the following framework.

$$o_t = cg_t + z_t \quad \textbf{(A-9)}$$

where z_t is a iid representing demand shock arising from the gaps between output and consumption such as government spending. Assuming a liner de-trending of output, i.e. $\overline{o}_t = o_t - \varepsilon_t$, we have:

$$\bar{o}_t = \overline{cg}_t + z_t \tag{A-10}$$

Now substituting Equations (A-7) and (A-8) in Equation (A-10) we get:

$$\bar{o}_t = \beta_{IS} + E_{t+1}[\bar{o}_{t+1}] - \frac{1}{\varphi}(rf_t - E_t[i_{t+1}]) + \omega ra_t + X_t^o \tag{A-11}$$

where β_{IS} represents all the constant terms and $X_t^o = -z_t$.

Table 6 (A-2): Summary Statistics of Macroeconomic and non-Macroeconomic Factors

Panel A: Summary Statistics

Variables	**Mean**	**Std. Dev.**	**Median**	**Kurtosis**	**Skewness**
Nominal Risk-free Rate *(rf)*	0.0372	0.0237	0.0422	-0.8852	-0.0566
Expected Output Gap *(o)*	0.0001	0.0101	0.0010	2.0031	-0.3057
Inflation *(i)*	0.0101	0.0005	0.0100	10.0148	2.2034
Risk Averseness *(ra)*	3.5402	0.1494	3.4763	-0.2398	0.8652
Output Uncertainty *(ou)*	-0.0533	0.0668	-0.0835	-0.7717	0.7849
Inflation Uncertainty *(iu)*	0.0249	0.0083	0.0225	0.1552	1.0038
Equity Market Illiquidity *(lr)*	0.5047	0.4245	0.6989	26.2029	-2.5877
Bond Market Illiquidity *(ds)*	0.0098	0.0040	0.0091	12.5236	3.0383
Variance Premium *(vp)*	0.0397	0.0282	0.0312	4.6614	1.9146
Term Spread *(ts)*	0.0011	0.0323	0.0004	6.3284	-0.5551
Depth of Recession *(dr)*	-0.4682	1.3215	-0.6490	12.7422	2.9179

Panel B: Factor Correlation

	rf	*o*	*i*	*ra*	*ou*	*iu*	*lr*	*ds*	*ts*	*vp*	*dr*
rf	1										
o	0.080	1									
i	0.063	0.037	1								
ra	0.324	-0.061	-0.008	1							
ou	0.468	0.019	0.147	-0.243	1						
iu	0.482	0.074	0.168	-0.039	0.575	1					
lr	0.019	0.021	0.320	-0.078	0.003	-0.010	1				
ds	-0.398	-0.058	-0.031	-0.151	-0.189	-0.179	-0.127	1			
ts	-0.118	-0.065	0.047	0.122	-0.001	-0.155	0.017	-0.287	1		
vp	-0.156	-0.003	0.213	0.258	-0.197	-0.094	-0.120	0.509	-0.180	1	
dr	-0.110	0.183	0.014	-0.145	-0.083	-0.042	-0.038	0.439	-0.265	0.451	1

Note: Panel A of the table reports the annualized summary statistics of the macroeconomic and non-macroeconomic factors considered in examining the determinants of the asset return commovements. In total 11 factors are used. They are: Nominal Risk-free Rate *(rf)*, Expected Output Gap *(o)*, Inflation *(i)*, Risk Averseness *(ra)*, Output Uncertainty *(ou)*, Inflation Uncertainty *(iu)*, Equity Market Illiquidity *(lr)*, Bond Market Illiquidity *(ds)*, Variance Premium *(vp)*, Term Spread *(ts)*, Depth of Recession *(dr)*. The first four factors constitute the macroeconomic factors and the rest are the non-macroeconomic factors. The variables: Nominal Risk-free Rate *(rf)*, Expected Output Gap *(o)*, Inflation *(i)* are considered as the macroeconomic factors based on extant literature (d'Addona and Kind, 2006; Fama and Schwert, 1977) and also because these variables are the commonly used macro factors in rational macroeconomic models (Baele et al. 2010). Since, Risk Averseness *(ra)* is estimated from historic consumption growth data, this variable measures the fundamental risk averseness and hence it is considered as a macroeconomic variable in this study. Alternatively, the non-linear dynamics of risk aversion is measured using Variance Premium *(vp)*, which is considered as a non-macroeconomic factor. The other non-macroeconomic factors include economic uncertainty measures, i.e. Output Uncertainty *(ou)*, Inflation Uncertainty *(iu)*, liquidity factors, i.e. Equity Market Illiquidity *(lr)*, Bond Market Illiquidity *(ds)*, and leading indicators of economic cycles, i.e. Term Spread *(ts)*, Depth of Recession *(dr)*. These variables are considered as non-macroeconomic variables as they do not directly feature in the standard macroeconomic model. All the factor shocks are estimated using two stage structural framework as elaborated in the sub-section 7.3.2. The summary statistics of the variables show excess skewness and kurtosis emphasises the evidence of extreme events during the time period 1st August 1987 to 1st September 2012. The frequency of the data used is quarterly. Panel B: The Panel B of the table reports the correlation among the macroeconomic and the non-macroeconomic factors. The correlation figures suggest that there is no evident possibility of multicollinearity issues in the models used.

CHAPTER 7

Examining the Determinants of the Bi-variate Dependence Structures

7.1 Introduction

In this chapter I examine the determinants of time varying dependence structure of the return comovements of three different asset classes using Markov switching stochastic volatility model and the structural frameworks developed in the previous chapter. As discussed in the previous chapters, identifying the determinants of asset return comovements across different asset classes has significant implications for investors, policymakers and financial regulators. It is fair to say that investors no longer invest in only conventional financial assets such as equities and bonds, but in a wide range of alternative financial assets including commodities and real estate. Novel to this work is the analysis of the determinants of the asset return comovements of three different asset classes. Previous studies have dealt with the determinants of conventional financial assets; however studies examining the combination of bivariate asset return dynamics are sparse. Moreover, research on the determinants of joint dependence structure of a portfolio of different asset classes, which I refer as multi-assets, is non-existent. I present such an analysis in the next chapter.

In this chapter I focus on the analysis of 10 different bivariate asset pairs comprising of stocks, bonds, gold, oil and real estate. Against this backdrop, the purpose of the chapter is three fold: First, I seek to analyse if the dependence structures exhibit evidence of regime switching behaviour. Second, I identify macro and non-macroeconomic factors and examine their impact on the dependence structure of the asset return comovements.

Third, I investigate whether the impact of these factors on the dependence structures is regime specific.

This empirical investigation has a number of distinct features. First, I not only include conventional financial assets, i.e. equities and bonds, but also commodities and real estate in our sample. Further, the period of analysis is from 1987 to 2012 (1st August 1987 to 1st September 2012), which allows me to capture the effects of economic contraction caused by several financial crises on the behaviour of different asset classes. Second, as elaborated in Chapter 4, I use conditional copula models to overcome the limitations of simple linear correlation in examining the extreme dependence structure of the asset return comovements. Third, this analysis considers a wide range of macro and non-macroeconomic variables to explore the determinants of the dynamics of the dependence structures for ten combinations of asset pairs. As macroeconomic variables included are interest rates, output gap and inflation and risk aversion. I also consider macroeconomic uncertainty measures to account for economic uncertainties. Additionally, liquidity, variance premium and depth of recession are included as non-macroeconomic. It is, to the best of my knowledge, the first study that comprehensively examines the macro and non-macro determinants of the dependence structure for three different asset classes. Fourth, I impose structural restrictions inspired by New-Keynesian dynamics in examining the dynamics of the macroeconomic variables. The regime-switching models accommodates for heteroskedastic shocks in the estimated state variables. Finally, I decompose the performance of the model to examine the impact of macroeconomic and the non-macroeconomic factors. This provides useful insights in identifying the key determinants of the dependence structures.

In the light of the above discussion, I investigate the robustness of the findings, providing a multivariate-GARCH (MGARCH) analysis to test the covariance dynamics of the asset return comovements. This study suggests a bivariate regime switching MGARCH framework that uses a regime state variable that varies across the covariance of the marginal distribution behaviour of the asset returns in examining the dynamics of the asset return comovements during economic expansion and economic contraction phases.

This study reports several key insights. My findings indicate that dependence measures tend to rise faster than they fall, which corroborates the anecdotal evidence of contagion in financial markets across different asset classes. Further, the results show that interest rate and inflation have significant effect on the dependence structure during the economic contraction regime, whilst risk aversion plays a significant in the economic expansion regime. Among the non-macro factors output uncertainty, bond illiquidity measure and depth of recession contribute significantly in explaining the variations of the dependence structures. The findings also show that in the economic expansion regime the illiquidity measure negatively load on equity-bond dependence structure. The significant impact of the liquidity factors corroborates the evidence for “flight-to-liquidity” phenomenon as reported in the previous literature (Connolly et al., 2005). Further, the significant influence of the economic uncertainty measures indicates that higher the uncertainty about future economic state variables, the more swiftly the investors are likely to react to news. This in turn affects both the variances and the covariance of the asset returns. I, therefore, also contribute to the literature on the learning models as proposed by Veronesi (1999) and David and Veronesi (2008). Finally, the changing regimes of the asset return comovements demonstrate the potentials gains of timely switching over from risky assets like stocks, oil to bond and gold. These regimes correspond to economic expansion and economic contraction periods characterized by low and high asset return covariance, respectively.

The rest of the chapter is organized as follows: Section 2 presents the description of the return comovement data and the state variables. Section 3 discusses the dynamics and the factor contribution of the bivariate dependence structures and finally Section 4 provides the summary of the chapter.

7.2 Examining the Dependence Structures of Bivariate Asset Return Comovements

7.2.1 Data Description

I examine the determinants of the dependence structure of the comovements of two conventional financial assets, i.e. Standard & Poor's (S&P) 500 index (E) and US 10 year Government bond return index (B), two commodities, i.e. S&P GSCI Gold index (G) and West Texas Intermediate – WTI Cushing crude oil spot prices per barrel (O) and S&P Case-Shiller Composite-10 home price index (RE) for real estate. The dependence measure of the various asset returns is formulated using monthly returns to calibrate the ex-post quarterly dependence structure from the fourth quarter 1987 to the fourth quarter 2012 (1st August 1987 to 1st September 2012). I estimate the dependence structures of 10 bivariate-asset pairs by using time-varying conditional copula models as discussed in Chapter 4.

Table 7-1: Summary Statistics

Panel A: Descriptive Statistics of Asset Returns (1987 – 2012)

	Equity (E)	Bond (B)	Real Estate (RE)	Gold (G)	Oil (O)
Mean (%)	6.274	5.524	3.394	5.438	6.331
Standard Deviation (%)	16.428	1.293	2.730	15.449	33.000
Kurtosis	3.854	0.138	0.611	1.986	1.687
Skewness	-1.114	-0.165	-0.726	0.064	-0.357

Panel B: Diagnostics (1987-2012)

	Equity (E)	Bond (B)	Real Estate (RE)	Gold (G)	Oil (O)
Jarque-Bera statistics	208.3**	7.7**	31.5**	45.7**	48.4**
	(0.000)	(0.020)	(0.000)	(0.000)	(0.000)
ARCH LM statistic (1)	31.586**	17.737**	1741.764**	4.586**	13.676**
	(0.000)	(0.000)	(0.000)	(0.033)	(0.000)
ARCH LM statistic (5)	17.489**	8.571**	371.920**	3.003**	4.563**
	(0.000)	(0.000)	(0.000)	(0.016)	(0.000)

ARCH LM statistic (10)	12.804**	4.903**	190.231**	1.927**	2.913**
	(0.000)	(0.000)	(0.000)	(0.041)	(0.001)
Ljung-Box statistic (1)	433.293**	9649.404**	4232.160**	4.433**	5.757**
	(0.005)	(0.000)	(0.000)	(0.036)	(0.017)
Ljung-Box statistic (5)	1.254	1932.252**	914.690**	3.005**	3.223**
	(0.282)	(0.000)	(0.000)	(0.011)	(0.007)
Ljung-Box statistic (10)	0.869	971.691**	452.606**	1.619	2.156**
	(0.562)	(0.000)	(0.000)	(0.100)	(0.022)

Panel C: Descriptive Statistics of the Dependence Structures

	Mean	Standard Error	Standard Deviation	Kurtosis	Skewness
Equity-Bond (EB)	0.1131	0.0124	0.1250	5.2245	1.9484
Equity-Real estate (ERe)	0.0777	0.0072	0.0720	-0.9398	-0.0323
Equity- Gold (EG)	-0.047	0.0037	0.0370	-0.3393	-0.0670
Equity-Oil (EO)	0.1048	0.0297	0.2980	-0.1854	0.1111
Bond-Real estate (BRe)	0.1125	0.0048	0.0487	-0.1293	-0.3535

Bond-Gold (BG)	0.0286	0.0072	0.0726	4.1310	-0.8807
Bond-Oil (BO)	0.0168	0.0007	0.0074	5.3784	-1.7145
Real estate-Gold (ReG)	-0.091	0.0035	0.0356	1.0910	1.0125
Real estate-Oil (ReO)	0.0046	0.0044	0.0437	1.8548	0.3699
Gold-Oil (GO)	0.1802	0.0166	0.1672	-0.3301	-0.2617

Note: Panel A represents the descriptive statistics of the asset returns. The sample period is from the fourth quarter of 1987 to the fourth quarter of 2012. The returns are annualized from the monthly observations. Annualized return = [(1+monthly mean return)^{12} - 1], Annualized standard deviation = [monthly standard deviation$\times 12^{1/2}$]. Panel B provides the diagnostic test results. Under the normality null hypothesis, Jarque-Bera test statistic follows a Chi-square distribution with fixed (2) degrees of freedom. The null hypothesis of the ARCH-LM test is: there is no evidence of ARCH effect. We conduct the test at lags 1, 5 and 10 with corresponding 1, 5, 10 degrees of freedom. Tests using other lags yield the same results. The Jarque-Bera test statistics in Panel (B) confirm that the unconditional distributions of the asset returns are not normal. We conduct the Ljung-Box test for serial correlation, corrected for heteroscedasticity at lags 1, 5 and 10. The p-values are reported in the parentheses. The significant LM statistics confirm the presence of autoregressive conditional heteroskedastic (ARCH) effects. The Ljung-Box test also reports that most of the asset returns are serially correlated for at least one of the lag orders. Panel C reports the descriptive statistics of the dependence measures of the different asset pairs for the period 1987 to 2012: equity and bond (EB), equity and real estate (Ere), equity and gold (EG), equity and oil (EO), bond and real estate (BRe), bond and gold (BG), bond and oil (BO), real estate and gold (ReG), real estate and oil (ReO) and gold and oil (GO). The estimates of the copula parameters can be provided on request. The summary statistics show excess skewness and kurtosis which suggests that the distributions have a fatter tail and thus extreme variance is highly probable. ** signifies rejection of the null hypothesis at 5 percent level.

Table 7-1 presents the summary statistics of the asset returns and the dependence structures of the return comovements. The statistics reported in Panel (A) and Panel (B) have already been discussed in Chapter 5, Table 5-2. In sum, the annualized mean return of oil (6.33 percent) is higher than any other assets followed by equity and bond returns of 6.27 and 5.52 percent, respectively. The standard deviation is highest for oil returns (33 percent) followed by equity returns (16.42 percent). Except for gold returns, the asset returns are negatively skewed. All the asset returns show excess kurtosis, indicating that the distributions have a fatter tail and the probability of extreme variance is more likely as compared to a normal distribution. Further, the Jarque-Bera test statistics in Panel (B) of Table 7-1 confirm that the unconditional distributions of the asset returns are not normal. Thus, it is less likely that multivariate Gaussian distribution will provide the best-fit for the dependence structure.

In this sub- section I focus on Panel (C) of Table 7-1 which presents the mean and the standard deviation of the dependence structure for the various pairs of the asset return comovements. The dependence structure for all the asset pairs are positive except for equity-gold (-0.047) and real estate-gold (-0.091). This suggests that gold provides a good hedge for equity and real estate. The average dependence structure is highest for the gold-oil pair (0.18) followed by equity bond (0.11). Higher average values of dependent structure imply greater comovements. The summary statistics show excess skewness and kurtosis which suggests that the distributions have a fatter tail and thus extreme variance is highly probable.

As elaborated in Chapter 4, the bivariate distributions are estimated using copula function. In doing so, I first estimate the univariate marginal distribution of each asset returns.

ARMA (p, q) – EGARCH (1, 1) model is used for each of the asset return time-series. The optimal lag orders for each of the return series is selected using the Akaike information criteria (AIC). The mean equations of equity, bond, real estate, gold and oils follow ARMA (2, 2), ARMA (5, 5), ARMA (7, 7), ARMA (6, 6) and ARMA (7, 6), respectively. I confirm that the marginal models are free from autocorrelation and heteroskedastic effects. The results are provided in details in Chapter 5.

Further, to evaluate the adequacy of the marginal models, misspecification tests are conducted following Diebold et al. (1998). I examine the correlograms of $(\hat{u}_t - \bar{u})^l$ and $(\hat{v}_t - \bar{v})^l$ for '*l*' ranging from one to four. The values *u* and *v* are the probability integral transformations of the estimates of the marginal models. The correlograms confirm absence of any serial correlation in the first four moments, which indicates that our marginal models for the different asset returns are correctly specified. The results of these tests are provided in Chapter 5, Table 5-4.

For examining the determinants of the dependence structure of asset return comovements, I include four macroeconomic variables, i.e., the risk free rate (rf), output gap (o), inflation (i), and risk aversion (ra) and seven non-macroeconomic variables, i.e. output uncertainty (ou), inflation uncertainty (iu), bond market illiquidity (ds), equity market illiquidity (lr), variance premium (vp), term spread (ts) and the depth of recession (dr). Next, I discuss each of these state variables and examine their regime switching behaviour.

7.2.2 The Dynamics of the State Variables

This sub-section provides the volatility dynamics of the state variables that are considered as the key determinants of the asset return comovements in the existing literature. Figure 7-1 plots the regime probabilities of the state variables and Figure 7-2 provides the conditional volatilities of the various structural factors. I present the discussion of these two figures in tandem.

Figure 7-1 reveals that all the structural factor models show significant regime-switching behaviour both in terms of statistics and economic significance. Panel (A) of Figure 7-1 shows the expansion regimes of the output gap and the inflation shocks. The inflation regime follows the real economy shocks closely. The probability of expansion regime is more than the probability of the contraction regime. Yet, the probability of an output shock is higher than the inflation shock. Both the state variables witness regime changes in four specific periods: the early 1990s period of economic prosperity, the early 2000s economic recession following the LTCM bailout, the recovery of the economy since 2004 after the dot com bubble burst and the September 11 terrorist attack and the economic contraction following the 2008 US subprime crisis. Examining the volatility of the output and inflation shown in Panel E of Figure 2 we observe a near permanent switch to low volatility regime for both output and inflation uncertainty. This is consistent with the phenomenon of a Great Moderation[10], which relates to declining business cycle volatility post 1980s. For output uncertainty, the switch in volatility occurs in 1991, and for

[10] The Great Moderation refers to the lower variability of inflation and output growth observed since the mid to late 1980s. The key reasons for reduced volatility in economic cycles are related to the institutional and structural changes in the developed economies during late 1980s till the beginning of the 21st century. During this time some of the key economic variables such as gross domestic product, industrial production and unemployment witnessed reduced volatility and uncertainty shocks.

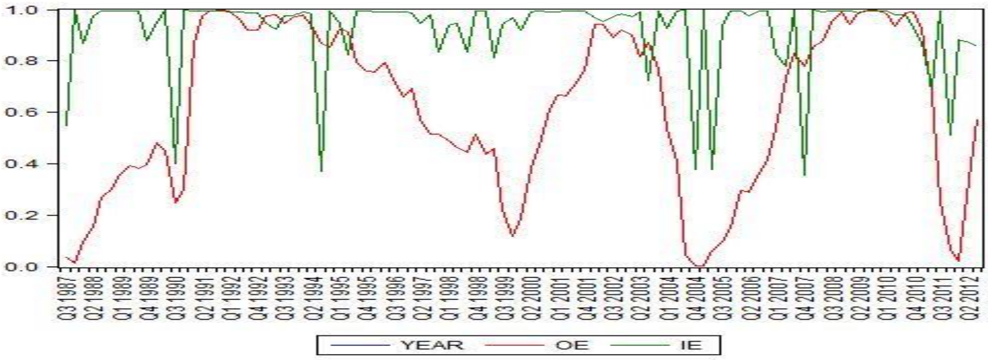
inflation the change occurs in 1998. In terms of volatility levels the inflation volatility is always higher than the output volatility. This is evident in both the contraction and in the economic expansion regimes.

In Panel (B) of Figure 7-1, risk version shows a stronger counter-cyclicality, which indicates that risk aversion expansion regime is most likely to occur during economic recession. The risk aversion is notably higher in three distinct periods: 1991-1995, 2002-2004 and 2008-2011. Panels (D) and (E) of Figure 7-1 present the regime changes in depth of recession with inflation and output, respectively. Note that depth of recession follows a counter-cyclical behaviour. Three distinct regimes are visible: the early 1990s, 2001-2003, and the years witnessing the sub-prime crisis 2008-2010. Likewise, in Panel (G) of Figure 7-1, term spread shows similar regime changes. Yet, the regimes for term spread differ from the former. In particular, term spread witness regime changes in the periods 1990-1992 and 2008-2010. Panel (D) of Figure 7-2 provides evidence that overall the level of volatility for depth of recession is higher than term spread.

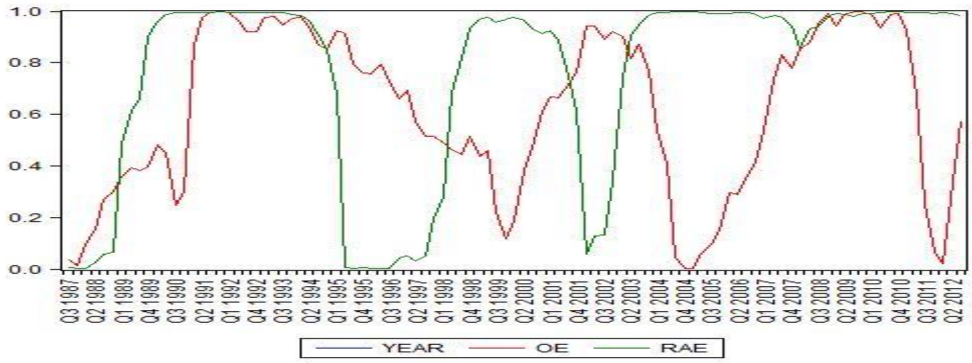
Panel (F) of Figure 7-1 shows the illiquidity regimes of the equity and bond markets. While for both the markets, the regime is in the high variance state, the variability is more in case of equity market illiquidity. For bond market illiquidity the spike is clearly observed in the period 2008-2010. The stock illiquidity follows a similar pattern, though the regime switches to the low volatility in the years during the recessionary periods. Panel (C) of Figure 7-2 confirms that the bond illiquidity is less volatile compared to the stock illiquidity.

Figure 7-1: Regime Probabilities of State Variables

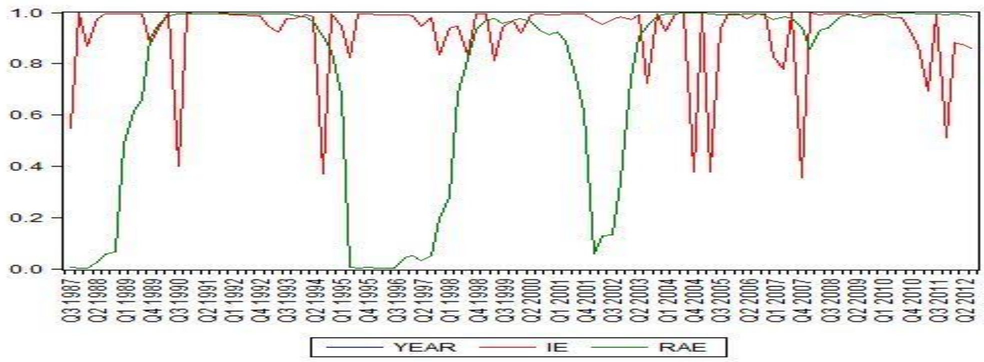
Panel A: Output and Inflation Regime



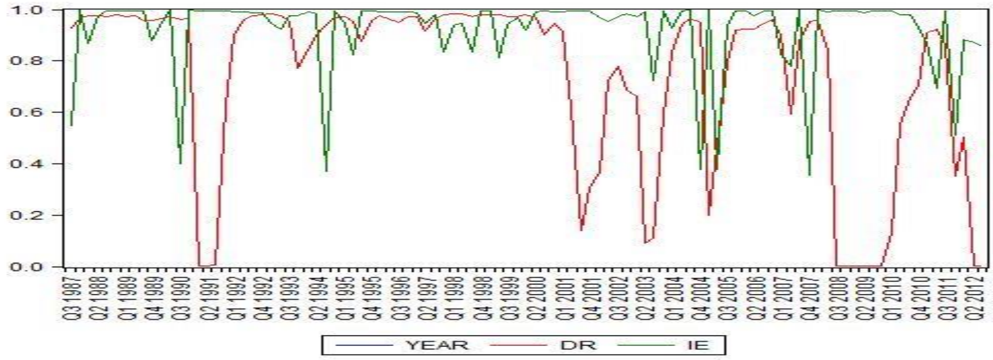
Panel B: Output and Risk Aversion Regime



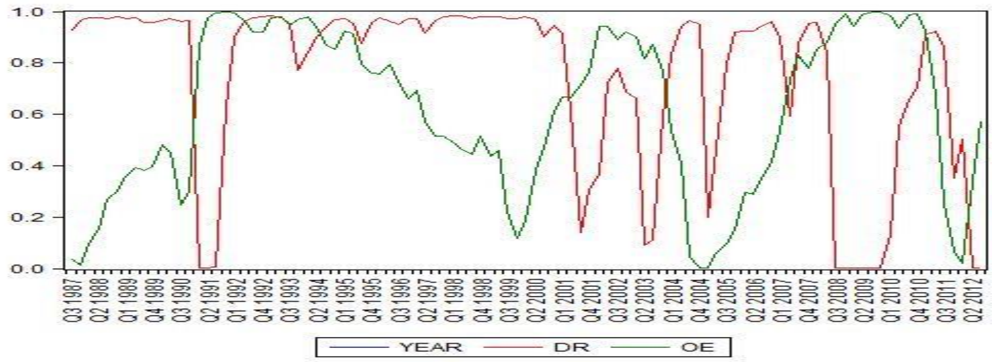
Panel C: Inflation and Risk Aversion Regime



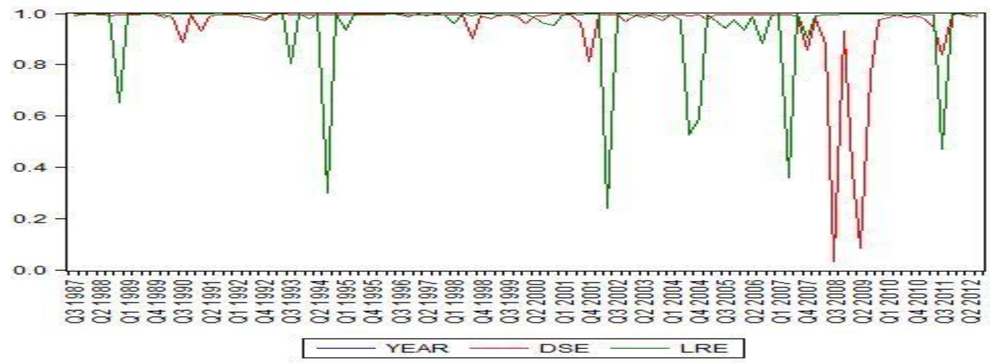
Panel D: Depth of Recession and Inflation Regime



Panel E: Depth of Recession and Output Regime



Panel F: Bond and Equity Market Illiquidity Regime

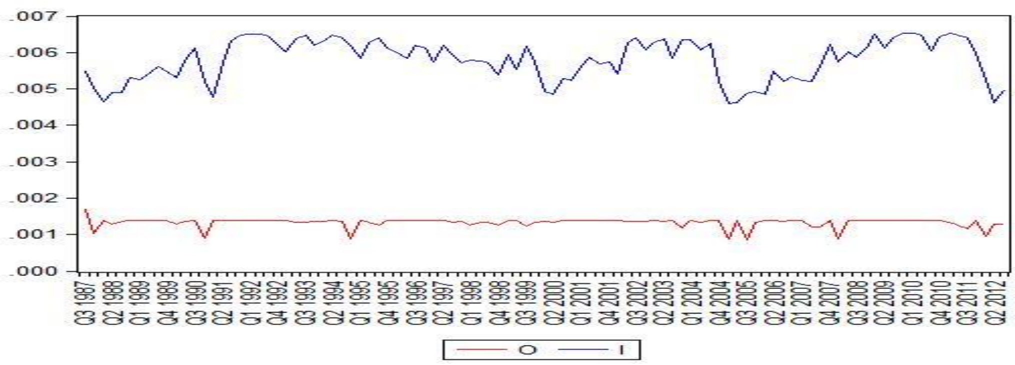


Panel G: Term Spread and Output Regime

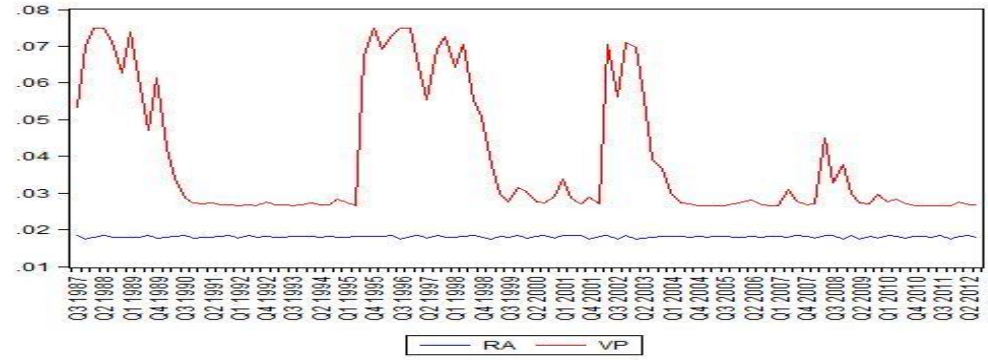
Note: The figures show the smoothed probabilities of the combinations of the different state variables in the expansion regime. The analyses of the two regimes are defined in section 5.2. Panel A shows the probabilities of the output expansion regime (OE) and the inflation expansion regime (IE). Panel B shows the probabilities of the output expansion regime (OE) and the risk aversion expansion regime (RAE). Panel C shows the probabilities of the inflation expansion regime (IE) and the risk aversion expansion regime (RAE). Panel D shows the probabilities of the depth of recession expansion regime (DR) and the inflation expansion regime (IE). Panel E shows the probabilities of the depth of recession expansion regime (DR) and the output expansion regime (OE). Panel F shows the probabilities of the bond market illiquidity expansion regime (DS) and the equity market illiquidity expansion regime (LR). Panel G shows the probabilities of the term spread expansion regime (TS) and the output expansion regime (OE). The period of analysis is from the fourth quarter 1987 to the fourth quarter 2012.

Figure 7-2: Conditional Volatilities of the Various Structural Factors

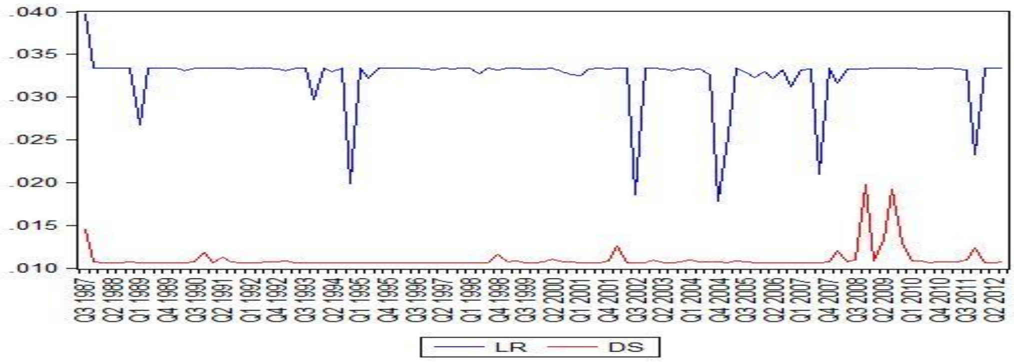
Panel A: Output and Inflation



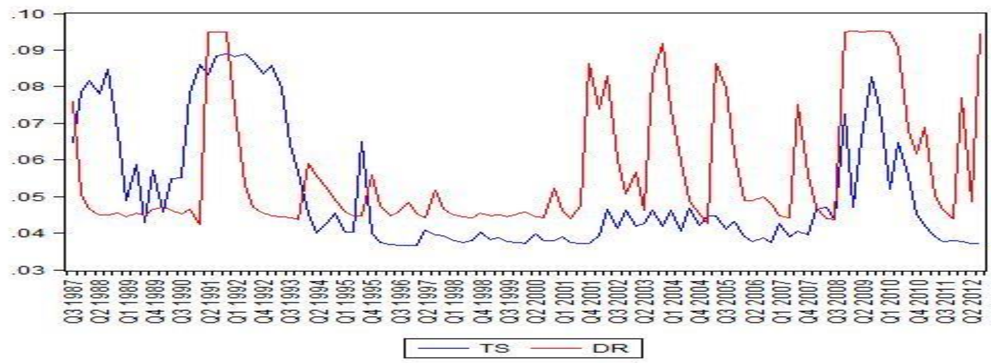
Panel B: Risk Aversion and Variance Premium



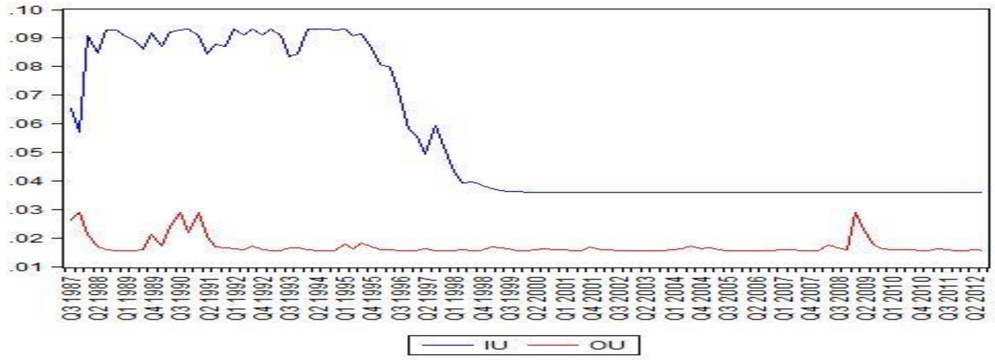
Panel C: Bond Illiquidity and Equity Illiquidity



Panel D: Term Spread and Depth of Recession



Panel E: Inflation Uncertainty and Output Uncertainty



Note: The figure shows the annualized conditional volatilities of the various factors identified in our variable model. Panel A shows output (O), inflation (I) and risk free rate (RF). Panel B shows risk aversion (RA) and variance premium (VP). Panel C shows bond (DS) and equity market illiquidity (LR). Panel D shows term spread (TS) and depth of recession (DR). Panel E shows inflation uncertainty (IU) and output uncertainty (OU). The period of analysis is from the fourth quarter of 1987 to the fourth quarter of 2012.

7.3 The Dynamics and the Factor Contributions of the Dependence Structures

7.3.1 Dependence Structure Dynamics

Let us begin by determining whether there is evidence of regime switching behaviour for each of the various dependence structures of the asset return comovements. Table 7-2 reports the transition probabilities of the two regimes, i.e. State 1 and State 2, along with the respective expected durations[11] of the regimes. The findings indicate significant transition probabilities for both the regimes. The two regimes are identified as the Dependence Structure High State (DSHS) regime (State 1) and the Dependence Structure

[11]Following Hamilton's (1989) formula we estimate the expected duration of the regimes as $\sum_{i=0}^{\infty} i p_{11(22)}^{i-1}(1-p_{11(22)})$, where $p_{11}(p_{22})$ are the transition probabilities in Regime 1 (Regime 2).

Low State (DSLS) regime (State 2). The appropriate number of regimes is identified based on the Regime Classification Statistic (RCS) as discussed in the previous chapter.

The transition probability and the expected duration values presented in Table 7-2 reveal that the DSHS regime tends to be considerably longer than the DSLS regime for the various dependence structures. Yet, it is interesting to note that this pattern is reverse for equity-gold and bond-oil return comovements, where the DSLS regime is longer than the DSHS regime. The standard deviations in Table 7-2 indicate the higher uncertainty in predictive power of the model in each of the states. It is worth noting that the standard deviation estimates are higher in the DSHS regime than in the DSLS regime. This indicates that the dependence structure in the DSHS is more volatile than in the DSLS. The key implication is that the dependence structure increases faster than it decreases. However, a reverse trend is visible for equity-gold and bond-oil return comovements. These results provide evidence of contagion in the financial market across different asset classes except for equity-gold and bond-oil pairs.

Moving on to Figure 7-3, I present the regime switching probabilities of the various dependence structures of the asset return comovements. The key finding is that the regime states vary for different pairs of asset return. This suggests that macroeconomic and non-macro factors affect different asset return comovements differently. This further implies that it is important to understand the dynamics of the dependence structure in order to construct more efficient portfolios. Clearly, a better understanding of the effects of economic and non-macroeconomic factors on the comovements of asset return dynamics will support strategic asset allocation. Panel (A) of Figure 7-3 shows the DSHS regime of equity-bond dependence structure, which captures periods of high economic uncertainty, characterized by increased output gap uncertainty and rising liquidity shocks.

In contrast, the DSLS regime captures economic expansion marked by rising interest rates and falling bond prices. The states identified for the other pairs have a similar interpretation. State 1, i.e. DSHS, captures economic contraction and State 2, i.e. DSLS, captures economic expansion with falling gold prices and rising equity prices. Panel (C) and Panel (G) show that the DSLS regime of the dependence structure is longer than the DSHS regime. The equity-gold, i.e. Panel (C), and bond-oil, i.e. Panel (D), dependence structures exhibit counter cyclical characteristics and in contract to other pairs, equity-gold and bond-oil dependence on average are negative. The findings indicate that i) investment in gold serves as a good hedge for equity and ii) investment in bonds provides a good hedge for oil. In Panel B for the equity-real estate dependence structure, State 1, i.e. DSHS, captures economic decline when housing rates tends to fall, whereas State 2, i.e. DSLS, corresponds to economic expansion where there is a high demand for real estate assets and rising stock prices. The volatility of the dependence measure in the economic contraction period is relatively higher than the economic expansion period. For the equity-oil pair (Panel D) the periods of economic decline is persistent over three distinct periods: i) June 1990 to March 1991, which relates to the first Persian Gulf War, ii) August 1998 to January 2003, the period that witnessed large mergers in the oil industry[12] and ii) the third quarter of 2008 corresponding to the sub-prime crisis. The period from August 1998 to January 2003 also witnessed bailout of LTCM and Russian and Brazilian government bond crisis. It is interesting to note that the dependence structure of real estate and oil pair shows evidence of two distinct periods. The economic expansion regime corresponds to period prior to September 2000. Post this period the

[12] The deals include the creation of the Exxon-Mobil, BP Amoco Plc and the merger of Arco with BP Amoco Plc.

dependence structure remains in State1, i.e. DSHS. From Panel H it is evident that post sub-prime crisis the dependence structure measure of real estate-gold return co-movements is in DSHS regime. A key implication of this finding is that some diversification benefits are lost in investing in gold post the sub-prime crisis.

The table below presents the summary of the significant impacts of the state variables. The detailed factor loadings are reported in the Appendix.

Table 7-2: Summary of Significant Factor Exposure

Panels	Dependence Structure States	**Macroeconomic Factors**				**Non-macroeconomic Factors**							**SD**	**TP**	**Dur.**
		RF	O	I	RA	OU	IU	LR	DS	TS	VP	DR			
A: Equity-Bond	State 1	(+)	(-)	(+)		(+)			(+)		(+)		0.078***	0.86***	29.9
	(DSHS)												(0.008)	(0.26)	
	State 2	(+)		(-)		(-)		(-)	(-)		(-)		0.069*	0.82**	10.66
	(DSLS)												(0.002)	(0.84)	
B: Equity-Real Estate	State 1	(+)		(+)									0.097***	0.88**	14.76
	(DSHS)												(0.0004)	(0.19)	
	State 2	(-)		(-)									0.03***	0.78**	6.14
	(DSLS)												(0.0003)	(0.22)	
C: Equity-Gold	State 1	(-)	(+)	(-)		(-)	(+)		(-)	(-)	(-)	(-)	0.021**	0.67***	7.56
	(DSHS)												(0.000)	(0.18)	
	State 2				(+)		(+)		(+)				0.064	0.73**	8.88
	(DSLS)												(0.99)	(0.56)	
D: Equity-Oil	State 1					(+)			(+)			(+)	0.133***	0.77***	19.84
	(DSHS)												(0.006)	(0.33)	
	State 2								(-)			(+)	0.071***	0.73**	14.46
	(DSLS)												(0.002)	(0.32)	

E:	State 1	(+)						(+)			(-)	0.030***	0.82**	25.32
Bond-Real estate	(DSHS)											(0.000)	(0.14)	
	State 2	(-)						(+)				0.0251	0.78**	6.52
	(DSLS)											(0.99)	(0.32)	
F:	State 1					(-)	(+)	(-)		(-)		0.027**	0.83**	10.02
Bond-Gold	(DSHS)											(0.00)	(0.37)	
	State 2					(+)	(-)	(+)				0.091**	0.77**	6.75
	(DSLS)											(0.00)	(0.29)	
G:	State 1	(-)		(-)		(+)		(-)				0.009**	0.72***	9.31
Bond-Oil	(DSHS)											(0.00)	(0.45)	
	State 2	(-)		(+)	(+)	(-)		(+)				0.012**	0.82**	13.5
	(DSLS)											(0.99)	(0.65)	
H:	State 1	(-)		(-)	(-)							0.080**	0.75**	13.78
Real estate-Gold	(DSHS)											(0.00)	(0.37)	
	State 2	(+)		(-)	(+)				(+)			0.025**	0.85**	5.70
	(DSLS)											(0.99)	(0.71)	
I:	State 1	(+)		(-)								0.036***	0.85***	21.91
Real estate-Oil	(DSHS)											(0.00)	(0.18)	
	State 2		(-)	(+)								0.019**	0.64**	4.56
	(DSLS)											(0.00)	(0.35)	

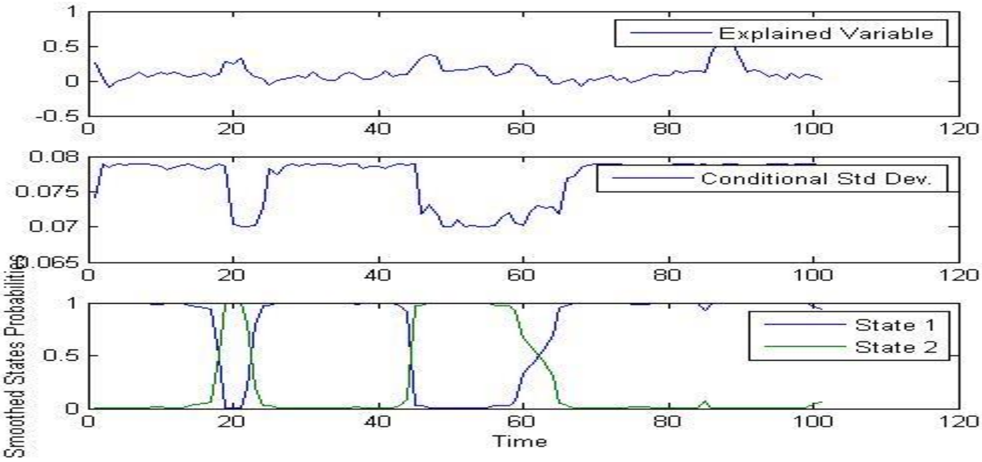
J: Gold-Oil	State 1 (DSHS)		(-)	(+)	(-)	0.21*** (0.00)	0.78** (0.99)	30.6
	State 2 (DSLS)		(-)	(+)	(-)	0.065** (0.99)	0.72** (0.98)	11.89

Note: The table reports the summary the parameter estimation results of the Markov switching stochastic volatility models of the ten state variables for the various dependence structure. The appropriate numbers of regimes are identified by the Regime Classification Statistic as stated in Equation (10). The findings indicate significant transition probabilities for both the regimes. The two regimes are identified as the Dependence Structure High State (DSHS) regime (State 1) and the Dependence Structure Low State (DSLS) regime (State 2). DSHS relates to economic contraction phase and DSLS relates to economic expansion phase. In the set of macroeconomic state variables RF is risk free rate, O is output gap, I is inflation and RA is risk aversion. In the set of non-macro factors OU is output uncertainty, IU inflation uncertainty, LR measure equity illiquidity, DS is bond illiquidity measure, TS is term spread, VP is variance premium and DR is depth of recession. Significant impacts of the independent variables are shown in the table. The significance levels are at five/one percent and the positive and negative signs in parenthesis denote the sign of the coefficient of the independent variable. SD reports the standard deviation of the regime states. TP corresponds to the transition probabilities of the two states. TP for state 1 refers to the probability of the dependence measure to stay in the expansion regime and TP for State 2 corresponds to the probability of the dependence measure to stay in contraction regime. The Standard errors are reported in parenthesis. Duration (Dur) corresponds to the expected duration of the Dependence Structure High State (DSHS) regime (State 1) and the Dependence Structure Low State (DSLS) regime (State 2). The sample period is from the fourth quarter 1987 to the fourth quarter 212. The coefficient estimates can be provided on request.

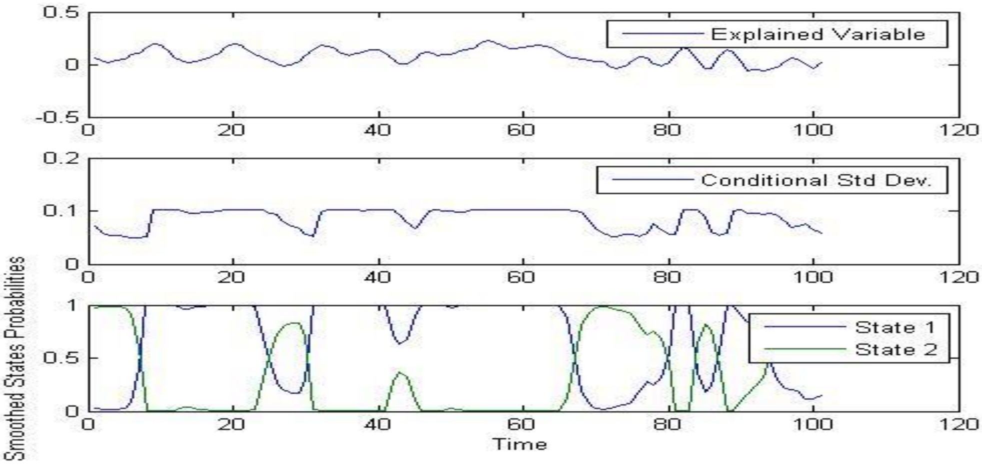
** corresponds to 5 percent significance level and *** corresponds to one percent significance level.

Figure 7-3: Regime Switching Probabilities of the Dependence Structures

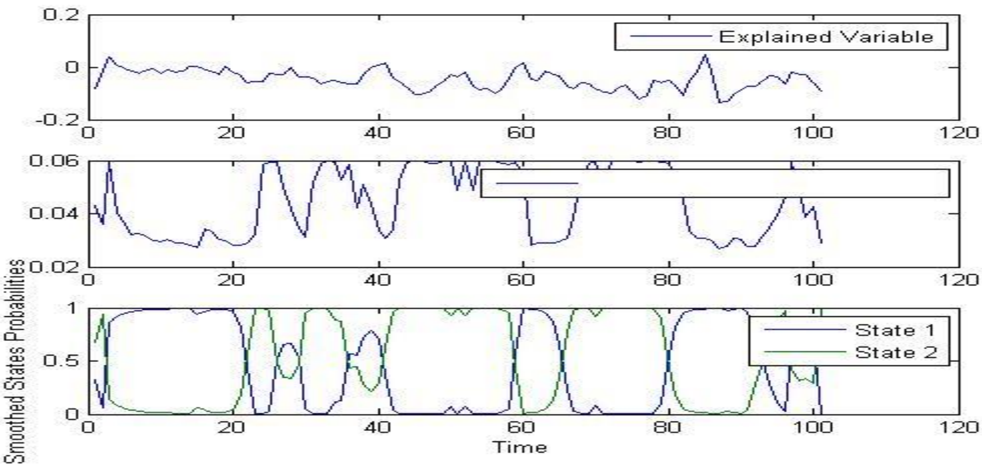
Panel A: Regimes of Equity-Bond Dependence Structure



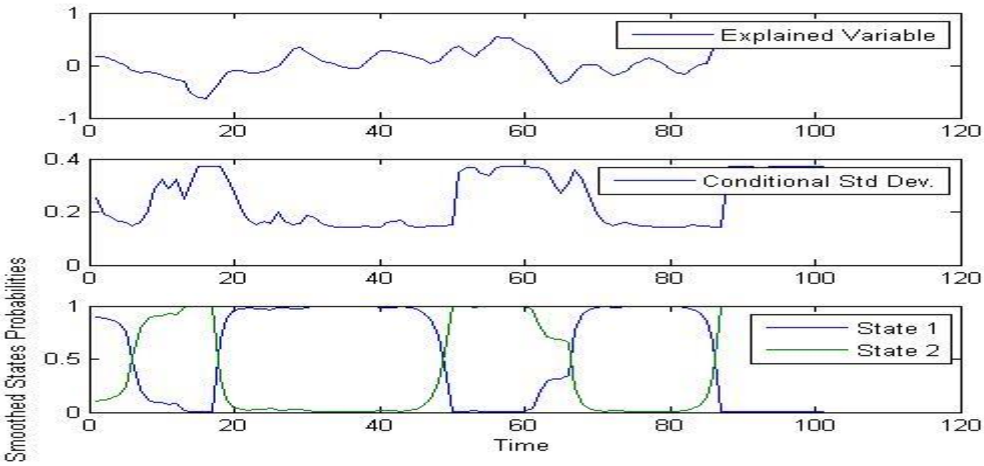
Panel B: Regimes of Equity-Real estate Dependence Structure



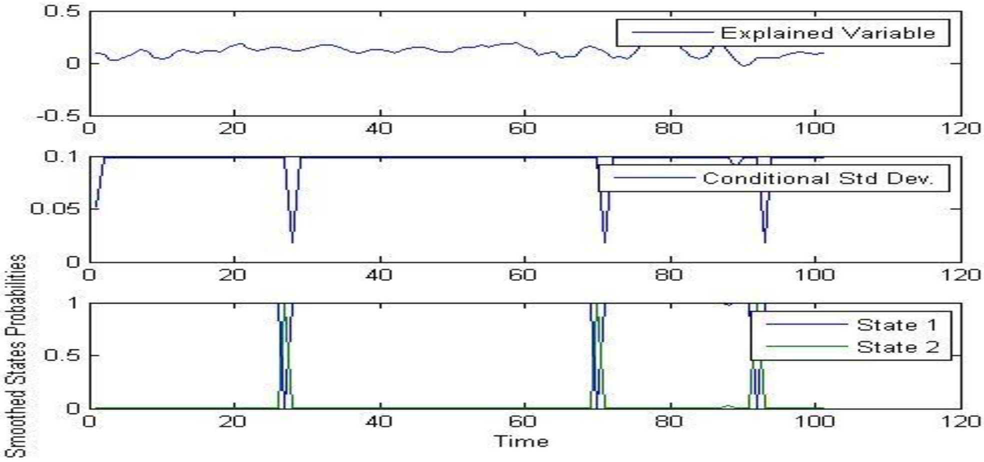
Panel C: Regimes of Equity-Gold Dependence Structure



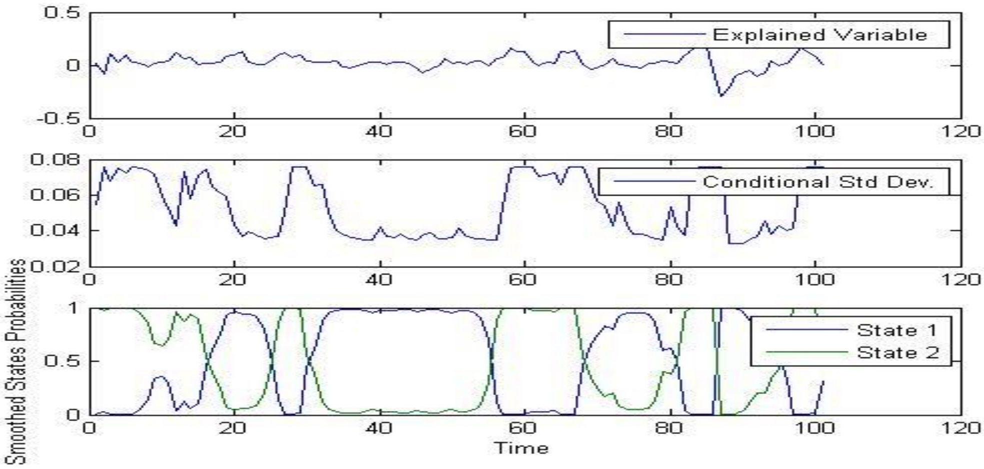
Panel D: Regimes of Equity-Oil Dependence Structure



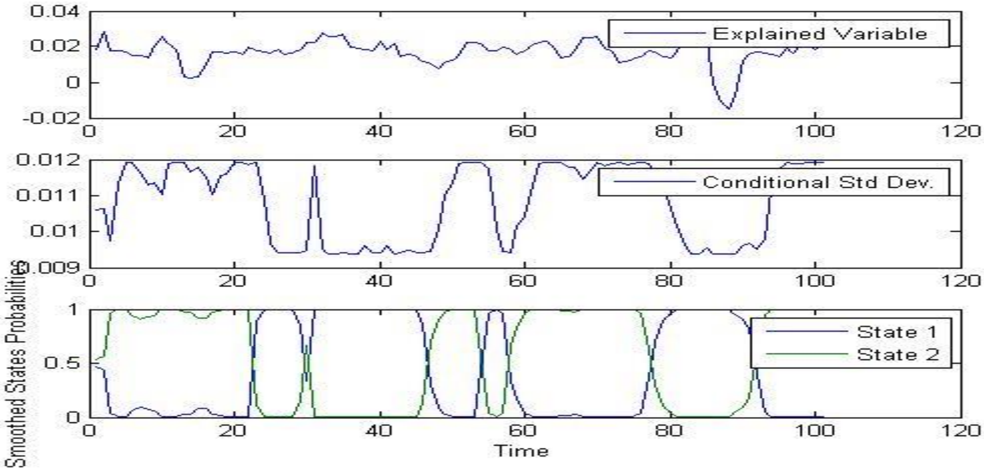
Panel E: Regimes of Bond-Real estate Dependence Structure



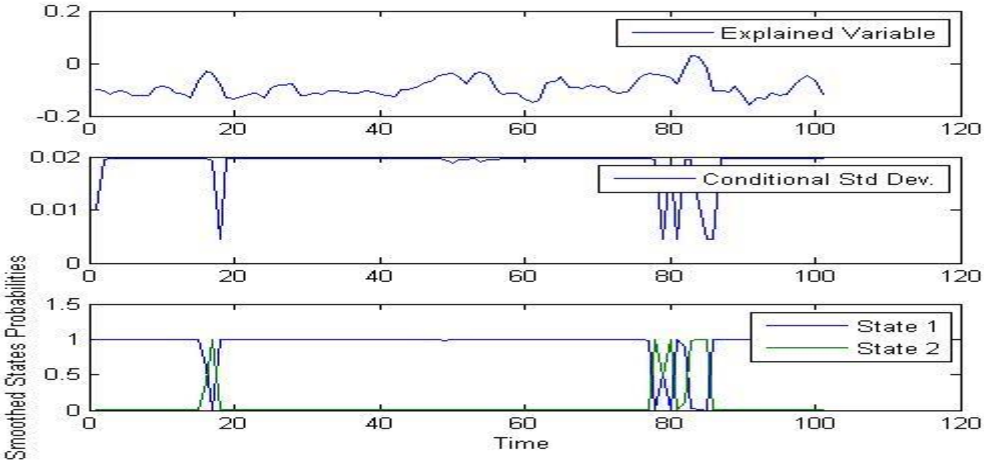
Panel F: Regimes of Bond-Gold Dependence Structure



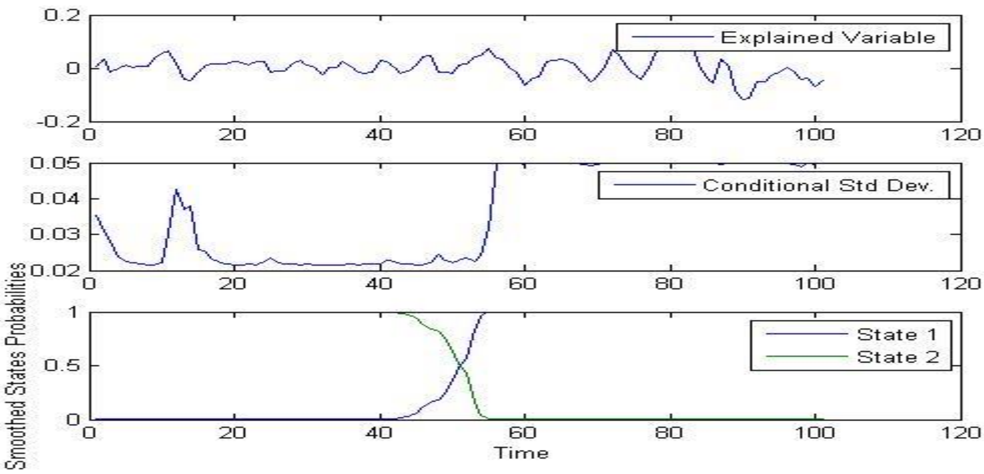
Panel G: Regimes of Bond-Oil Dependence Structure



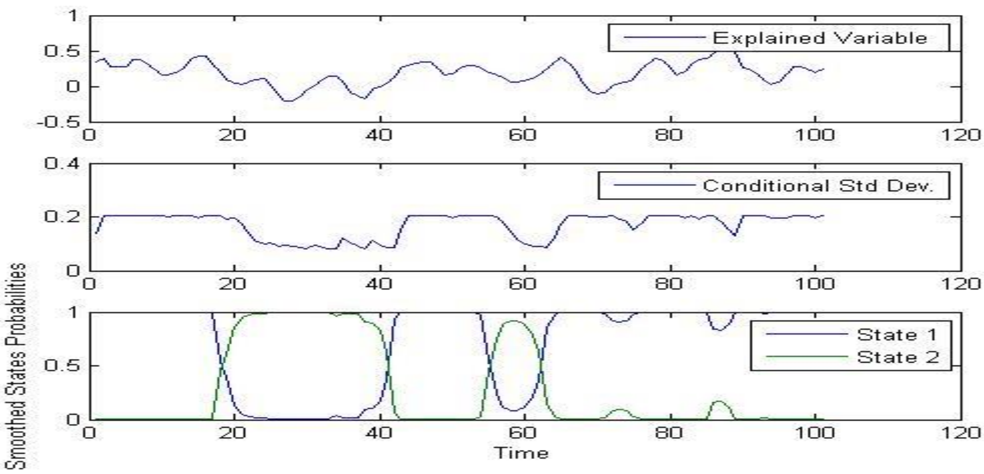
Panel H: Regimes of Real estate-Gold Dependence Structure



Panel I: Regimes of Real estate-Oil Dependence Structure



Panel J: Regimes of Gold-Oil Dependence Structure



Note: The figure shows the Markov switching model-implied regimes of the ten dependence structures. Panels A to J show the time path of the model-implied regimes of the bivariate asset pairs. State 1 corresponds to the expansion regime of the dependence measure. State 2 corresponds to the contraction regime of the dependence measure. The explained variable in the dependence structure of the various asset return comovements. The conditional std. is the standard deviation of the two states. The period of analysis is from the fourth quarter 1987 to the fourth quarter 2012.

7.3.2 Factor Exposure

The factor exposures of the macro and the non-macro variables for the dependence structure high state - DSHS (State 1) and for the dependence structure low state - DSLS (State 2)[13] are reported in Table 7-2. Panel A: For the equity-bond dependence structure majority of the factors are significant in both the regimes. All macro-economic variables except for risk aversion (RA) are significant and among the non-macro factors, output uncertainty (OU), liquidity measures (LR and DS) and variance premium (VP) are significant. In the DSHS regime output gap (O) has a negative coefficient, indicating that positive output gap shocks have an inverse effect on the return comovement. In the DSLS

[13] The appropriate number of regimes is identified based on the Regime Classification Statistic (RCS) as discussed in the previous chapter.

regime all the factors are negatively loaded except for risk-free rate. Negative sign indicates that a positive factor shocks leads to a decline in the asset return covariance.

Panel B: For equity-real estate dependence structure, only macro-economic factors, i.e. risk-free rate (RF) and output gap (O) are significant. The factors produce positive coefficients in the DSHS regime and negative coefficients in the DSLS regime. Panel C: In the DSHS regime of the equity-gold dependence structure, the macro-economic factors (risk-free rate, output gap, inflation) and all of the non-macro variables except for stock illiquidity measure (LR) are significant. However, in the DSLS regime only risk aversion (RA), inflation uncertainty (IU), bond illiquidity (DS) factors are significant. It is interesting to note that the factor coefficients are negative in the DSHS regime and positive in the DSLS regime. Therefore in contrast to the DSLS regime, a positive factor shock reduces the dependence in the DSHS regime.

Panel D: The non-macro variables, i.e. output uncertainty (OU), bond illiquidity (DS) and depth of recession, are significant in the DSHS regime of the equity-oil dependence structure. Yet, in the DSLS phase only bond illiquidity (DS) and depth of recession (DR) are significant. Since a negative value in the depth of recession signifies economic recovery and vice versa, the coefficient bears a negative sign in the DSHS regime and a positive sign in the DSLS regime. Panel E: In the DSHS regime of bond-real estate dependence structure only risk-free rate (RF) and the non-macro factors such as bond illiquidity (DS) and depth of recession (DR) are significant. In contrast, in the DSLS regime only the former two variables are significant.

Panel F: It is interesting to note that for bond-gold dependence structure only non-macro variables are significant. The factors include output and input uncertainty (OU and IU), bond illiquidity (DS) and variance premium (VP). Panel G: For bond-oil dependence structure the macro variables (risk-free rate and inflation) and the non-macro variables (output uncertainty and bond illiquidity measure) are significant in the DSHS regime. Apart from these factors risk aversion (RA) is significant in the DSLS regime. Panel H: In case of real estate-gold dependence structure risk-free rate (RF), inflation (I) and risk aversion (RA), i.e. only macroeconomic variables, are significant in both the regime. Within the non-macro variables only term spread (TS) is significant in the DSLS regime. Panel I: The macroeconomic factors risk-free rate (RF) and risk aversion (RA) are significant in the DSHS regime of the real estate-oil dependence structure. In the DSLS regime apart from risk aversion (RA), output gap (O) is also significant. Panel J: In contrast for gold and oil the dependence structure only non-macro variables are significant. The factors include inflation uncertainty (IU), bond illiquidity (DS) and term spread (TS). These variables are significant in both the regimes. The factor loadings are provided in the Appendix.

7.3.3 Factor Contributions

This section reports to what extent the various factors contribute to the model fit in explaining the asset return comovements. I test the explanatory power of the determinants by constraining my MSSV model to various factors and examining the model fit. Table 7-3 reports the results.

Based on the information criteria, i.e. AIC and BIC, the findings indicate that the fit worsens considerably when the non-macro factors are dropped for equity-bond and equity-oil pairs' dependence structure. Yet, the macroeconomic factors play a dominant role in explaining the dependence structure of the equity-real estate, the real estate-gold and the real estate-oil pairs. In particular, the study identifies that interest rate and inflation have significant effect on the dependence structure during the DSHS regime, whilst risk aversion is significant in particular during the DSLS regime. Among the non-macro factors output uncertainty, bond illiquidity measure and depth of recession contribute significantly in explaining the variations of the dependence structure.

Overall, my findings indicate that non-macro factors contribute significantly in explaining the dynamics of the dependence structure. In particular, it is interesting to note that in the DSLS regime the illiquidity measure negatively load on equity-bond dependence structure. This suggests that an increase in illiquidity in the market triggers higher demand for bonds resulting in lower interest rates. This cross-market effect indicates that a negative shock in the equity market increases the comovements as opposed to a positive shock in the bond market. This results in outflow of investment from equity to treasury bonds and gold.

Table 7-3: Factor Contributions to Model Performance

Model Performance	Full Model	Minus non-Macro Factors	Minus Macro Factors
Panel A: Equity-Bond Dependence Structure			
AIC	-115.170	-101.657	-113.973
BIC	-91.947	-63.045	-66.671
Panel B: Equity-Real Estate Dependence Structure			
AIC	-157.069	-176.795	-150.834
BIC	-83.845	-140.184	-98.532
Panel C: Equity-Gold Dependence Structure			
AIC	-391.583	-280.013	-253.836
BIC	-355.241	-243.402	-201.534

Panel D: Equity-Oil Dependence Structure			
AIC	-40.769	-44.864	-36.437
BIC	-113.993	-81.4765	-58.739
Panel E: Bond-Real estate Dependence Structure			
AIC	-192.375	-121.128	-112.478
BIC	-119.152	-84.516	-60.176
Panel F: Bond-Gold Dependence Structure			
AIC	-239.127	-245.289	-246.278
BIC	-165.904	-208.677	-193.976
Panel G: Bond-Oil Dependence Structure			
AIC	-520.391	-518.871	-478.333
BIC	-497.168	-482.260	-426.031
Panel H: Real estate-Gold Dependence Structure			
AIC	-168.608	-243.788	-189.917
BIC	-95.384	-207.176	-137.615
Panel I: Real estate-Oil Dependence Structure			
AIC	-349.523	-357.599	-351.277
BIC	-276.299	-320.987	-298.973
Panel J: Gold-Oil Dependence Structure			
AIC	-12.133	-39.949	-130.545
BIC	-60.902	-3.337	-78.242

Note: The table reports the factor contributions for the Markov switching stochastic volatility models. Panels A to J reports the factor contributions of the various dependence structure. The set of macroeconomic state variables include risk free rate, output gap, inflation, and risk aversion. The non-macro factors are output uncertainty, inflation uncertainty, equity illiquidity measure, bond illiquidity measure, term spread, variance premium and depth of recession. AIC is Akaike information criterion and BIC is Bayesian information criterion. Based on the information criteria, i.e. AIC and BIC, the findings indicate that the fit worsens considerably when the non-macro factors are dropped for equity-bond and equity-oil pairs' dependence structure. The macroeconomic factors play a dominant role in explaining the dependence structure of the equity-real estate, the real estate-gold and the real estate-oil pairs.

7.3.4 The MGARCH framework and Covariance Dynamics – Robustness Check

In this section, I examine the robustness of my previous results. Since the dependence structures are a scaled statistic of the covariances and the asset return volatilities, for robustness check, I examine the factor exposure of the conditional asset return co-volatility using regime switching MGARCH framework.

While in my above discussion I estimate the appropriate regime using the Regime Classification Statistic, here I characterize the latent regime shift variable between two possible states of the return covariance dynamics. Considering $S_{i,t}$ as the endogenous latent regime variable dependent of the asset return co-variance over time, I characterize the value of $S_{i,t}$ to High (HS) and Low (LS) state if they exceed one standard deviate away from the mean on either direction. The two states/regimes are defined as

$$S_{i,t} = 1, if\left[\rho_{j,k} > \left\{mean\left(\rho_{j,k}\right) + 1st.dev.\left(\rho_{j,k}\right)\right\}\right]$$

$$S_{i,t} = 0, if\left[\rho_{j,k} < \left\{mean\left(\rho_{j,k}\right) - 1st.dev.\left(\rho_{j,k}\right)\right\}\right]$$

This allows me to check for the robustness of our regime switching analysis discussed in the previous section. The regime states evolve through a Markov process with conditional probabilities of the switching states given by

$$P_{S_{i,t}} = \left[Prob\left(\frac{S_{i,t} = 1}{S_{i,t} = 0}\right)\right], \sum P_{S_{i,t}} = 1$$

In the above equation $\rho_{j,k}$ is the time-varying conditional asset return correlation for the asset pairs j and k. The time-varying correlation values are calculated using diagonal BEKK MGARCH model (Baba et. al, 1990).

In conducting the robustness check, I use BEKK model to estimate the dependence of the asset return comovements. The diagonal BEKK model is selected over other MGARCH models because of its following advantages i) the specifications allow for parsimonious model estimation, ii) the model is flexible to examine the dynamics of the conditional covariances and iii) the model ensures positive definiteness of the conditional covariances. More importantly I do not use the generalized BEKK model because it is likely that the parameter estimates of the generalized BEEK model are biased by the fact that they influence two variance equations simultaneously or by sole number of regressors (Tse, 2000). These critics do not all apply to the diagonal BEKK model that is used as the off-diagonal elements are equal to zero. Moreover the parameters to be estimated are lower while maintaining the positive definiteness of the conditional covariance matrix. I define the variance equations of the diagonal BEKK model by the following set of equations:

$$h_{11,t} = a_{11} + b_{11}^2 \varepsilon_{1,t-1}^2 + c_{11}^2 h_{11,t-1}$$

$$h_{22,t} = a_{22} + b_{22}^2 \varepsilon_{2,t-1}^2 + c_{22}^2 h_{22,t-1}$$

$$h_{12,t} = a_{12} + b_{11} b_{22} \varepsilon_{i,t-1}^2 + c_{11} c_{22} h_{12,t-1} \tag{7-1}$$

$$h_{12,t} = h_{21,t}$$

In the above equations $h_{11,t}$ and $h_{22,t}$ represent the conditional variance of the asset returns and $h_{12,t}$ is the covariance. Using the above specification I estimate the values of $h_{12,t}$, $h_{11,t}$ and $h_{22,t}$ to compute the time-varying conditional correlation estimates measuring the asset return comovements. The correlation coefficient is transformed from range $[-1,1]$ to $(-\infty,\infty)$ using Fisher's transformation, i.e. $\rho_{j,k}^{T} = \frac{1}{2} ln\left(\frac{1+\rho_{j.k}}{1+\rho_{j.k}}\right)$. The estimates of the diagonal BEKK parameters are provided in the Appendix. Next, I discuss the influence of the macroeconomic and non-macroeconomic variables on the regime switching behaviour of the asset return comovements.

Table 7-4 presents the factor exposures for the time varying conditional correlation estimates during the regimes, high (HS) and low (LS) states. The MGARCH regimes HS and LS correspond to the DSHS and DSLS regimes as discussed in the previous section. It is observed that the findings from our MGARCH framework are consistent with my previous results.

In particular, the findings show that the interest rate and inflation plays a significant role during the economic contraction phase. The impact of risk aversion on the asset return comovements is evident during the economic expansion regime. Considering the non-macroeconomic factors, uncertainty and liquidity measures significantly impact the return comovement. The findings also indicate the only the macroeconomic factors have an influence on the real estate-oil return comovements. Most importantly the influences of the factor exposures bear the same sign as our previous MSSV models. This adds to the robustness of the arguments made on the impact of the determinants of the asset return comovements during periods of economic expansion and economic contraction.

Table 7-4: Factor Exposure Using Regime Switching MGARCH Framework

Regimes	Macro-economic Factors				Non-macroeconomic Factors							
	RF	**O**	**I**	**RA**	**OU**	**IU**	**LR**	**DS**	**TS**	**VP**	**DR**	**TP**
Panel A: Equity-Bond Dependence Structure												
HS	1.34**	-0.53**	0.54**	-0.09	0.42**	-0.28	0.00	3.23**	0.37	0.14**	0.008	0.74***
	(0.006)	(0.009)	(0.092)	(0.99)	(0.001)	(0.767)	(0.999)	(0.021)	(0.910)	(0.051)	(0.999)	(0.026)
LS	1.82**	-0.04	-1.78**	-0.07	-0.48**	-0.08	-0.36*	-0.07	0.46	-0.20**	0.01	0.26**
	(0.026)	(0.992)	(0.024)	(0.993)	(0.025)	(0.739)	(0.056)	(0.949)	(0.975)	(0.053)	(0.981)	(0.004)
LL	106.058											
Panel B: Equity-Real Estate Dependence Structure												
HS	1.17***	-0.05	1.29**	0.01	-0.097	-0.040	0.00	0.10	0.36	0.20	0.01	0.72**
	(0.016)	(0.939)	(0.017)	(0.971)	(0.998)	(0.003)	(0.998)	(0.997)	(0.962)	(0.971)	(0.996)	(0.019)
LS	-0.96**	-0.01	-1.16**	0.01	0.25	0.11	0.00	0.06	-0.09	-0.38	0.02	0.28**
	(0.005)	(0.976)	(0.031)	(0.993)	(0.946)	(0.997)	(0.991)	(0.997)	(0.842)	(0.995)	(0.995)	(0.022)
LL	109.4											

Panel C: Equity-Gold Dependence Structure												
HS	-1.92**	5.54**	-1.96**	-0.23	-0.42**	6.75**	0.00	-1.40**	-0.30*	-0.19*	-0.14*	0.67***
	(0.009)	(0.011)	(0.009)	(0.918)	(0.004)	(0.006)	(.999)	(0.040)	(0.001)	(0.001)	(0.022)	-0.18
LS	0.08	0.41	0.07	0.13**	0.05	1.94**	0.00	-1.22**	-0.09	-0.07	-0.06	0.33**
	(0.964)	(0.955)	(0.994)	(0.003)	(0.968)	(0.005)	(0.998)	(0.025)	(0.819)	(0.992)	(0.996)	(0.001)
LL	110.048											
Panel D: Equity-Oil Dependence Structure												
HS	-0.05	0.07	0.35	0.35	1.60**	-0.05	0.00	0.54**	0.02	0.07	-0.11**	0.77***
	(0.974)	(0.995)	(0.995)	(0.977)	(0.004)	(0.992)	(0.999)	(0.005)	(0.991)	(0.765)	(0.976)	(0.033)
LS	-0.17	0.34	-0.69	0.31	0.57	0.31	0.00	-0.39*	-0.15	-0.01	0.19**	0.23**
	(0.957)	(0.719)	(0.944)	(0.959)	(0.993)	(0.796)	(0.889)	(0.032)	(0.889)	(0.994)	(0.009)	(0.032)
LL	107.563											
Panel E: Bond-Real estate Dependence Structure												
HS	2.28**	0.21	0.066	0.03	-0.03	-0.07	0.00	7.70**	-0.01	-0.12	-0.21*	0.68**
	(0.013)	(0.949)	(0.834)	(0.977)	(0.936)	(0.979)	(0.997)	(0.002)	(0.997)	(0.899)	(0.029)	(0.009)

LS	-0.22*	0.03	0.075	-0.12	0.30	0.01	0.00	1.97**	0.01	-0.06	0.04	0.32**
	(0.009)	(0.988)	(0.925)	(0.995)	(0.953)	(0.991)	(0.999)	(0.006)	(0.959)	(0.996)	(0.972)	(0.032)
LL	104.187											
Panel F: Bond-Gold Dependence Structure												
HS	0.14	0.16	0.07	0.07	-0.15**	0.28***	0.00	-0.13**	-0.06	-0.02	0.00	0.73**
	(0.991)	(0.991)	(0.999)	(0.999)	(0.007)	(0.028)	(0.997)	(0.007)	(0.993)	(0.996)	(0.999)	(0.007)
LS	0.16	-0.47	-0.08	0.00	0.38***	-0.51***	0.00	1.52**	0.02	-0.11	0.00	0.27**
	(0.996)	(0.979)	(0.993)	(0.999)	(0.001)	(0.002)	(0.999)	(0.005)	(0.996)	(0.996)	(0.999)	(0.029)
LL	117.592											
Panel G: Bond-Oil Dependence Structure												
HS	-0.21*	-0.06	-0.89**	0.15	0.36*	0.03	0.00	-0.64**	-0.080	0.29	-0.01	0.72***
	(0.002)	(0.968)	(0.005)	(0.993)	(0.017)	(0.989)	(0.999)	(0.002)	(0.996)	(0.997)	(0.998)	(0.005)
LS	-1.10**	0.28	0.44**	0.12**	-0.45*	-0.08	0.00	1.86**	0.12	0.09	0.02	0.82**
	(0.969)	(0.016)	(0.005)	(0.998)	(0.996)	(0.976)	(0.999)	(0.009)	(0.991)	(0.976)	(0.997)	(0.005)
LL	288.195											

Panel H: Real estate-Gold Dependence Structure												
HS	-1.29**	-0.17	-0.88*	-0.85***	0.06	-0.07	0.00	0.13	-0.06	-0.01	0.00	0.65**
	(0.002)	(0.998)	(0.996)	(0.002)	(0.996)	(0.992)	(0.999)	(0.995)	(0.997)	(0.999)	(0.999)	(0.003)
LS	1.08**	0.15	-3.51*	0.22*	-0.16	0.07	0.00	0.05	1.93**	0.06	0.00	0.35**
	(0.004)	(0.894)	(0.001)	(0.9)89	(0.783)	(0.992)	(0.999)	(0.996)	(0.011)	(0.994)	(0.999)	(0.001)
LL	101.06											
Panel I: Real estate-Oil Dependence Structure												
HS	1.80**	0.03	0.83**	0.045	0.15	-0.18	0.00	0.01	-0.08	0.09	0.00	0.68***
	(0.005)	(0.996)	(0.006)	(0.992)	(0.994)	(0.968)	(0.999)	(0.999)	(0.994)	(0.985)	(0.999)	(0.018)
LS	-0.01	-0.60*	1.06**	-0.28	0.10	0.13	0.00	-0.20	0.16	0.25	-0.04	0.32**
	(0.997)	(0.004)	(0.001)	(0.967)	(0.998)	(0.992)	(0.999)	(0.971)	(0.891)	(0.935)	(0.997)	(0.035)
LL	110.836											
Panel J: Gold-Oil Dependence Structure												
HS	0.05	-0.03	-0.10	0.06	0.13	-1.01**	0.00	1.78***	-0.39**	-0.06	0.02	0.69**
	(0.993)	(0.988)	(0.977)	(0.991)	(0.908)	(0.998)	(0.997)	(0.005)	(0.048)	(0.939)	(0.991)	(0.001)

LS	0.02	0.09	0.34	0.01	0.12	-1.69**	0.00	-0.62**	-0.76**	0.07	-0.07	0.31**
	(0.990)	(0.982)	(0.970)	(0.998)	(0.916)	(0.002)	(0.999)	(0.012)	(0.032)	(0.995)	(0.962)	(0.008)
LL	114.16											

Note: The table reports the summary the parameter estimation results of regime switching MGACH framework of the ten state variables for the various dependence structure. The estimates presents the factor exposures for the time varying conditional correlation estimates during the regimes, high (HS) and low (LS) states. The MGARCH regimes HS and LS correspond to the DSHS and DSLS regimes as discussed in Table 2. The HS regime relates to economic contraction phase and LS regime relates to economic expansion phase. In the set of macroeconomic state variables RF is risk free rate, O is output gap, I is inflation and RA is risk aversion. In the set of non-macro factors OU is output uncertainty, IU inflation uncertainty, LR measure equity illiquidity, DS is bond illiquidity measure, TS is term spread, VP is variance premium and DR is depth of recession. LL corresponds to the Log-Likelihood values of the regime switching model. The standard errors are reported in parenthesis. The sample period is from the fourth quarter 1987 to the fourth quarter 212.

** corresponds to 5 percent significance level and *** corresponds to one percent significance level.

7.4 Summary

Considerable time variation in the asset return comovements has been of key interest to portfolio managers and academic researchers. Much of the research in this area has been restricted to the conventional financial assets, i.e. stocks and bonds. There is little research on the impact of changes in the real economy and non-macroeconomic factors on the return dynamics of assets comprising financial, commodity and real estate. Further, the extant research has examined the asset return comovements by using linear correlation as a measure of comovements. However, it is well recognized in the literature that linear correlation fails to provide an accurate estimate of the dependence structure when dealing with multivariate distributions with complex dynamic characteristics. In this work this limitation is addressed using the copula approach.

Using quarterly US data from 1987 to 2012 (1^{st} August 1987 to 1^{st} September 2012) for three different asset classes and several macro and non-macroeconomic variables, this study reports a number of significant findings. First, I confirm that the dependence structures of asset return comovements of all asset pairs show significant regime-switching behaviour both in terms of statistical and economic significance. Two regimes are identified which corresponds to economic expansion and economic contraction phases. Specifically, the DSLS corresponds to the economic expansion phase and the DSHS corresponds to the economic contraction phase. Second, examining the factor contributions, it is evident that the model fit worsens considerably when the non-macro factors are dropped for the equity-bond and equity-oil pairs. Third, the results indicate that interest rate and inflation have significant effect on the dependence structure during the economic contraction regime, whilst risk aversion plays a significant in the economic expansion regime. Among the non-macro factors output uncertainty, bond illiquidity measure and depth of recession contribute significantly in explaining the variations of the dependence structures. Fourth, the findings reveal that real estate-oil dependence structure is influenced only by macroeconomic developments. Finally, the study shows that the dependence structure regimes are asset return comovement specific. This suggests that macroeconomic and non-macro variables affect different asset return comovements differently.

Overall, the regime switching analysis of the dependence structure has two key implications for asset allocation and portfolio diversification. First, the changing regimes of the asset return comovements demonstrate the potentials gains of timely switching over from risky assets like stocks, oil to bond and gold. These regimes correspond to economic expansion and economic contraction periods characterized by low and high asset return covariance, respectively. Second, the dependence structure of all asset pairs is higher during the economic decline phase than during economic expansion phase, except for equity-gold and bond-oil pairs. This implies that investment in gold provides diversification for equity-based portfolio, while bond provides a good hedge for oil.

7.5 Appendix

Table 7 (A-1): Parameter Estimates of the Two-State Markov Switching Stochastic Volatility Model

	Macro-economic Factors				Non-macroeconomic Factors									
	RF	**O**	**I**	**RA**	**OU**	**IU**	**LR**	**DS**	**TS**	**VP**	**DR**	**Std. Dev.**	**TP**	**Dur.**
Panel A: Equity-Bond Dependence Structure														
DSHS	7.43**	-3.4**	10.4**	0.007	4.41**	-0.53	-0.002	4.13**	0.55	1.16***	-0.02	0.078***	0.86***	29.9
	(0.58)	(0.78)	(0.43)	(0.005)	(0.53)	(0.58)	(0.00)	(0.32)	(0.35)	(0.32)	(0.01)	(0.008)	(0.26)	
DSLS	13.16**	-0.254	-6.42**	-0.016	-11.4***	-0.977	-0.16**	-1.65**	0.94	-1.37**	-0.043	0.069*	0.82**	10.66
	(0.78)	(0.88)	(0.66)	(0.82)	(0.9)	(0.75)	(0.92)	(0.67)	(0.86)	(0.98)	(0.92)	(0.002)	(0.84)	
AIC	-115.170													
BIC	-91.947													
LL	85.585													
Panel B: Equity-Real Estate Dependence Structure														
DSHS	12.9***	-0.04	11.98**	0.005	-0.09	-0.43	-0.01	-0.15	0.27	0.49	-0.02	0.097***	0.88**	14.76
	(0.34)	(0.64)	(0.48)	(0.87)	(0.44)	(0.92)	(0.99)	(2.49)	(0.20)	(0.99)	(0.00)	(0.0004)	(0.19)	
DSLS	-2.93*	0.03	-13.98**	-0.001	0.20	0.60	0.01	0.08	-0.07	-0.4	0.01	0.03***	0.78**	6.14
	(0.71)	(0.53)	(0.90)	(0.92)	(0.24)	(0.93)	(0.99)	(0.99)	(0.96)	(0.99)	(0.99)	(0.0003)	(0.22)	
AIC	-157.069													
BIC	-83.845													

LL	106.534													
Panel C: Equity-Gold Dependence Structure														
DSHS	-3.00***	3.02**	-23.1**	-0.001	-0.52**	3.35**	0.005	-1.51**	-0.4**	-0.5**	-0.13**	0.021**	0.67***	7.56
	(0.19)	(0.26)	(0.21)	(0.002)	(0.264)	(0.514)	(0.93)	(0.13)	(0.09)	(0.12)	(0.002)	(0.000)	(0.18)	
DSLS	-0.06	-0.08	-0.07	0.14*	0.033	7.55**	-0.001	1.12*	0.012	0.034	0.01	0.064	0.73**	8.88
	(0.99)	(0.99)	(0.99)	(0.002)	(0.99)	(0.99)	(0.91)	(1.73)	(0.99)	(0.99)	(0.99)	(0.99)	(0.56)	
AIC	-391.583													
BIC	-355.241													
LL	209.926													
Panel D: Equity-Oil Dependence Structure														
DSHS	-0.083	0.26	0.06	0.025	5.24**	-0.24	0.003	0.15**	0.646	0.09	-0.06**	0.133***	0.77***	19.84
	(0.93)	(0.94)	(0.89)	(0.87)	(0.239)	(0.51)	(0.99)	(0.119)	(0.94)	(0.99)	(0.029)	(0.006)	(0.33)	
DSLS	-0.399	0.029	-0.14	0.015	0.018	0.187	0.0012	-0.73**	-0.65	-0.85	0.54**	0.071***	0.73**	14.46
	(0.169)	(0.27)	(0.21)	(0.025)	(0.205)	(0.557)	(0.95)	(0.03)	(0.99)	(0.92)	(0.026)	(0.002)	(0.32)	
AIC	40.769													
BIC	113.993													
LL	7.615													
Panel E: Bond-Real estate Dependence Structure														
DSHS	8.44**	0.67	0.23	0.002	-0.35	-0.90	-0.041	3.9*	-0.145	-0.29	-0.57*	0.030***	0.82**	25.32
	(0.29)	(0.99)	(0.42)	(0.002)	(0.93)	(0.93)	(0.99)	(0.17)	(0.90)	(0.99)	(0.00)	(0.000)	(0.14)	

DSLS	-2.1**	0.08	-0.37	-0.01	0.061	0.02	0.01	6.71*	-0.05	0.30	0.04	0.0251	0.78**	6.52
	(0.106)	(0.99)	(0.99)	(0.99)	(0.99)	(0.97)	(0.99)	(0.135)	(0.99)	(0.93)	(0.99)	(0.99)	(0.32)	
AIC	-192.375													
BIC	-119.152													
LL	124.187													
Panel F: Bond-Gold Dependence Structure														
DSHS	0.091	0.03	0.09	0.08	-2.73**	0.53**	-0.003	-1.06**	-0.31	-0.82**	0.005	0.027**	0.83**	10.02
	(0.94)	(0.78)	(0.87)	(0.00)	(0.01)	(0.20)	(0.99)	(0.06)	(0.75)	(0.36)	(0.99)	(0.00)	(0.37)	
DSLS	0.06	-0.19	-0.07	0.02	3.48**	-1.19**	0.002	3.31***	0.49	-0.22	0.002	0.091**	0.77**	6.75
	(0.98)	(0.91)	(0.97)	(0.99)	(0.07)	(0.08)	(0.99)	(0.07)	(0.94)	(0.83)	(0.99)	(0.00)	(0.29)	
AIC	-239.127													
BIC	-165.904													
LL	147.563													
Panel G: Bond-Oil Dependence Structure														
DSHS	-1.72**	-0.01	-0.30**	0.083	1.39**	0.069	0.00	-0.33**	-0.01	0.031	-0.01	0.009**	0.72***	9.31
	(0.04)	(0.98)	(0.49)	(0.91)	(0.061)	(0.92)	(0.99)	(0.39)	(0.92)	(0.96)	(0.99)	(0.00)	(0.05)	
DSLS	-0.95**	0.12	0.76**	0.124**	-1.06**	-0.46	0.00	3.86**	0.005	0.025	0.002	0.012**	0.82**	13.5
	(0.04)	(0.83)	(0.01)	(0.01)	(0.061)	(0.99)	(0.99)	(0.23)	(0.99)	(0.95)	(0.99)	(0.00)	(0.05)	
AIC	-520.391													
BIC	-497.168													

LL	288.195													
Panel H: Real estate-Gold Dependence Structure														
DSHS	-7.01**	-0.07	-0.58**	-0.67**	0.00	-0.33	0.01	0.480	-0.40	-0.40	-0.001	0.080**	0.75**	13.78
	(0.19)	(0.97)	(0.14)	(0.00)	(0.99)	(0.92)	(0.99)	(0.91)	(0.99)	(0.91)	(0.99)	(0.00)	(0.07)	
DSLS	1.60**	0.37	-0.22**	0.71**	-0.07	0.54	0.00	0.28	0.24*	0.011	-0.001	0.025**	0.85**	5.70
	(0.01)	(0.99)	(0.01)	(0.00)	(0.99)	(0.99)	(0.99)	(0.99)	(0.01)	(0.00)	(0.99)	(0.00)	(0.01)	
AIC	-168.608													
BIC	-95.384													
LL	112.280													
Panel I: Real estate-Oil Dependence Structure														
DSHS	5.01**	0.06	-0.68**	0.003	0.483	-0.21	0.01	0.49	-0.24	0.20	-0.04	0.036***	0.85***	21.91
	(0.02)	(0.98)	(0.335)	(0.99)	(0.94)	(0.85)	(0.99)	(0.91)	(0.96)	(0.97)	(0.99)	(0.00)	(0.18)	
DSLS	-0.2.0	-0.92**	1.08**	-0.02	0.34	0.05	-0.11	-0.07	0.13	-0.12	0.07	0.019**	0.64**	4.56
	(0.94)	(0.07)	(0.30)	(0.99)	(0.92)	(0.99)	(0.84)	(0.99)	(0.93)	(0.99)	(0.99)	(0.00)	(0.35)	
AIC	-349.523													
BIC	-276.299													
LL	202.761													
Panel J: Gold-Oil Dependence Structure														
DSHS	0.35	-0.09	-0.07	0.00	0.31	-0.41**	0.001	4.28**	-0.81**	-0.08	0.01	0.21***	0.78**	30.6
	(0.71)	(0.93)	(0.68)	(0.99)	(0.96)	(0.25)	(0.99)	(0.04)	(0.41)	(0.94)	(0.99)	(0.00)	(0.99)	

DSLS	0.07	0.05	0.19	0.01	0.07	-1.01**	-0.02	4.23**	-0.22**	0.04	-0.03	0.065**	0.72**	11.89
	(0.99)	(0.99)	(0.91)	(0.99)	(0.99)	(0.09)	(0.99)	(0.11)	(0.07)	(0.99)	(0.99)	(0.00)	(0.08)	
AIC	-12.133													
BIC	60.902													
LL	34.160													

Note: The table reports the summary the parameter estimation results of the Markov switching stochastic volatility models of the ten state variables for the various dependence structure. The appropriate numbers of regimes are identified by the Regime Classification Statistic as stated in Equation (10). The findings indicate significant transition probabilities for both the regimes. The two regimes are identified as the Dependence Structure High State (DSHS) regime (State 1) and the Dependence Structure Low State (DSLS) regime (State 2). DSHS relates to economic contraction phase and DSLS relates to economic expansion phase. In the set of macroeconomic state variables RF is risk free rate, O is output gap, I is inflation and RA is risk aversion. In the set of non-macro factors OU is output uncertainty, IU inflation uncertainty, LR measure equity illiquidity, DS is bond illiquidity measure, TS is term spread, VP is variance premium and DR is depth of recession. Significant impacts of the independent variables are shown in the table. SD reports the standard deviation of the regime states. TP corresponds to the transition probabilities of the two states. TP for state 1 refers to the probability of the dependence measure to stay in the expansion regime and TP for State 2 corresponds to the probability of the dependence measure to stay in contraction regime. The Standard errors are reported in parenthesis. Duration (Dur) corresponds to the expected duration of the Dependence Structure High State (DSHS) regime (State 1) and the Dependence Structure Low State (DSLS) regime (State 2). The sample period is from the fourth quarter 1987 to the fourth quarter 212. The coefficient estimates can be provided on request.

** corresponds to 5 percent significance level and *** corresponds to one percent significance level.

Table 7 (A-2): Parameter Estimates of Diagonal BEKK – MGARCH model

		Variance Equation Parameters						
		a_{11}	a_{12}	a_{22}	b_{11}	b_{22}	c_{11}	c_{22}
Equity-Bond	Coefficient	0.000	0.000	0.000	0.634**	0.032**	0.780***	0.844**
	Std. Error	0.000	0.000	0.000	0.174	0.149	0.099	0.311
	LL	420.619						
Equity-Gold	Coefficient	0.000	0.000	0.000	-0.624**	0.267***	0.792***	0.949***
	Std. Error	0.000	0.000	0.000	0.174	0.094	0.082	0.057
	LL	346.942						
Equity-Real Estate	Coefficient	0.001	0.000	0.000	0.163**	0.698**	0.819***	0.743***
	Std. Error	0.000	0.000	0.000	0.103	0.148	0.068	0.058
	LL	543.997						
Equity-Oil	Coefficient	0.000	0.000	0.003	0.794**	0.512**	0.705**	0.657**
	Std. Error	0.000	0.000	0.002	0.167	0.115	0.092	0.200
	LL	280.883						
Bond-Gold	Coefficient	0.000	0.000	0.000	-0.024**	0.288**	0.914**	0.947***
	Std. Error	0.000	0.000	0.000	0.294	0.109	0.132	0.064
	LL	423.010						

Bond-Real Estate	Coefficient	0.000	0.000	0.000	0.188**	0.717**	0.840**	0.729***
	Std. Error	0.000	0.000	0.000	0.103	0.157	0.231	0.059
	LL	626.505						
Bond-Oil	Coefficient	0.000	0.000	0.003	-0.216**	0.608**	0.844**	0.605***
	Std. Error	0.000	0.000	0.002	0.179	0.110	0.259	0.223
	LL	351.603						
Real Estate-Gold	Coefficient	0.000	0.000	0.000	0.229**	0.745**	0.957***	0.709***
	Std. Error	0.000	0.000	0.000	0.092	0.148	0.066	0.053
	LL	550.264						
Real Estate-Oil	Coefficient	0.000	0.000	0.005	0.782**	0.409**	0.744***	0.470**
	Std. Error	0.000	0.000	0.002	0.107	0.087	0.041	0.311
	LL	476.061						
Gold-Oil	Coefficient	0.000	0.000	0.002	0.392**	0.604**	0.916***	0.656**
	Std. Error	0.000	0.000	0.002	0.129	0.170	0.063	0.202
	LL	280.937						

Table 7 (A-2) presents the diagonal BEKK – MGARCH estimates of the 10 bivariate asset pairs. These asset pairs consist of three different asset classes. The asset pairs are Equity-Bond, Equity-Gold, Equity-Real Estate, Equity-Oil, Bond-Gold, Bond-Real Estate, Bond-Oil, Real Estate-Gold, Real Estate-Oil and Gold-Oil. In this study the variance equations of the diagonal BEKK model are defined by the following set of equations:

$h_{jj,t} = a_{11} + b_{11}^2 \varepsilon_{j,t-1}^2 + c_{11}^2 h_{jj,t-1}$, $h_{kk,t} = a_{22} + b_{22}^2 \varepsilon_{k,t-1}^2 + c_{22}^2 h_{kk,t-1}$, $h_{jk,t} = a_{12} + b_{11} b_{22} \varepsilon_{j,t-1} \varepsilon_{k,t-1} + c_{11} c_{22} h_{jk,t-1}$ and $h_{jk,t} = h_{kj,t}$. In these equations $h_{jj,t}$ and $h_{kk,t}$ represent the conditional variance of the asset returns$j$ and k and $h_{jk,t}$ is asset return covariance. The matrices 'b'

and 'c' are assumed to be diagonal matrices. Using the above specification the values of $h_{jk,t}$,$h_{jj,t}$ and $h_{kk,t}$ are estimated to compute the time-varying conditional correlation estimates measuring the asset return comovements.

** corresponds to 5 percent significance level and *** corresponds to one percent significance level.

Table 7 (A-3): Diagnostic Check of the Diagonal BEKK – MGARCH models

	Equity-Bond		Equity-Gold		Equity-Real Estate		Equity-Oil		Bond-Gold	
Lags	Q-Stat	Prob.	Q-Stat	Prob.	Q-Stat	Prob.	Q-Stat	Prob.	Q-Stat	Prob.
1	1.920609	0.7504	7.131075	0.1291	6.761696	0.1490	3.528402	0.4736	8.067143	0.0891
2	7.037174	0.5326	8.704601	0.3678	13.18022	0.1058	5.362587	0.7182	10.81184	0.2126
3	14.05220	0.2974	11.16584	0.5148	19.33946	0.0807	7.140146	0.8482	14.60964	0.2635
4	17.33161	0.3645	13.55977	0.6315	25.75927	0.0575	10.58926	0.8341	18.29890	0.3067
5	23.34273	0.2723	14.94830	0.7794	37.32855	0.0107	13.48406	0.8557	23.42872	0.2682
6	25.09550	0.4006	16.45047	0.8711	41.71569	0.0139	18.17736	0.7943	24.53787	0.4312
7	29.76401	0.3746	20.98426	0.8260	45.39450	0.0201	22.23211	0.7704	29.56928	0.3841
8	30.97365	0.5183	22.52350	0.8928	46.61476	0.0459	25.56056	0.7827	32.15103	0.4593
9	35.77808	0.4791	25.52824	0.9030	52.25894	0.0390	30.09536	0.7448	36.40412	0.4498
10	38.79038	0.5246	32.86939	0.7807	57.30889	0.0373	32.93864	0.7781	43.95188	0.3078

11	41.64262	0.5732	39.70749	0.6560	62.07737	0.0374	34.42498	0.8493	54.47330	0.1339
12	42.95235	0.6793	41.53405	0.7334	64.60179	0.0551	35.23641	0.9147	58.02773	0.1523
	Bond-Real Estate		Bond-Oil		Real Estate-Gold		Real Estate-Oil		Gold-Oil	
Lags	Q-Stat	Prob.	Q-Stat	Prob.	Q-Stat	Prob.	Q-Stat	Prob.	Q-Stat	Prob.
1	1.939815	0.7468	6.694748	0.1529	3.563686	0.4683	7.202386	0.1256	5.572912	0.2334
2	7.159745	0.5195	12.98617	0.1123	5.434926	0.7102	8.807700	0.3588	10.74244	0.2167
3	14.38952	0.2765	18.96247	0.0894	7.266899	0.8395	11.34429	0.4997	13.00194	0.3689
4	17.80416	0.3355	25.12803	0.0676	10.85825	0.8181	13.83693	0.6109	15.31505	0.5017
5	24.12835	0.2368	36.12457	0.0149	13.90382	0.8353	15.29778	0.7591	16.58735	0.6796
6	25.99183	0.3536	40.25108	0.0201	18.89354	0.7576	16.89483	0.8531	20.02658	0.6953
7	31.00800	0.3167	43.67493	0.0299	23.25023	0.7204	21.76624	0.7920	25.32240	0.6102
8	32.32170	0.4509	44.79853	0.0660	26.86500	0.7241	23.43788	0.8640	33.33293	0.4022
9	37.59612	0.3960	49.93977	0.0612	31.84343	0.6666	26.73657	0.8691	35.98532	0.4693
10	40.93944	0.4291	54.48973	0.0630	34.99915	0.6946	34.88444	0.6995	45.14968	0.2655
11	44.14028	0.4657	58.73886	0.0677	36.66715	0.7757	42.55831	0.5335	50.94354	0.2192
12	45.62661	0.5706	60.96336	0.0991	37.58800	0.8603	44.63115	0.6117	51.82609	0.3270

Table 7 (A-3) reports the Q-statistics of the autocorrelation function of the standardized residuals of the diagonal BEKK models. In total the results are presented for 10 bivariate pairs – a combination of three different asset classes. The asset pairs are Equity-Bond, Equity-Gold, Equity-Real Estate, Equity-Oil, Bond-Gold, Bond-Real Estate, Bond-Oil, Real Estate-Gold, Real Estate-Oil and Gold-Oil. The Null Hypothesis of the Q-test is: There is no residual autocorrelations up to lag h. The tests are performed for 12 lags. The findings indicate that the Null Hypothesis cannot be rejected. Thus, there is no evidence of autocorrelation in the residuals of the diagonal BEKK – MGARCH models. This ensures the adequacy of the BEKK – MGARCH models in attaining reliable estimates and inference.

CHAPTER 8

Examining the Determinants of the Joint Dependence Structure

8.1 Introduction

This chapter examines the macroeconomic and the non-macroeconomic variables that influence the Joint Dependence Structure (JDS) of the non-linear asset returns of three different asset classes. This study is important because it presents the first empirical evidence examining the factors that drive the joint return distribution combining different asset classes.

But, why study the joint dependence structure? It is fair to say that investors no longer invest in only conventional financial assets such as equities and bonds, but in a wide range of alternative financial assets including commodities and real estate. Therefore, in constructing an optimal portfolio, it is critical to identify the economic circumstances and understand the impact of macro and non-macro factors on asset return comovements.

Fewer studies have dealt with a combination of bivariate asset return dynamics; however, research on the joint dependence structure of a portfolio of all the different asset classes, which I refer as multi-assets, is non-existent. Against this backdrop, the purpose of this examination is three fold: First, I seek to analyse if the JDS of the multi-asset return comovements exhibit evidence of regime switching behaviour. Second, this study examines the factor exposure of various macro and non-macroeconomic variables on the JDS. Third, I investigate the factor contributions in different regimes.

This empirical investigation has a number of distinct features. First, similar to my previous examination of the bivariate dependence structure, this analysis considers i) three different asset classes, ii) a wide range of macroeconomic and non-macroeconomic variables and iii) the period of analysis is from 1987 to 2012 (1^{st} August 1987 to 1^{st} September 2012), which allows me to capture the effects of economic contraction caused by several financial crises on the behaviour of different asset classes. It is, to the best of my knowledge, the first study that examines the factors that drive the joint dependence structure for a portfolio of three different asset classes. Second, while research widely acknowledges that return distributions of financial assets are non-normal, the extant literature primarily uses linear dependence measure to examine the asset market linkages. I, therefore, use dynamic conditional multivariate model as an alternative measure of association which overcomes the limitations of simple linear correlation in examining the extreme dependence structure of the asset return comovements.

Third, I use two stage structural factor model framework in examining the dynamics of the state variables and their influence on the JDS. Further, the state variables are estimated through a New-Keynesian framework. Importantly, the regime-switching model accommodates for heteroskedastic shocks in the state variables. The details of the model development and the model specifications are provided in Chapter 6. Finally, this study decomposes the performance of the Markov switching stochastic volatility (MSSV) model to examine the impact of the macroeconomic and the non-macroeconomic factors. This provides useful insights in identifying the key determinants of multi-asset return comovements.

Finally, towards the end of this chapter, I examine the practical applications of this research work. I examine the forecasting performance and the economic value of understanding asset return comovements. Specifically, I present the forecasting analysis of the MSSV models that capture the dynamic behaviour of the asset return comovements. Further, I check whether regime switching forecast provides more accurate results than a single regime stochastic volatility model. This adds to the robustness of the application of the developed regime switching model.

This chapter reports several key findings. First, the findings confirm that the joint dependence structures of asset return comovements show significant regime-switching behaviour both in terms of statistical and economic significance. The two regimes identified represent economic expansion and economic contraction phases. Second, the findings show that among the macroeconomic variables, inflation plays a central role (positive influence) during both the phases of the economy. Also, risk aversion is positively significant during the economic contraction phase, whereas risk free rate negatively affects the JDS during the economic expansion period. This indicates that when risk aversion is high during periods of economic contraction, interest rates may be low, increasing the bond prices, but riskier assets like stocks which are positively correlated with interest rate shocks during economic contraction may witness fall in prices. Third, among the non-macroeconomic factors, uncertainty variables and bond illiquid play a dominant role in both the phases of the economy. The findings also report that input uncertainty and bond illiquidity have the highest coefficient values. The significant impact of the liquidity factor provides evidence for “flight-to-liquidity” phenomenon as reported in the previous literature (Connolly et al., 2005). While more research is accounted for in the field of “flight-to-liquidity” and its interaction with liquidity, some previous studies give credence to our findings. For instance, Li (2007) shows that systematic liquidity risk is priced in bond markets. However, they do not conduct study for other financial assets. Further, the significant influence of the economic uncertainty measures indicate that higher the uncertainty about future economic state variables, the more swiftly the investors are likely to react to news. This in turn affects both the variances and the covariances of the asset returns. Fourth, examining the factor contributions, it is observed that the model fit worsens considerably when the non-macro factors are dropped. Thus, it is fair to say that the non-macroeconomic factors play a vital role in explaining the variations in the JDS. My findings are also conclusive from the quartile regressions, which are conducted to test for robustness of the findings. An additional contribution of this thesis relates to the forecasting performance of the MSSV models. The findings show that MSSV framework enhances the flexibility in the model accommodating the persistence of volatility shocks. For instance, if shocks are more persistent in periods of economic contraction than in periods of economic recovery, this can be captured by the regime parameters. Moreover, the Markov switching model is able to capture the 'pressure smoothening' effects of those shocks that are not persistent and are followed by low volatility regimes. The results also indicate that the dynamic strategy which considers the factors that drive the return comovements outperforms the portfolio returns constructed based on multivariate conditional covariance strategy.

The rest of the chapter is organized as follows: Section 2 discusses the factor exposure and the factor contributions of the state variables on the JDS. Section 3 provides the robust tests using quantile regressions. Sections 4 and 5 explores the contributions to practise of the research work. Specifically, Section 4 examines the forecasting performance of the Markov switching models and Section 5 analysis the economic value of understanding asset return comovements. Finally, Section 6 concludes the chapter.

8.2 Examining the Determinants of the Multi-Asset Return Comovements

As reported in the previous chapter, this work examine the determinants of the dependence structure of the comovements of two conventional financial assets, i.e. Standard & Poor's (S&P) 500 index (E) and US 10 year Government bond return index (B), two commodities, i.e. S&P GSCI Gold index (G) and West Texas Intermediate – WTI Cushing crude oil spot prices per barrel (O) and S&P Case-Shiller Composite-10 home price index (RE) for real estate. I characterize the dependence measure of the various asset returns using monthly returns to calibrate the ex-post quarterly dependence structure from the fourth quarter 1987 to the fourth quarter 2012 (1st August 1987 to 1st September 2012).

For examining the determinants of the joint dependence structure (JDS) of the comovement asset return, we include four macroeconomic variables, i.e., the risk free rate (rf), output gap (o), inflation (i), and risk aversion (ra) and seven non-macroeconomic variables, i.e. output uncertainty (ou), inflation uncertainty (iu), bond market illiquidity (ds), equity market illiquidity (lr), variance premium (vp), term spread (ts) and the depth of recession (dr). A detailed discussion on each of these state variables and their regime switching behaviour are presented in Chapters 6 and 7, respectively.

8.2.1 Regime Switching Behaviour of the Joint Dependence Structure

Let us begin by determining whether JDS shows evidence of regime switching. Panel A of Table 8-1 reports the transition probabilities of the two regimes, i.e. Regime 1 and

Regime 2, along with the respective expected durations[14] of the regimes. The two regimes are identified using the Regime Classification Statistic (RCS) as discussed in Chapter 6. The findings indicate significant transition probabilities for both the regimes. These identified regimes represent i) the Dependence Structure High State (DSHS) (Regime 1) and the Dependence Structure Low State (DSLS) (Regime 2).

The transition probability and the expected duration values presented in Panel A of Table 8-1 reveal that the JDS DSLS regime (Regime 2) tends to be considerably longer than its DSHS regime. This has key economic significance, suggesting that investments in various asset classes lead to considerable diversification as the JDS tends to stay in its lower state. It is worth noting that the standard deviation estimates are higher in the DSHS regime than in the DSLS regime (see Panel A). This indicates that the dependence structure is more volatile during the economic contraction regime, which corresponds to DSHS, than during the economic expansion regime, which corresponds to DSLS.

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[14]Following Hamilton's (1989) formula we estimate the expected duration of the regimes as $\sum_{i=0}^{\infty} i p_{11(22)}^{i-1}(1-p_{11(22)})$, where $p_{11}(p_{22})$ are the transition probabilities in Regime 1 (Regime 2).

Table 8-1: MSSV Model Estimates and Factor Exposure

Panel A: Model Characteristics

	Tr. Prob.	Std. Dev.	Exp. Duration	AIC
Regime 1 (DSHS)	0.850	0.050	6.657	-311.587
Regime 2 (DSLS)	0.904	0.011	10.385	

Panel B: Coefficient Estimates

		Macroeconomic Variables				Non-Macroeconomic Variables						
	Constant	RF	O	I	RA	OU	IU	LR	DS	TS	VP	DR
Regime 1- DSHS (Economic Contraction)	-0.173	0.100	-0.180	0.546**	0.166***	0.532***	-4.522***	-0.001	5.238**	0.097	0.013	-0.012**
	(0.164)	(0.779)	(0.120)	(0.012)	(0.006)	(0.005)	(0.003)	(0.258)	(0.038)	(0.421)	(0.914)	(0.032)
Regime 2 –DSLS (Economic Expansion)	-0.111	-1.552***	-0.056	0.722**	0.026	-0.135*	3.010***	0.000	-3.544***	0.048	0.037	0.002
	(0.479)	(0.000)	(0.167)	(0.044)	(0.448)	(0.052)	(0.000)	(0.721)	(0.000)	(0.676)	(0.672)	(0.356)

Panel C: Model Performance

	Full Model	(-) non-Macro	(-) Macro	(-) non-Macro & I	(-) Macro, IU & DS
AIC	-311.587	-240.045	-259.311	-232.11	-233.075
BIC	-238.363	-203.433	-207.008	-200.091	-203.011

Note: The table reports the Markov Switching Stochastic Volatility (MSSV) Model characteristics, the model estimates and the factor contribution to the model performance. Regime 1 corresponds to the expansion regime of the dependence measure (DSHS) and Regime 2 corresponds to the contraction regime of the dependence measure (DSLS). The expansion regime of the dependence structure (DSHS) relates to economic contraction (EC) phase and the contraction regime of the dependence structure (DSLS) relates to economic expansion (EE) phase. Panel A: Tr. Prob. (TP) corresponds to the transition probabilities of the two states. TP for state 1 refers to the probability of the dependence measure to stay in the expansion regime (DSLS) and TP for State 2 corresponds to the probability of the dependence measure to stay in contraction regime (DSLS). Std. Dev. reports the standard deviation of the regime states. The Standard errors are reported in parenthesis. Expected (Exp.) Duration (Dur.) corresponds to the expected duration of the dependence measure in the expansion regime (DSHS - Regime 1) and in the contraction regime (DSLS - Regime 2). The sample period is from the fourth quarter 1987 to the fourth quarter 212. Panel B: In the set of macroeconomic state variables RF is risk free rate, O is output gap, I is inflation and RA is risk aversion. In the set of non-macro factors OU is output uncertainty, IU inflation uncertainty, LR measure equity illiquidity, DS is bond illiquidity measure, TS is term spread, VP is variance premium and DR is depth of recession. Panel C: It reports the factor contributions of five different model characteristics. The corresponding AIC and BIC values are reported. It is evident that non-macroeconomic variables play a central role in enhancing the model fit. Further, among the non-macro variables illiquidity and uncertainty factors are significantly important. Among the macroeconomic variables, inflation plays an important role in defining the JDS.

* corresponds to 10 percent significance level, ** corresponds to 5 percent significance level and *** corresponds to one percent significance level.

8.2.2 Factor Exposure of the State Variables

The factor exposures of the macro and the non-macro variables for the JDS DSHS regime (Regime 1) and for the dependence structure DSLS regime (Regime 2) are reported in Table 8-1. Concerning the macroeconomic factors, in the economic contraction phase, inflation and risk aversion factor are significant, while in the economic expansion phase, risk-free rate and inflation are significant. Findings show that increase in risk averseness in the contraction phase increase the joint dependence of the return comovements. This suggests that when the risk aversion is high in a recession or crisis, interest rates may be low that increase the bond prices, further the risky assets positively correlated with the interest rates witness a decrease in their prices as well. More interestingly, inflation shows a positive influence on the JDS during both the regimes. This implies that (expected) inflation may reflect information about the real interest rate and hence may induce positive correlation between different asset returns. While no studies in the past have looked into the relationship between inflation and the combined return movement of different asset classes, some past literature on the effect of inflation and stocks gives credence to our finding on the positive influence inflation on the JDS. In particular, Fama and Schwert (1977) show that stocks are very poor hedges against inflation, an interpretation of this finding relates to the concept of money illusion (Campbell and Vuolteenaho, 2004).

Considering the non-macroeconomic factors, in the economic contraction regime, output uncertainty, inflation uncertainty, bond market illiquidity and depth of recession factors are significant, whereas in the economic expansion regime, inflation uncertainty and bond illiquidity factors are significant and 5 percent level or less. Overall, the factor coefficients indicate that the non-macroeconomic factors play a more dominant role in defining the multi-asset return comovements. This being said, the input uncertainty (IU) and bond illiquidity factors have the highest coefficient values. However, the influences of these factors are not alike. While IU negatively influences the dependence structure during the economic contraction phase, it has a positive influence during the economic expansion regime. The positive impact of IU reveals that during the economic expansion phase increasing economic uncertainties impact risk-premiums and asset valuations. This finding is also consistent with the learning models of Veronesi (1999), in which uncertainty decreases the equity risk premium. More interesting is the evidence of negative impact during the economic contraction phase, which suggests that through precautionary savings effect during periods of economic recession an increase in economic uncertainty lowers the interest rates. In contrast to the uncertainty factor, bond liquidity has a positive influence during the economic contraction phase and has a negative influence during the economic expansion phase. The former could simply emphasize how liquidity shocks comove across markets, whereas the latter is potentially consistent with the fact that economic recovery may drive investors and traders from less liquid Treasury bonds into highly liquid riskier assets like stocks, and the resulting price-pressure effects may induce negative return correlations among the more and the less risky financial assets. Thus, the findings' liquidity effects correlate to the "flight-to-liquidity" phenomenon.

8.2.3 Factor Contribution of the State Variables

In this section I present to what extent the various factors contribute in explaining the JDS of the multi-asset return comovements. To determine this, the MSSV model is re-estimated, leaving out various factors and reporting the determination in the model fit.

Panel C of Table 8-1 reports the results. The factors are divided into pure macro variables (the interest rate, output gap, inflation and risk aversion measure calibrated from consumption data) and the rest of the variables, i.e. non-macroeconomic factors (uncertainty measures, illiquidity measures, variance premium and depth of recession). Based on the information criteria, i.e. AIC and BIC, the message is clear and consistent across both the regimes. The findings indicate that the fit worsens considerably when the non-macro factors are dropped. Within the set of macroeconomic factors inflation plays the most significant role in both the regimes. Among the non-macroeconomic variables, uncertainty measures and the illiquidity factors are dominant in both the economic cycles in explaining the variations in multi-asset return comovements.

Overall, the findings indicate that non-macro factors contribute significantly in explaining the dynamics of the dependence structure. In particular, it is observed that the non-macro variables influence the JDS differently in different regimes. Finding that illiquidity measure load positively during the economic contraction phase, suggests that liquidity variation induces positive correlation among the asset returns. Though, more work in this area is needed, some previous studies give credence to my findings. Goyenko and Sarkissian (2008) report a strong linkage between bond illiquidity and stock returns. Li (2007) shows that systematic liquidity risk is priced in the bond market, while they do not consider other assets. Finally, Bansal et al. (2010) show that stock illiquidity aids in predicting stock-bond correlation.

8.3 Robustness Check of the Factor exposures

To make sure that my main conclusions are robust to measurement issues, I estimate the quantile regression model to further investigate the factors that drive the dependence structure. Though this approach permits estimating various quantile regressions (Koenker and Bassett, 1978), I rely on least absolute deviation regression to overcome the low-power problem of the ordinary least square regressions (Connolly, 1989). The results from the different quantile regressions help to provide robust description of the factors that drive underlying dependence structure in different regimes.

The coefficients of the quantile regression are estimated at θ (denotes the quartiles for which the relation between the dependence structures and the explanatory variables is estimated) at 0.10, 0.25, 0.50 and 0.75. I also include two additional extreme percentiles at 0.99 and 0.01 levels to observe the changes in the dependence structure when large deviations are present. The statically inferences from these regression models are drawn by the bootstrapping method (Andrews and Buchinsky, 2000; Angelis, Hall and Young, 1993). It is necessary to state here that lower θ values indicate economic expansion phase and the higher θ values indicate economic contraction phase.

The results are presented in Table 8-2. The findings are consistent with the previously stated MSSV model estimations. During the economic expansion phase, among the macro economic factors risk-free rate and inflation have significant influence and among the non-macro factors inflation uncertainty and bond illiquidity measures are significant. In the economic contraction phase, among the macro factors inflation and risk aversion factor is significant, while among the non-macro factors uncertainty and illiquidity measures have a significant impact on the JDS. Nevertheless more often than not the signs are consistent with the previous findings. The interest rate shock is negative in the economic expansion, which reflects the effect of discount rate on the asset returns. More intriguing is the insignificance of the variance premium in both the regimes. The variance premium measure allows in capturing the non-linearities in the consumption growth technology. Since, variance premium dependents positively with implied volatility of risky asset (such as stocks) returns but negatively with observed volatility, I can establish whether the "flight-to-liquidity" effect is due to the risk-premium component. Recall that the variance premium has counter cyclical pattern, being high in recession (discussed in Chapter 6). Thus, a positive coefficient suggests that the exposure of asset returns to cash flow shocks such as the output gap is increased in absolute terms in recession.

Table 8-2: Quantile Regressions and Factor Contributions to Model Performance

		Quantile Regression(θ)						OLS
Factors	Variables	0.01	0.10	0.25	0.50	0.75	0.99	Regression
Macroeconomic variables	RF	-1.150**	-0.862	-0.781	-0.873	-0.708	0.511	-0.085***
		(0.022)	(0.192)	(0.162)	(0.144)	(0.121)	(0.559)	(0.001)
	O	-0.348	-0.632	-0.095	-0.007	-0.062	-0.048	-0.087
		(0.545)	(0.287)	(0.144)	(0.067)	(0.183)	(0.319)	(0.194)
	I	0.883**	0.729***	0.587***	0.782***	0.502***	0.351***	0.772***
		(0.018)	(0.003)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
	RA	0.051	0.075	0.076	0.032**	0.032**	0.085***	0.064**
		(0.428)	(0.205)	(0.266)	(0.036)	(0.031)	(0.001)	(0.026)
Non-Macroeconomic variables	OU	-0.185	-0.132	-0.172*	0.163*	0.169**	0.432***	0.324**
		(0.156)	(0.189)	(0.092)	(0.065)	(0.011)	(0.004)	(0.038)
	IU	2.931***	1.847***	1.591***	2.300**	-2.156***	-4.994***	-2.453***
		(0.006)	(0.001)	(0.000)	(0.035)	(0.000)	(0.000)	(0.000)
	LR	0.000	0.000	0.000	0.000	0.000	0.000	0.000

	(0.672)	(0.789)	(0.841)	(0.811)	(0.500)	(0.805)	(0.774)
DS	-3.101***	-3.427***	-4.781***	2.872***	3.580***	6.930***	2.713***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TS	0.011	-0.106	-0.219	-0.131	-0.223	0.072	-0.245
	(0.956)	(0.636)	(0.339)	(0.457)	(0.178)	(0.810)	(0.136)
VP	0.033	0.186	0.099	-0.192	-0.004	-0.091	-0.057
	(0.874)	(0.401)	(0.658)	(0.247)	(0.982)	(0.790)	(0.653)
BS	0.004	0.001	0.006	0.003	0.001	-0.011**	0.002
	(0.556)	(0.906)	(0.234)	(0.421)	(0.805)	(0.022)	(0.581)
Constant	0.247	0.307	0.245	-0.107	-0.223	-0.223	-0.266*
	(0.357)	(0.195)	(0.370)	(0.623)	(0.319)	(0.491)	(0.072)
R^2Measure	0.576	0.538	0.466	0.458	0.583	0.645	0.623
JDS Mean	0.007	0.022	0.046	0.061	0.079	0.154	0.063

Note: The table reports quantile regression estimates at θ (denotes the quartiles for which the relation between the dependence structures and the explanatory variables is estimated). The lower θ values represent economic expansion regime and the higher θ values represent expansion regime.In the set of macroeconomic state variables RF is risk free rate, O is output gap, I is inflation and RA is risk aversion. In the set of non-macro factors OU is output uncertainty, IU inflation uncertainty, LR measure equity illiquidity, DS is bond illiquidity measure, TS is term spread, VP is variance premium and DR is depth of recession.

* corresponds to 10 percent significance level, ** corresponds to 5 percent significance level and *** corresponds to one percent significance level.

8.4 Examining the Forecasting Performance of MSSV Models

Thus far we have seen that this work provides rich insights for the practitioners and policy makers in three key domains: i) asset allocation, ii) Value at Risk and iii) asset pricing theory. The first domain relates to asset allocation: Consider an investor seeking to allocate resources between various assets, a classic approach is to design a portfolio that minimizes the return variances. But, in order to achieve this it is necessary to have the deeper insight on the asset return comovements that we analyse and present in this work. The second domain relates to Value at Risk (VaR): A key feature of VaR studies is to examine the extreme behaviour asset behaviour (Dave and Stahl, 1998). In this study I not only examine the dynamic behaviour of the asset return comovements during periods of economic expansion and contraction but also examine the factors that influence the return comovements. The third domain relates to establishing the link between higher moments of asset return and the factors that impact the return comovements. This primarily relates to the key feature of asset pricing theory in establishing the link between expected returns and covariance of returns (Ross 1976). A parametric approach assuming that asset returns (r_t) follow a classic factor analysis framework is expressed as $r_t = \alpha + \Sigma F_t + \varepsilon_t$, where $(\varepsilon_t' F_t')' \sim NID\left\{0, \begin{pmatrix} 1 & 0 \\ 0 & \sigma_F^2 \end{pmatrix}\right\}$, Σ is a matrix of factor loadings and F_t is a k-dimensional vector of factors. The asset pricing theory suggests that as the dimension of asset returns increase to such an extent that it well represents the market then α converges to $\alpha \cong Ir_f + \Sigma R_p$, where r_f is risk-free interest rate, I is a vector of ones and R_p represents a matrix of factor risk premiums associated with F_t. Applied researches in the field of asset pricing theories consider factor risk premiums as the variance of the factors. In line with the application of asset pricing theory, this study does not directly consider the asset returns but analyses the second moment of return comovements of N dimensional asset return series. In sum, this study presents a way of tackling asset pricing theory, portfolio analysis problems and Value at Risk. However, knowing that volatility of financial returns plays an important role in many financial decisions, it is important and useful for practitioners and policy makers to have one time ahead forecast of asset return comovements in taking investment and corrective decisions. Therefore, in this sub-section, I present the forecasting analysis of the MSSV models that capture the dynamic behaviour of the asset return comovements. Further, I check whether regime switching forecast provides more accurate results than a single regime stochastic volatility model. This adds to the robustness of the application of our regime switching model.

Since the main goal is to examine the asset return comovement forecasting performance using Markov switching stochastic volatility model, the study considers a reasonably adequate hold-off sample. Thus, 16 years of observation is chosen to estimate the model parameters and forecasting is estimated for 10 years. Moreover, since it is not a priori assumption that our switching model outperforms a single regime model, the exercise of forecasting is repeated for different subsamples. In essence, I fit the model for four years and estimate one step ahead forecast, delete the first observation and add the next one and then again re-estimate a one-step ahead forecast. In order to evaluate the possible changes in the pattern of the asset return comovements, this work performs the forecasting exercise for two subsamples. In the first one, the model is estimated for the period 1987 to 2002 and forecast for the period 2003 to 2012. For the second part I fit the model for 2003 to 2012 and forecast for the period 1987 to 1996.

To investigate the quality of the forecast, the median of squared errors (minimizes the impact of outlying observations on forecasting evaluation) of the forecasting period of both the regime switching MSSV model and the non-regime switching stochastic volatility model are calibrated. Further, based on Pagan and Schwert (1990) I run a forecast efficiency regression to examine whether the regime switching model out performs the non-regime model (NRM) in accommodating the dynamic volatility of the asset return comovements. I model the forecast efficiency regression as $v_{rc,t} = \alpha + \beta \hat{v}_{rc,t} + \epsilon_t$. In this framework, if the mean and the variance forecast of the asset return comovements are unbiased, then the regression implies that $\alpha = 0$ and $\beta = 1$. To test the forecasting efficiency the regression model is estimated using ordinary least square wherein standard errors are corrected for autocorrelation and heteroskedastic following Newey and West (1987). Further, the standard errors are corrected for the uncertainty originating from the estimation of the factors, i.e. the macro and the non-macroeconomic state variables, used to compute the forecasting. As rolling sample for forecasting is used, based on West and McCracken (1983) I multiply the Newey-West standard errors by $\sqrt{(1-\pi^2/3)}$, where $\pi = 10/16$, i.e. forecasting period by parameter estimation period.

Table 8-3 presents the median of squared errors (the difference between the median of squared errors of MSSV and the non-regime models) and the parameters of the forecast efficiency regression, i.e. α and β, for the MSSV and the non-regime switching models, respectively. The results are reported for the rolling forecasting for both the sub-samples. It is evident that the median of squared errors are significantly lower of the MSSV models. Moving on to the parameters of the forecast efficient regressions for the MSSV models it is observed that the null hypotheses $\alpha = 0$ and $\beta = 1$ are not rejected. The economic significance of this is that the MSSV models adequately capture the dynamics of the asset return comovements. In contrast for the non-regime switching model, the null hypotheses, i.e. $\alpha = 0$ and $\beta = 1$, are significantly rejected at 10 and 5 percent levels. This indicates that the non-regime switching models are inefficient in capturing the dynamics of the return comovements.

The findings of $\alpha \neq 0$ and $\beta \neq 1$ indicate that the non-regime switching model forecasts either underestimates or overestimates the true volatility of asset return comovements or both during phases of high and low volatility in return comovements. To distinguish between the two cases, i.e. high and low volatility of return comovements, I re-estimate the forecast efficiency regression by allowing a break in the regression line at the median forecast. That is to say that I have two pairs of (α, β) estimates, one pair (α^{+}, β^{+}) for forecasts above the median and (α^{-}, β^{-}) for below the median. The results are presented in the Table 8-4. The findings indicate that (α^{+}, β^{+}) are significantly different from $(0,1)$. The estimated negative coefficients of β^{+} indicates that non-regime models overestimate the true variance. This observation is in line with both the samples.

The findings imply that single-regime models provide inefficient estimates of asset return comovements during regimes of high volatility which is more profound during periods of economic contraction. Alternatively, my MSSV framework enhances the flexibility in the model accommodating the persistence of volatility shocks. For instance, if shocks are more persistent in periods of economic contraction than in periods of economic recovery, this can be captured by the regime parameters. Moreover, the Markov switching model is able to capture the ‘pressure smoothening’ that are not persistent and are followed by low volatility regimes.

Table: 8-3: Out-of-Sample Volatility Forecasting Using MSSV and Non-Regime Switching Model

Forecasted Asset-Return Comovements	Sample 1					Sample 2				
	MSE	α		β		MSE	α		β	
	(MSSV-NRSM)	MSSV	NRSM	MSSV	NRSM	(MSSV-NRSM)	MSSV	NRSM	MSSV	NRSM
Equity-Bond	0.013	0.000	0.003	0.995	-0.248	0.014	0.000	0.004	0.968	2.514
	0.042	1.000	0.059	0.826	0.038	0.011	1.000	0.049	0.113	0.028
Equity-Real Estate	0.006	0.000	0.001	0.976	1.269	0.010	0.000	0.002	1.017	1.160
	0.081	1.000	1.000	0.234	0.087	0.038	1.000	0.098	0.162	0.061
Equity-Gold	0.036	0.000	0.002	1.013	3.245	0.082	0.000	0.000	1.019	-0.016
	0.024	1.000	0.099	0.808	0.000	0.019	1.000	1.000	0.166	0.000
Equity-Oil	0.033	0.000	-0.001	1.042	1.590	0.053	0.000	0.028	0.962	0.141
	0.044	1.000	1.000	0.178	0.025	0.068	1.000	0.031	0.411	0.000
Bond-Real Estate	0.063	0.000	-0.001	0.898	7.295	0.003	0.000	0.001	1.009	0.308
	0.069	1.000	1.000	0.181	0.000	0.029	1.000	1.000	0.922	0.000
Bond-Gold	0.019	0.000	0.001	0.931	0.479	0.063	0.000	0.002	1.020	0.799
	0.068	1.000	1.000	0.176	0.000	0.076	1.000	0.099	0.775	0.048
Bond-Oil	0.049	0.000	0.000	0.900	18.045	0.020	0.000	0.000	0.984	0.217
	0.014	1.000	1.000	0.102	0.000	0.049	1.000	1.000	0.870	0.000
Real Estate-Gold	0.041	0.000	0.002	0.917	-0.461	0.025	0.000	0.000	0.909	2.781
	0.040	1.000	0.099	0.179	0.006	0.028	1.000	1.000	0.176	0.000

Real Estate-Oil	0.040	0.000	0.008	0.943	4.926	0.010	0.000	0.000	0.944	1.450
	0.018	1.000	0.049	0.149	0.004	0.088	1.000	1.000	0.449	0.041
Gold-Oil	0.012	0.000	0.003	0.961	-0.056	0.029	-0.001	-0.004	1.094	14.256
	0.048	1.000	0.057	0.149	0.000	0.051	1.000	0.061	0.122	0.000
Joint Dependence Structure	0.024	0.000	0.000	1.015	1.709	0.022	0.000	0.000	0.934	3.050
	0.019	1.000	1.000	0.743	0.048	0.042	1.000	1.000	0.108	0.000

Note: This table reports the difference between the median of square errors of MSSV models and the non-regime switching models (NRSM) and forecast efficiency regression estimates of the MSSV model and the non-regime switching model (NRSM). The parameters are estimated for two forecasting periods, i.e. Sample 1 and Sample 2. In sample 1, the models are estimated for the period 1987 to 2002 and forecasting is done for the period 2003 to 2012. In sample 2, the models are estimated for the period 2003 to 2012 and forecasted for the period 1987 to 1996. The forecasting estimates are calibrated for ten pairs of asset return comovements and for the joint dependence structure. For each of the asset pairs, it is evident that the MSSV model's median square errors are significantly lower than the non-regime switching models. This indicates that MSSV models outperform the non-regime switching models in out-of-sample forecasting of asset return comovements. This finding is observed for both the samples. The forecast efficient regression estimates show that the (α, β) values are not significantly different from (0, 1). In the forecast efficiency regression framework, if the mean and the variance forecast of the asset return comovements are unbiased, then the regression implies that $\alpha = 0$ and $\beta = 1$. However, the (α, β) estimates for the non-regime models are significantly different from (0, 1). The findings of $\alpha \neq 0$ and $\beta \neq 1$ indicate that the non-regime switching model forecasts either underestimates or overestimates the true volatility of asset return comovements or both during phases of high and low volatility in return comovements. The findings indicate that in contrast to the MSSV approach, the non-regime switching models yield biased forecasts.

Table: 8-4: Forecasting Performance of MSSV and Non-Regime Switching Model

Panel A: Sample 1

Forecasted Asset-Return Comovements	Below Median Forecast				Above Median Forecast			
	α^-		β^-		α^+		β^+	
	MSSV	NRSM	MSSV	NRSM	MSSV	NRSM	MSSV	NRSM
Equity-Bond	0.000	-0.003	0.994	4.435	0.000	0.003	1.016	-0.122
	1.000	0.098	0.126	0.000	1.000	0.091	0.128	0.021
Equity-Real Estate	0.000	-0.001	0.952	12.887	0.000	0.000	0.977	0.307
	1.000	0.109	0.101	0.000	1.000	1.000	0.107	0.000
Equity-Gold	0.000	-0.002	1.058	3.989	0.000	0.020	0.927	0.700
	1.000	0.091	0.279	0.000	1.000	0.047	0.109	0.000
Equity-Oil	0.000	0.018	1.015	2.301	0.000	0.002	0.989	0.046
	1.000	0.015	0.100	0.000	1.000	0.102	0.126	0.000
Bond-Real Estate	0.000	0.002	0.905	1.475	0.000	0.000	0.924	0.447
	1.000	0.090	0.108	0.000	1.000	1.000	0.101	0.000
Bond-Gold	0.000	-0.004	0.938	1.907	0.000	0.000	0.903	0.029
	1.000	0.092	0.112	0.000	1.000	1.000	0.100	0.000
Bond-Oil	0.000	0.000	0.905	1.935	0.000	0.001	1.033	0.464
	1.000	1.000	0.106	0.000	1.000	0.180	0.421	0.000
Real Estate-Gold	0.000	0.000	1.027	5.600	0.000	0.003	1.038	-4.116

	1.000	1.000	0.546	0.000	1.000	0.091	0.604	0.000
Real Estate-Oil	0.000	0.009	0.911	3.353	0.000	0.006	1.033	0.122
	1.000	0.091	0.101	0.000	1.000	0.091	0.5067	0.046
Gold-Oil	0.000	0.012	1.025	7.324	-0.001	0.000	1.055	-0.017
	1.000	0.039	0.258	0.000	1.000	1.000	0.258	0.000
Joint Dependence Structure	0.000	0.000	0.931	2.376	0.000	0.000	1.019	0.107
	1.000	1.000	0.119	0.000	1.000	1.000	0.529	0.039

Panel B: Sample 2

Forecasted	Below Median Forecast				Above Median Forecast			
Asset-Return	Alpha		Beta		Alpha		Beta	
Comovements	MSSV	NRSM	MSSV	NRSM	MSSV	NRSM	MSSV	NRSM
Equity-Bond	0.000	0.004	1.019	7.531	0.000	0.007	0.981	-0.593
	1.000	0.091	0.234	0.000	1.000	0.091	0.654	0.000
Equity-Real Estate	0.000	0.003	1.029	1.666	0.000	0.001	0.932	-2.479
	1.000	0.090	0.595	0.060	1.000	0.182	0.288	0.000
Equity-Gold	0.000	0.000	1.017	0.986	0.000	0.003	0.986	-0.017
	1.000	1.000	0.329	0.372	1.000	0.091	0.649	0.029
Equity-Oil	0.000	0.000	1.060	0.755	0.000	0.040	0.977	-0.299
	1.000	1.000	0.129	0.047	1.000	0.026	0.329	0.032
Bond-Real Estate	0.000	0.000	1.017	1.591	0.000	0.000	0.987	0.169

	1.000	1.000	0.378	0.000	1.000	1.000	0.629	0.000
Bond-Gold	0.000	0.000	1.022	2.699	0.000	0.004	0.954	-6.029
	1.000	1.000	0.281	0.000	1.000	0.091	0.322	0.000
Bond-Oil	0.000	0.000	1.004	1.321	0.000	0.000	0.969	0.107
	1.000	1.000	0.529	0.047	1.000	1.000	0.627	0.000
Real Estate-Gold	0.000	-0.001	0.908	5.070	0.000	0.000	0.989	-0.667
	1.000	0.091	0.418	0.000	1.000	1.000	0.482	0.002
Real Estate-Oil	0.000	0.000	0.992	3.074	0.000	0.000	0.967	0.359
	1.000	1.000	0.483	0.000	1.000	1.000	0.258	0.027
Gold-Oil	0.000	-0.030	1.017	2.469	-0.001	0.010	0.955	0.408
	1.000	0.042	0.329	0.000	1.000	0.037	0.386	0.032
Joint Dependence Structure	0.000	0.004	1.026	1.159	0.000	0.000	0.932	0.619
	1.000	0.091	0.432	0.047	1.000	1.000	0.152	0.047

Note: This table reports the forecast efficiency regression estimates of the MSSV model and the non-regime switching model (NRSM). The parameters are estimated for two forecasting periods, i.e. Sample 1 and Sample 2. In sample 1, the models are estimated for the period 1987 to 2002 and forecasting is done for the period 2003 to 2012. In sample 2, the models are estimated for the period 2003 to 2012 and forecasted for the period 1987 to 1996. Panel A and Panel B report the forecast efficient regression estimates for Sample 1 and Sample 2, respectively. The forecasting estimates are calibrated for ten pairs of asset return comovements and for the joint dependence structure. For each of the samples the forecast efficient regression is estimated allowing for a break in the regression at the median forecast. Therefore, for each sample, the table reports the forecast efficiency regression estimates for below median (α^{-}, β^{-}) and for above median (α^{+}, β^{+}). In this framework, if the mean and the variance forecast of the asset return comovements are unbiased, then the regression implies that $\alpha = 0$ and $\beta = 1$. For the MSSV model, the (α^{-}, β^{-}) and the (α^{+}, β^{+}) estimates are not significantly different from (0, 1). However, for the non-regime switching model the (α^{+}, β^{+}) estimates are significantly different from (0, 1). In particular, it is evident that the β^{+} values are significantly less than one. This shows that in periods of high asset return comovements (economic contraction phase) , the estimates are biased. In a similar vein the positive β^{+} values during periods of low asset return comovements suggests that the non-regime switching model underestimates the true variance of the return covariance during economic expansion phase. Alternatively, the findings indicate that the non-regime switching models provide biased out-of-sample forecasts. This observation is consistent across both the samples.

8.5 Economic Value of Asset Return Comovements

Up till now, I have argued that understanding the factors that drive the asset return comovements provides an opportunity for the investors to enhance their asset allocation decisions. This subsection examines whether this opportunity generates significant economic value using short-horizon dynamic strategy. In short-horizon dynamic strategy investors seek to maximize their one-period utility and do not hedge against future changes in the investment opportunity set (Fleming et al., 2001). Since short-horizon dynamic strategy ignores the hedging component, it is expected to underperform the optimal strategy under Merton's (1973) framework. Therefore, compared to an optimal strategy, a short-horizon strategy sets a higher bar for significant economic value added. To distinguish the value of asset return comovement estimation from that of return and volatility forecasting, I assume that the expected return and the volatility of the assets as constant. This assumption can be interpreted as the perspective of an investor who ignores the short run volatility of the returns and saves for retirement.

Fleming et al.'s (2001) framework does not allow an analytical solution for the optimal portfolio. Therefore, they evaluate their short-horizon dynamic strategy by examining two sub-optimal portfolios relating to maximum-mean and minimum-variance. To overcome this issue, I assume power utility function over terminal wealth, i.e. $U(W_T) = W_T^{1-\gamma}/(1-\gamma)$, where γ is the risk aversion coefficient of the utility function. Based on Campbell and Viceira (2002), one-period optimal asset allocation is defined as

$$A_t^w = \frac{1}{\gamma}\Sigma_t^{-1}(E_t r_{t+1} - Rf_t.I - \sigma_t^2/2) \tag{8-1}$$

where A_t^w is the vector of asset weights, Σ_t is the conditional asset return covariance matrix, $E_t r_{t+1}$ is the expected asset return vector, Rf_t is the risk-free rate, $I = [1, 1]'$ and σ_t^2 is the vector of asset variances.

Below, I present a comparison of two strategies: a multivariate conditional covariance (MCC) strategy and dynamic strategy, using three different asset classes, which comprises of five different assets, i.e. stocks, bonds, gold, oi and real estate. The MCC strategy investor employs multivariate conditional covariance using diagonal BEKK model for his/her one-period ahead forecast and the dynamic strategy investor takes into consideration the macroeconomic and the non-macroeconomic factors as his/her basis for forecasting one-period ahead asset return comovements. The investors form their portfolio based on the above Equation 10-1 and rebalance them after the end of each quarter. The portfolio formation starts with 16 years of information (1987 to 2002) and the investment period is from 2003 to 2012.

I use Willing-to-Pay (WTP) as a measure of certainty equivalence to evaluate the economic value. WTP is defined as the maximum fee (f) an investor is willing to pay for holding a dynamic strategy over the other strategy. WTP is defined as:

$$WTP = sup\left\{f \middle| E\left(U\left(W^{EMA/MCC}\right)\right) \leq E\left(U\left(W^{dynamic} - f\right)\right)\right\} \tag{8-2}$$

Considering terminal wealth $W_T = W_i \prod_{t=1}^{T}(1+r_t)$, where W_i is investor's initial wealth, expected log-utility is defined using:

$$Wlog\big(U(W_T)\big) \tag{8-3}$$

$$= (1-\gamma)\sum_{t=1}^{T} log(1+r_t) + (1-\gamma)logW_i - log(1-\gamma)$$

$$= (1+\gamma)T.\overline{\log(1+r_t)} + (1-\gamma)logW_i - log(1-\gamma)$$

The above equation suggests that $U(W_T)$ is log normally distributed. Therefore, expected utility is computed as

$$\overline{U(W_T)} = exp\Bigg((1+\gamma)T.\overline{\log(1+r_t)} \tag{8-4}$$

$$+\frac{1}{2}(1-\gamma)^2T^2\widehat{Var}\big(\overline{log(1+r_t)}\big)\Bigg).\frac{W_i^{1-\gamma}}{1-\gamma}$$

The table below compares the performance of the two strategies under various assumptions of risk aversion and the-risk free rate. The last column reports the bootstrapped p-values of the hypothesis: $H_{null}: WTP \leq 0$. The economic significance of the findings are as follows. First, for constant relative risk aversion investors, the dynamic strategy outperforms the MCC strategies, i.e. for all instances the hypothesis $WTP \leq 0$ is rejected. Second, the findings show that the dynamic strategy is more risky. In other words the mean and the volatility is higher for the dynamic strategy. However, the Sharpe ratios indicate that the dynamic strategy investors are better rewarded for their risky portfolios. Third, the WTP decreases with increase in risk aversion (γ). This suggests that higher risk aversion discourages investors in holding riskier assets, thus making it difficult to differentiate between either of the strategies. Fourth, the WTP increase with increase in risk-free rate. This is because the dynamic strategy investors are more informed in taking advantage of the diversification opportunities arising from the influence of risk-free rate on the asset return comovement.

Overall, the findings reported in Table 8-5 indicate that the dynamic strategy outperforms the MCC strategy. This, therefore, justifies that understanding the dynamics and the influence of macroeconomic and non-macroeconomic factors on asset return comovements enhance asset allocation decisions.

Table 8-5: Economic Value of Forecasting Asset Return Comovements

	MCC Strategy			Dynamic Strategy				
	Mean	Std. Dev	SR	Mean	Std. Dev	SR	WTP	p-value
$\gamma = 5$								
0.5%	18.00	19.02	0.92	21.16	20.71	0.99	0.19	0.091
1.0%	17.25	18.26	0.89	19.80	19.79	0.95	0.36	0.071
1.5%	16.63	17.39	0.87	19.04	19.07	0.92	0.41	0.055
2.0%	15.89	16.34	0.85	18.72	19.00	0.88	0.56	0.046
2.5%	15.04	15.48	0.81	18.01	18.03	0.86	0.87	0.024
3.0%	14.34	14.18	0.80	17.80	17.62	0.84	1.24	0.001
3.5%	13.65	12.85	0.79	16.90	16.54	0.81	1.66	0.001
$\gamma = 10$								
0.5%	10.71	11.10	0.92	14.69	14.33	0.99	0.11	0.092
1.0%	9.76	9.84	0.89	14.19	13.88	0.95	0.34	0.064
1.5%	8.66	8.23	0.87	13.34	12.87	0.92	0.39	0.059
2.0%	7.96	7.01	0.85	12.14	11.52	0.88	0.51	0.047
2.5%	7.36	6.00	0.81	11.14	10.04	0.86	0.53	0.040
3.0%	6.36	4.20	0.80	10.39	8.79	0.84	0.68	0.015
3.5%	5.66	2.73	0.79	9.14	6.96	0.81	0.82	0.007

$\gamma = 15$								
0.5%	6.41	6.42	0.92	10.72	10.32	0.99	0.10	0.092
1.0%	5.81	5.40	0.89	9.60	9.05	0.95	0.32	0.080
1.5%	5.06	4.09	0.87	8.65	7.77	0.92	0.33	0.079
2.0%	4.57	3.02	0.85	7.90	6.71	0.88	0.47	0.041
2.5%	3.73	1.52	0.81	6.65	4.83	0.86	0.50	0.038
3.0%	3.65	0.81	0.80	5.80	3.33	0.84	0.56	0.022
3.5%	3.60	0.13	0.79	5.10	1.98	0.81	0.62	0.010

Note: The table compares the performance of MCC strategy and the dynamic strategy. The portfolio formation starts with 16 years of information (1987 to 2002) and the investment period is from 2003 to 2012. The annualized mean, standard deviation and the Sharpe ratios are reported for both the strategies. It is evident that the dynamic strategy yields higher returns and is more volatile than the MCC strategy. However, the Sharpe ratios are higher for the dynamic strategy, suggesting that investors are better rewarded for their risky portfolios. The investors are assumed to have power utility function and constant relative risk aversion represented as γ. The Willing-to-pay (WTP) certainty equivalence measure computes the maximum fee (f) an investor is willing to pay for holding a dynamic strategy over the other strategy. The last column reports the bootstrapped p-values of the hypothesis: $H_{null}: WTP \leq 0$. The hypothesis is rejected for all the cases at 10, 5 or 1 percent significance levels. The findings show that the dynamic strategy outperforms the MCC strategy.

*, **, *** represents significance at 10, 5 and 1 percent levels

8.6 Summary

Understanding financial asset return correlation is a key facet in portfolio construction. But, in designing efficient portfolio strategies it is not only critical to know what factors influence the asset returns but also their impact on the return comovements during the various phases of the economic cycle. For the last decades, several studies have probed this cardinal relationship between stock and bond returns. But, more importantly, present studies thus far have not examined the influence of these factors on the joint return distribution of a portfolio consisting of different class of assets. In practice, investors do not only investment in only conventional assets, i.e. stocks and bonds, but also in other financial assets such as commodities and real estate. Thus an examination of the time varying dynamics of the joint dependence structure (JDS) of the return comovements is of key importance. Further, without assessing what time variation in the comovements a formal model of fundamentals can generate, the examination may remain as a premature judgment. While it is difficult to think of factors that causes sudden and steep increase or decrease in the JDS, nevertheless it remains useful to quantify and examine the factors that most significantly influence the multi-asset return comovement. Additionally, the extant research has examined the asset return comovements by using linear correlation as a measure of comovements. However, it is well recognized in the literature that linear correlation fails to provide an accurate estimate of the dependence structure when dealing with multivariate distributions with complex dynamic characteristics (Barsky, 1989; Chan, et al., 2011; Reboredo, 2011). The copula technique that is employed in this work, thus, enables us to examine scale-free dependence structure.

Using data from 1987 to 2012 (1st August 1987 to 1st September 2012) for three different asset classes and several macro and non-macro variables, this study reports a number of significant findings. First, the findings indicate that the joint dependence structures of asset return comovements show significant regime-switching behaviour both in terms of statistical and economic significance. The two regimes identified correspond to economic expansion and economic contraction phases. Second, the findings state that among the macroeconomic variables, inflation plays a central role (positive influence) during both the phases of the economy. Also, risk aversion is positively significant during the economic contraction phase, whereas risk free rate negatively affects the JDS during the economic expansion phase. Third, among the non-macroeconomic variables, the uncertainty and illiquidity variables play a dominant role in both the phases of the economy. The findings also reveal that the input uncertainty and bond illiquidity factors have the highest coefficient values. Fourth, examining the factor contributions, I confirm that the model fit worsens considerably when the non-macro factors are dropped. Thus, it is fair to say that the non-macroeconomic factors play a critical role in explaining the variations in the JDS. The findings of this study are also conclusive from the quartile regressions, which are estimated for robustness check.

Towards the end of this chapter, I evaluate the practical contributions of this research study. Overall, the findings indicate that the dynamic strategy outperforms the multivariate conditional covariance strategy. This, therefore, justifies that understanding the dynamics and the influence of macroeconomic and non-macroeconomic factors on asset return comovements enhance asset allocation decisions. Moreover, the findings imply that single-regime models provide inefficient estimates of asset return comovements during regimes of high volatility which is more profound during periods of economic contraction. Alternatively, the MSSV framework enhances the flexibility in the model accommodating the persistence of volatility shocks.

8.7 Appendix

Table 8 (A-1): Turning Points in the Business Cycle

Turning Point	Date	Expansion (E)/Contraction (C)	Months in Phase
0	8/1987	E1	35
1	7/1990	C1	8
2	3/1991	E2	120
3	3/2001	C2	8
4	11/2001	E3	73
5	12/2007	C3	18
6	6/2009	E4	40

Notes: The turning points of the business cycle are based on the NBER-official dates of troughs and peaks (NBER, 2012). The sample period is from the fourth quarter of 1987 to the fourth quarter of 2012, yielding 302 monthly observations. Each month in the sample is divided into either an expansionary phase or a contractionary phase based on the turning point. The expansionary period has 268 months and the contractionary period has 34 months.

CHAPTER 9

Examining International Equity Market Comovements: Evidence from Emerging Equity Market

9.1 Introduction

In this chapter I extend my work of asset return comovements by examining the international equity market linkages between the emerging Indian equity market and the developed economies.

But, why study the asset market linkages between emerging Indian equity market and the developed equity markets? With globalisation of financial markets international investors face both challenges and opportunities. On one hand, they are able to diversify their portfolio risk much more easily as the emerging economies have opened their markets to international investors. However, on the other hand, the markets have become closely integrated thereby increasing the risk of contagion. It has therefore become ever so critical to accurately estimate return comovements in different economic regimes and more importantly to identify the factors which drive these comovements. The existing evidence on return comovements largely focuses on developed markets and research involving emerging markets is relatively sparse. An investigation of the drivers of comovements and how they change during bearish and bullish economic conditions has significant implications for policymakers and international investors. If returns comovements of emerging and developed markets are positive during periods of economic turbulence, then an understanding of key determinants will aid in implementation of appropriate policy interventions in containing financial contagion. Equally, greater insights of the drivers of comovements will help international investors in their asset allocation decisions. The study examines the extreme stock return comovements of emerging Indian market and selected developed markets in different economic conditions. Further the work identifies key determinants of the equity return comovements by considering a variety of international and Indian economic factors.

It is widely acknowledged that India is playing an ever increasing role in driving the world economic growth. India with its large and skilled human capital, access to natural resources and growing markets for goods and services offers an attractive destination for the international investors. Aloui et al. (2011) report that among the BRIC (Brazil, Russia, India and China) nations, India's well established trade links with the world is next only to China. Thus, there is little doubt that amongst the emerging economies, India is going to play an increasingly important role in shaping the world's economy in the coming years. Further, since the economic liberalisation in 1992, the cumulative annual Foreign Institutional Investments (FIIs) in the Indian equity markets have surged from a mere \$4 million in 1992-93 to approximately \$125 billion in 2012 (SEBI 2012). However, during the US led sub-prime crisis in 2008-2009, India experienced an outflow of \$12 billion (SEBI 2011). Thus, the high volatility of the portfolio flows during the recent global economic crisis has triggered serious macroeconomic challenges for emerging economies like India since the stock markets are a leading indicator of a country's economic well-being. An understanding of the causes of comovements during the different phases of the economy, i.e. economic contraction phase and economic expansion phase, will therefore provide greater insights to both Indian policy makers and international investors. The study aims to achieve this by investigating the economic sources of stock return comovements of the emerging Indian equity market and the developed equity markets of US, UK, Germany, France, and Canada.

This study makes two key contributions to the existing literature. First, I propose an alternative approach, i.e. the copula framework, in examining the time-varying evolutionary effects of the extreme return comovements especially during periods of financial turmoil and economic contraction. Second, I identify the various channels which influence the return comovements, thus identifying the key drivers of equity market linkages.

This research reports several interesting and relevant findings. First, consistent with existing literature (Yilmaz, 2010; Kenourgios et al., 2011) I show that probability of extreme comovements in the economic contraction regime is relatively higher. Second, the findings show that both Indian and international inflation uncertainty are likely to adversely affect international portfolio's risk diversification potential since they positively impact the return comovements. Third, the results indicate that an increase in the international interest rates has a positive impact on the return comovements. This suggests that both international and Indian equity markets are adversely affected by the hike in international interest rates. However, while an increase in the Indian interest rates negatively affects its stock market, it has no impact on the international equity markets. Fourth, the findings show that increase in stock market volatility in the developed markets during the economic contraction phase does not adversely impact the Indian stock market returns. Finally, the findings show that Indian dividend yield (DY) and price-to-earnings (PE) ratios seem to have a greater positive impact on return comovements during the economic expansion phase as compared to the economic contraction phase. However an increase in international dividend yield during the economic contraction phase increases the return comovements suggesting that it fails to uplift the investors' sentiments in both international and Indian equity markets.

The rest of the chapter is presented as follows: Section 2 discusses the relevant literature on dependence structure of return comovements. Section 3 discusses the methodology. Section 4 discusses the empirical findings and finally Section 5 concludes the chapter.

9.2 Literature Review

Understanding the asset market linkages, especially during the economic contraction periods, enables in predicting financial contagion. For investors this allows to better manage their risk exposure to foreign contracts. Further, establishing the factors that influence the return comovements between emerging economy and developed economies will enable the policy makers to understand the effect of their monetary and fiscal policy decisions on the dynamics of the equity markets. Existing studies usually consider the issues related to market integration and financial contagion together in examining the comovements between stock markets, i.e. if financial markets are segmented, financial contagion cannot occur. In this regard, though the past studies report significant linkages between emerging and developed equity markets (Ghosh et al., 1999 for Asian emerging markets; Fujii, 2005 for latin American emerging makets), research on extreme comovements during the economic contraction and economic expansion phases is sparse.

In examining financial contagion, one body of literature examines volatility spillover which characterizes the structure of asset return relationships across markets. However, from empirical point of view, methodologies vary considerably. For instance, Asgharian and Nossman (2013) use stochastic volatility models with jumps to examine the volatility spillover effects from the US and regional stock markets on the local markets for Pacific Basin region and China. The results indicate significant spillovers for almost all the countries except China. However, the stochastic volatility models with jumps are exposed to potential misspecifications as i) jumps in the returns can generate large movements, but the impact may be temporary, ii) the diffusive stochastic volatility process may be persistent but it assumes small normally distributed increments that are considered by the Brownian motion and iii) we do not always have jumps in mean and variance, but a smooth diffusion process where clusters can be found. Li (2007) examines the volatility linkages between Chinese stock exchanges and the US stock market using multivariate GARCH framework. This approach too has several limitations. Since the GARCH process assumes equal weight for small and large changes in return, it fails to account for the differential impact caused due to abnormal returns (Zhang et al., 2009). While Zhang et al. (2009) accommodates for these differential impacts, their study is restricted to Shanghai and Hong Kong stock markets. Further, they do not consider an evolutionary process of the dependence structure. Additionally, far few studies consider the asymmetric nature of the comovements in modelling market interdependence (see Vaz De Melo Mendes, 2005). Consequently, this study differs from the previous studies as it allow the marginal distributions of the equity returns to follow an appropriate GARCH process that accommodates for risk-return trade-off. Further, my analytical framework takes into account the autoregressive evolutionary process and also considers the asymmetric nature of the return comovements.

Another body of literature examines contagion using cross-market returns' correlations during stable and crisis periods. For example King and Wadhwani (1990) and Lee and Kim (1993) provide evidence of contagion when the correlation during the crisis period is relatively higher than the stable period. They find that the likelihood of contagion increases during highly volatile periods. However, this approach has several limitations.

Forbes and Rigobon (2002) argue that the presence of heteroskedasticity problem during periods of high market volatility causes biased linear correlation estimates. Pesaran and Pick (2007) suggest that contagion involves a dynamic increase in return correlation rather than a static estimate. Further, Chiang et al. (2007) highlight the potential issues of omitted variable bias in estimating cross-market correlations. To overcome these limitations, authors have used alternative techniques, such as vector autoregressive (VAR) and autoregressive conditional heteroskedastic (ARCH)-type of models, to study cross-market return comovements. These studies report mixed evidence. For example Baele (2005) finds evidence of contagion between the US and several European stock markets during periods of high market volatility. In contrast, Bekaert et al. (2005) report no contagion between the US and the countries in Europe, Asia and Latin America caused by the Mexican crisis. In more recent studies, Pesaran and Pesaran (2010) show that movements in asset return volatilities are shared across markets during the global financial crisis of 2008. Seelanatha (2011) report similar findings suggesting that the decline in stock prices in the emerging markets during the crisis periods reflect their high dependency with the US market.

Extant research has shown that modelling stock return comovements is a challenging task. It is essential to note that though research widely acknowledges that return distributions of financial assets are non-normal, most studies primarily use linear dependence measure to examine the asset market linkages. While the linear dependence structure is widely used, this measure of association fails to accurately characterize the non-normal distribution of the financial returns (Jondeau and Rockinger 2006). Poon et al.,(2004) show that the linear measure of correlation fails to distinguish extreme positive and negative returns. Thus, the asymmetric correlation between the stock returns during periods of economic expansion and contraction cannot be explained by the conventional measure of comovements (Beine, Capelle-Blancard and Raymond 2008). Further, linear correlation measure assumes a Gaussian return distribution which is unrealistic. Under such scenario, Multivariate Generalized Autoregressive Conditional Heteroskedastic (GARCH) models (ŞErban, Brockwell, Lehoczky and Srivastava 2007) and/or the use copula functions (Longin and Solnik 2001) are highly effective in modelling return comovements (Cherubini et al. (2004) and Paton (2006)). While the multivariate GARCH accommodates of non-normally distributed stock returns, Copula approach specifically deals with the extreme comovements of stock market returns. Using copula approach, Jondeau and Rockinger (2006) show that dependence is higher and more persistent in the European markets than between other global stocks. Similarly, Kenourgois et al. (2011) and Yang and Hamori (2013) provide evidence for increase in dependence during crisis periods between the emerging nations and the developed markets. In this line, my work adds to the literature by considering the evolutionary effect of the dependence structure.

Considering India, given the evidence that it has emerged as one of the fastest growing developing nations in the world, one would expect Indian equity market to show strong linkages with the developed equity markets. However, empirical work provides mixed evidence. For example, in one of the early studies, Sharma and Kennedy (1977) examine the equity return comovements of the Indian with London and New York stock markets. They report no significant comovements of asset returns. Their results could be attributed to the closed nature of the Indian economy and the regulated capital flows which existed till the 1980s. In contrast, Kumar and Mukhopaday (2002) using GARCH framework provide evidence of volatility spillover between the US and the Indian equity market for the period 1999-2001. Similarly, Wong et al. (2005) use weekly data for the period 1991 to 2003 in examining the relationship between Indian equity market and the US, UK and Japan stock markets. They show that i) all the developed equity markets are cointegrated with the Indian stock market and ii) provide evidence of unidirectional causality from only the US and the Japan stock markets. On the contrary, Kolluri and Wahab (2010) show that during the period 1997 – 2009 the UK stock market influences Indian capital markets more than the US stock market. Whilst Poshakwale and Thapa (2010) document the evidence of increased integration of Indian equity markets with global markets and attribute this to the rapid growth of foreign equity portfolio investment flows, they do not explicitly test for the determinants of stock return comovements. Similarly, though Gupta and Donleavy (2009) provide evidence of time varying return comovements, they neither examine the dependence structures nor the factors influencing the return comovements of Indian and global stock return comovements. In this context, this empirical work examines extreme return comovements during periods of economic expansion and contraction across Indian and international markets and identifies the factors that influence stock market linkages.

9.3 Empirical Model

The method used in the study is based on the theory of copula. As I elaborately discussed the dependence structure modelling process in Chapter 4, here I present a brief note on the copula model used in this particular study.

Nelsen (2006) describes copula, C, as a function that couples multiple distribution functions of random variables (RV) to their unit-dimensional distribution function. Application of this cumulative distribution function (CDF) is derived from Sklar Theorem

(Sklar 1959). The theorem states that for a joint distribution function $H_{X,Y}(x,y)$ for all x,y, a function, copula $C(u,v)$, can be characterized in $\overline{R} \in (-\infty,\infty)$ such that $H_{XY}(x,y) = C(F_X(x), F_Y(y))$, where $F_X(x)$ and $F_Y(y)$ are the marginal distribution functions.

9.3.1 Conditional Copula

I consider two RV, X and Y and introduce a conditioning vector K. Let the conditional CDF of the RV be $H_{XY|K}(x,y|K)$ and the marginal distributions be $F_{X|K}(x|K)$ and $F_{Y|K}(y|K)$ given K. Then there exists a copula C, such that

$$H_{XY|K}(x,y|k) = C((F_{X|K}(x|k), F_{Y|K}(y|k)) = C(u,v) \quad (9\text{-}1)$$

where, $(x,y|K)=k$ and υ is the support of k for all $k \in \upsilon$ and $(x,y) \in \overline{R} \times \overline{R}$. In equation (4-5), u and v are the realizations of $U \equiv F_{X|K}(x|k)$ and $V \equiv F_{Y|K}(y|k)$ given $K = k$. U and V are the conditional probability integrals of the RV, X and Y (Sklar 1959). The details on conditional copulas are presented in Chapter 4. Next, I focus on the model specifications.

9.3.2 Copula Model Specifications

It is well established that financial returns generally fail to follow a normal distribution and rather adhere to Student's t-distribution (Hu 2010). Building on this, I model each marginal distribution of the asset returns employing an Autoregressive Moving Average ARMA (p, q)-Exponential Generalized Autoregressive Conditional Heteroskedastic

EGARCH (1, 1)-t model to accommodate for differential impacts in return volatility clustering. Based on these marginal return distributions, the dependence structures are estimated.

9.3.2.1 Marginal Model

The marginal distributions of the equity returns are assumed to follow an ARMA (p, q)-EGARCH (1, 1)-t process (Nelson 1991). The model is characterized as

$$X_{i,t} = \theta_i + \sum_{j=1}^{p} \beta_j X_{i,t-j} + \sum_{k=i}^{q} \alpha_k \varepsilon_{t-k} + \varepsilon_{i,t} \tag{9-2}$$

$$\log(\sigma_t^2) = a_0 + \sum_{j=1}^{p} a_{1i} \log(\sigma_{t-j}^2) + \sum_{i=1}^{q} a_{2j} \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{j=1}^{q} a_{3j} \left(\frac{\varepsilon_{t-j}}{\sigma_{t-j}} \right) \tag{9-3}$$

$$\sqrt{\frac{d}{\sigma_{i,t}^2 (d-2)}} \cdot \varepsilon_{i,t} \mid I_{t-1} \sim i.i.d.t_{di} \tag{9-4}$$

where $X_{i,t}$ is the asset return series, θ_i and $\varepsilon_{i,t-1}$ are the conditional mean and error term, which is the news relating to the volatility from one lag period. β_j is the autoregressive component and α_k is the moving average parameter. The noise process ε_t represented in Equation 9-4 follows a skewed Student-t distribution with *(d)* degrees of freedom and σ_t^2 conditional variance. σ_{t-j}^2 is the GARCH component and the leverage effect is captured by a_3. The information contained about the volatility of the lagged period is captured by ε_{t-1} which represents the ARCH component. The information set is considered as the condition vector *‘k’*. The order of the ARMA term *‘p’* is determined using Akaike Information Criteria (AIC).

This study estimates the ARMA (p, q) – EGARCH (1, 1) model for each of the financial return time-series. The most appropriate lag orders for each of the return series are selected using the Akaike information criteria (AIC), observing the conditional variance equation as an EGARCH(1, 1)-t process. The mean equations of the equity returns of India, US, UK, Germany, France and Canada follow ARMA (1, 1), ARMA (3, 3), ARMA (4, 4), ARMA (1, 1), ARMA (1, 1) and ARMA (1, 1) processes, respectively. I confirm that the marginal models are free from autocorrelation and heteroskedastic effects. To evaluate the adequacy of the marginal estimations, misspecification tests are conducted following Diebold et al. (1998). The correlograms of $(\hat{u}_t - \bar{u})^l$ and $(\hat{v}_t - \bar{v})^l$ for ‘l’ ranging from one to four are examined. The values u and v are the probability integral transformations of the estimates of the marginal models. The correlograms confirm absence of any serial correlation in the first four moments, which indicates that our marginal models are correctly specified. This ensures that the copula models correctly estimate the dependence structure of the stock return comovements.

9.3.2.2 Tail Dependence Measure

The tail dependence measure is another property of the copula that is very useful in analyzing the joint tail dependence of bivariate distributions. Tail dependence estimates the probability of the RV in lower or upper joint tails. Intuitively, this measures the tendency of the asset returns to co-move up and down together.

$$\tau^U = Lt_{u\to 1} P\left[X \geq F_X^{-1}(u) / Y \geq F_Y^{-1}(u)\right] = Lt_{u\to 1} \frac{1-2u+C(u,u)}{1-u} \tag{9-5}$$

$$\tau^L = Lt_{u\to 0} P\left[X \geq F_X^{-1}(u) / Y \leq F_Y^{-1}(u)\right] = Lt_{u\to 0} \frac{C(u,u)}{u} \tag{9-6}$$

where $\tau^U, \tau^L \in [0,1]$ and F_X^{-1} and F_Y^{-1} are the marginal density functions of the RV series. If the tail dependence measures are positive then upper or lower tail dependence exists, i.e. $\tau^U(\tau^L)$ measures the probability of the RV-X is above (below) a high (low) quantile, given that the RV-Y is above (below) a high (low) quantile.

Further, I allow for the tail dependence estimate to follow an evolution process that captures the level changes. The evolution process is characterized as

$$\tau_t^{U/L} = \Theta\left(\beta_0^{U/L} + \beta_1^{U/L}\tau_{t-1}^{U/L} + \beta_2^{U/L}\frac{1}{q}\sum_{i=1}^{q}\left|u_{t-i} - v_{t-i}\right| + \beta_3^{U/L}D\right) \tag{9-7}$$

The dependence parameter follows an ARMA (1, q) process, characterized by β_1, the autoregressive term, and β_2, the forcing variable. While the former term accounts for the persistence effect, the latter term captures the variation effect of the dependence parameter. A dummy variable term $\beta_3 D$ is added to allow for level variation in the dependence. The dummy variable takes the value '0' for economic expansion phase and '1' otherwise. I obtain the dependence parameter of the Student-t and modified Joe-Clayton (MJC) using maximum likelihood (ML) method (the estimation process is provided in chapter Appendix, and the details are presented in Chapter 4).

The performance of the copula models are examined based on Akaike information criterion (AIC), and Bayesian information criterion (BIC). The former is adjusted for small sample bias (Rodriguez, 2007) and the latter is a goodness-of-fit test for the copula models to compare the different dependence structures.

9.3.3 The Dynamic Model to Examine Dependence Structures

Similar to the methodology explained in Chapter 6, I employ Markov Switching Stochastic Volatility (MSSV) model in investigating the dependence structures. While the details are present in Chapter 6, here I present a brief description of the model used in this study.

Each of the state variables follow an evolutionary process. Although autoregressive conditional heteroskedasticity (ARCH) models can be employed to tackle this issue (Bollerslev, Engle and Wooldridge 1988; Engle 1982), the assumption that the error term is normally and independently distributed (NID) does not hold good in practice. Therefore, I, specify a model for the state variables that allows each of the vectors to follow an independent stochastic volatility (ISV) process. The stochastic volatility (SV) specification builds in a time-varying variance process for each of the elements of the structural factors, by allowing the variance to be a latent process.

This model allows the volatility to vary across different regimes since assuming constant volatility in two regimes will yield in either underestimation or overestimation of the volatility. Thus, the main motivation for using Markov Switching Stochastic Volatility (MSSV) is that it allows different estimates of the elasticity of variance (γ). The MSSV model is characterized as

$$
\begin{aligned}
z_t &= g_t + 2\gamma \log x_{t-1} + \log \varepsilon_t^2 \\
g_t &= \omega_m + \varphi g_{t-1} + \eta_t
\end{aligned}
\tag{9-8}
$$

In contrast to Stochastic Volatility (SV) model, in the above equation I define $\omega_m = \log \sigma_m^2$, which allows in capturing the different regimes at a particular point in time. Duffee (1993) provides evidence for structural breaks with the monetarist experiment and shows that even the SV models lack in analysing these effects in the economy. With the regimes governing the dynamic behaviour of the state variables, I condition a particular regime and calibrate the density of the dependence structures and the state variables. In this parameterization of the MS model, the transition probabilities from state *m* to state *n* in time *t* are defined as $p_{mn} = \Pr[S_t = m | S_{t-1} = n]$. It should be noted that for $m = 1, \ldots, M$, only $M(M-1)$ needs to be specified as $p_{mn} = \Pr[S_t = M | S_{t-1} = n] = 1 - \sum_{m=1}^{M-1} \Pr[S_t = m | S_{t-1} = n]$. This model allows the unconditional volatility to change between different states by allowing σ_m in taking values $m \in \{1, \ldots, M\}$ at time *t*.

The appropriate number of regimes is chosen based on the Regime Classification Statistic (RCS) as explained in Chapter 6. The Appendix of this chapter provides a description of the same. I use Kalman filter of the estimation of the MSSV model. However, it should be noted that the above procedures makes our process exclusively path dependent. Hence, to remove the path dependence I compute the conditional expectation of the log-volatility forecast by taking the weighted average output of the previous iteration. I then calculate the regime probabilities based on Smith's (2002) modification of Hamilton's (1989) filter (the estimation process is given in the chapter Appendix, and the details are presented in Chapter 6).

9.4 Empirical Results

9.4.1 Data Description

In this study I use monthly data from April 1997 to March 2013 for examining the dependence structure of stock return comovements of Indian and developed equity markets. The sample includes i) Standard & Poor's (S&P)CNX Nifty Index of the National Stock Exchange of India, ii) US S&P 500 composite index, iii)Financial Times Stock Exchange (FTSE) - 100 index of UK, iv) DAX-30 index of Germany, v) CAC all-tradable index of France, and vi) S&P composite index of Canada. The price indexes are obtained from DataStream. The equity returns are computed on a continuous compounding basis, calculated as 100 times the logarithmic difference of the dollar adjusted index/price values, i.e. $R_t = 100 \times Ln(P_t/P_{t-1})$ where P_t is the value of the index/price at time *t*.

Previous studies show that changing economic conditions affect asset returns, (Fama and French 1989). Consequently, I examine the dependence structure of the monthly stock returns in different economic cycles. The data is obtained from the National Bureau of Economic Research (NBER) for the United States and the Economic Cycle Research Institute (ECRI) for the United Kingdom Germany, France and Canada. The analysis of the stock return comovements for the economic cycle phases is based on the economic expansion and contraction periods of the respective developed economies.[15] The economic phases for the developed economies included in the sample are reported in the

[15] We consider economic expansion and contraction periods only for developed economies because according to ECRI, the Indian economy has been in the expansionary phase throughout ours ample period, i.e., April 2997- March 2013.

chapter Appendix. Every month is classified as either an economic expansion or an economic contraction month. This is based on the turning point, i.e. trough to peak dates, as specified by the NBER's and ECRI's Economic cycle dating committee[16]. Thus, two sub-samples are created, the business expansion (E) phase and the business contraction (C) phase. In Table 9-1, in the next page, provides the summary statics of the stock returns.

[16] The NBER and ECRI considers recession, i.e. contraction phase, as a significant decline in economic activities spread over several months. The various economic indicators include real GDP, real income, whole-retail sales and industrial production. An expansionary phase marks the end of a contraction phase and beginning of the recovery phase in the economic cycle (for details see NBER 2012; ECRI 2014).

Table 9-1: Summary Statistics of Asset Returns

Panel A: Descriptive Statics

	Contraction Period				Expansion Period				April 1997 – March 2013	
	Mean (%)	S.D. (%)	Kurtosis	Skewness	Mean (%)	S.D. (%)	Kurtosis	Skewness	Mean (%)	S.D. (%)
In(E)	-	-	-	-	11.64	26.32	1.23	-0.51	11.64	26.32
US(E)	-25.64	23.16	-0.09	-0.25	10.30	14.62	1.07	-0.67	4.65	16.44
UK(E)	-1.25	18.41	0.09	-0.59	3.45	14.06	0.65	-0.71	2.50	14.98
G(E)	-24.33	32.86	0.69	-0.39	14.63	20.34	2.26	-0.72	5.26	23.91
F(E)	-30.84	27.57	-0.07	0.07	7.95	17.89	0.54	-0.66	2.91	19.52
C(E)	-17.57	26.31	0.47	-0.65	7.60	15.13	4.40	-1.24	5.00	16.57

Panel B: Diagnostics (1997 – 2013)

	J-B stat.	ARCH LM (1)	ARCH LM (5)	ARCH LM (10)	B-G LM (1)	B-G LM (5)	B-G LM (10)
In(E)	19.29***	-0.02*	0.26***	0.13***	-1.90**	0.01	0.07
	(0.000)	(0.070)	(0.004)	(0.004)	(0.038)	(0.385)	(0.665)
US(E)	31.35***	0.18**	0.02	-0.01	0.64**	0.01	0.02
	(0.005)	(0.018)	(0.731)	(0.913)	(0.032)	(0.807)	(0.749)
UK(E)	18.64***	0.16**	-0.02	0.08	0.06	0.17**	-0.01
	(0.000)	(0.036)	(0.714)	(0.272)	(0.404)	(0.034)	(0.923)

G(E)	62.38***	0.16**	0.04	0.08	0.78**	0.01	-0.02
	(0.000)	(0.034)	(0.582)	(0.241)	(0.043)	(0.860)	(0.759)
F(E)	16.97***	0.17**	0.08	0.055	0.16**	-0.02	0.04
	(0.000)	(0.022)	(0.270)	(0.464)	(0.028)	(0.710)	(0.570)
C(E)	162.52**	0.15**	0.038	-0.02	0.20**	-0.08	0.01
	(0.000)	(0.047)	(0.617)	(0.763)	(0.006)	(0.250)	(0.931)

Notes: This table provides the summary statistics of annualized monthly stock dollar-adjusted returns of India and the developed economies. In (E), US (E), UK (E), G (E), F (E), C (E) are the dollar-adjusted equity returns of India, US, UK, Germany, France, France and Canada respectively. The time period of the study is from April 1997 to March 2013. The sample is divided into two-samples to examine the return comovements during the economic contractionary and expansionary phase. These phases are determined based on the turning points of the business cycle are based on the National Bureau of Economic Research (NBER) official dates of troughs and peaks the United States and the Economic Cycle Research Institute (ECRI) for the United Kingdom, Germany, France, Canada and India. The sample period is from April 1997 to March 2013, yielding 192 monthly observations. Each month in the sample is divided into either an expansionary phase or a contractionary phase based on the turning point. Panel A represents the descriptive statistics. The average monthly dollar-adjusted return figures are annualized using the formulae: Annualized return = [(1+monthly mean return)^{12} - 1], and annualized standard deviation = [monthly standard deviation$\times 12^{1/2}$]. Panel B provides the test results. Under the normality null hypothesis, Jarque-Bera test statistic follows a Chi-square distribution with fixed (2) degrees of freedom. The null hypothesis of the ARCH- Lagrange multiplier (LM) test is: there is no evidence of ARCH effect. We conduct the test at lags 1, 5 and 10 with corresponding 1, 5, 10 degrees of freedom. Tests using other lags yield the same results. We conduct the Breusch-Godfrey (B-G) LM test for serial correlation, corrected for heteroskedasticity at lags 1, 5 and 10.The p-values are reported in the parentheses.

***and ** signifies rejection of the null hypothesis at 1 and 5percent significant levels, respectively.

Panel A of Table 9-1 presents the annualized dollar-adjusted stock returns and standard deviations including the summary statistics for the expansion and the contraction periods and for the whole period from April 1997 to March 2013. The economic sub-periods show significant variations in average returns compared to the returns for the whole sample period. As expected, equity returns are positive during the expansionary phase and negative during the contractionary phase. Germany reports the highest equity returns of 14.63 percent followed by India (11.64 percent) during the expansionary phase. Whereas in the contraction period, France records lowest returns of -30.84 percent followed by US (-25.64 percent). Standard deviations of average returns confirm that returns during the economic expansion period are more stable compared to the contractionary period. The summary statistics confirm the presence of excessive skewness and kurtosis relative to Gaussian distribution, which suggests that the return distributions have fatter tails increasing the probability of extreme variance.

Panel B of Table 9-1 confirms that the Jarque-Bera test statistics strongly reject the normality assumption of the unconditional distribution of the equity returns. The Lagrangian Multiplier (LM) test confirms presence of autoregressive conditional heteroskadastic (ARCH) effects. Further, the Breusch-Godfrey (BG) LM tests suggest that stock returns for most markets are serially correlated for at least one of the lag orders. Results violate Gaussian distribution assumption which implies that linear measures of comovements are not likely to provide an accurate estimation of return comovements. These findings emphasize the use of copula function approach as an alternative method to predict a more reliable dependence structure of the asset returns.

9.4.2 Dependence Structure Dynamics

Table 9-2 reports the copula parameter estimates of the time-varying MJC copula models for the Indian and foreign stock return pairs. Panel A reports the probability of extreme comovements during economic expansion, i.e. the lower tail (τ_L), and economic contraction, i.e. the upper tail (τ_U). The results indicate that there is evidence of higher likelihood of extreme comovements during economic contraction phase than in the economic expansion phase. Consistent with this finding we see that the average degree of association between the Indian and the equity returns of the developed economies is higher in the contractionary phase than in the expansionary phase (see Panel B). For example in the case of India-US the dependence measure during the contraction period is 0.831 whereas during the expansion period it is 0.517. The economic significance of this finding is that the international investors will forgo some diversification benefits due to high equity market dependence during the contractionary phase. One of the key reasons for the high degree of market linkage during the contractionary phase can be attributed to the increased market openness post Indian economic liberalization.

The beta values in Panel A capture the persistence and variation effects in the dependence structure of the asset return comovements. The significant beta values indicate importance of considering the evolutionary path of the dependence structure while modelling the return comovements. Since, the static case is a restricted approximation of the time-varying evolution of dependence parameters; I conduct a Likelihood Ratio (LR) test to confirm the suitability of the time-varying conditional copula model. The null hypothesis that there is no significant difference in the dependence measure estimated via static and the time-varying model is rejected as the LR test statistics are highly significant for the different market pairs. This signifies that the time-varying copula models account for the dynamics of the dependence structure. The table also reports the AIC, BIC measures to evaluate the goodness-of-fit of the different copulas. In sum, the Indian and international market stock return comovements are time-varying and asymmetric in nature. It is, therefore, critical to examine the factors that influence the return comovements during the different phases of the economic cycle. I present this analysis in the subsequent sub-sections.

Table 9-2: Parameter Estimates of Copula Models

	In/US	In/UK	In/G	In/F	In/C
Panel A: Time-varying Modified Joe-Clayton (MJC) Copula					
β_o^L	2.168**	2.410*	2.810**	2.753**	2.850**
	(0.159)	(0.129)	(0.054)	(0.210)	(0.045)
β_1^L	-8.442	-1.731**	-0.010	-1.999	-0.091
	(5.877)	(0.465)	(0.807)	(0.138)	(0.981)
β_2^L	0.032	0.294	-0.902	-0.944***	0.212
	(0.195)	(0.325)	(0.730)	(0.027)	(0.391)
β_3^L	0.004	0.001	0.002	0.001	0.002
	(0.871)	(0.911)	(0.650)	(0.761)	(0.810)
β_0^U	3.410**	1.678	1.920**	1.333**	-5.421***
	(2.682)	(0.272)	(0.045)	(0.375)	(0.018)
β_1^U	0.998**	0.199**	0.100	0.180	0.017**
	(.026)	(0.074)	(0.450)	(0.781)	(0.091)
β_2^U	-0.842***	-0.584**	-0.920***	-0.828**	-0.902***
	(0.040)	(0.525)	(0.055)	(0.045)	(0.061)
β_3^U	0.310**	0.20**	0.002	0.001	0.190**
	(0.019)	(0.078)	(0.451)	(0.090)	(0.051)
AIC	-47.317	-50.609	-50.060	-52.110	-55.375
BIC	-27.772	-31.064	-30.515	-32.565	-35.830
LR (6) statistics (p-value)	40.65***	18.02***	13.07**	20.75***	29.26***
	(0.000)	(0.006)	(0.041)	(0.000)	(0.000)
Lower Tail Average (τ_L) (p-value)	0.299***	0.230***	0.350***	0.313***	0.056***
	(0.056)	(0.016)	(0.014)	(0.009)	(0.036)

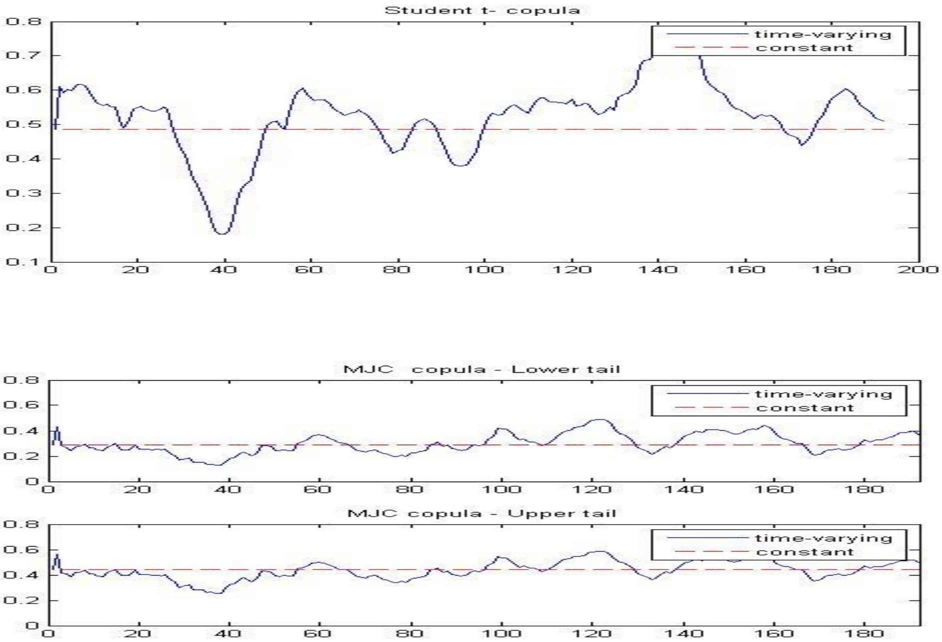
Upper Tail Average (τ_U) (p-value)	0.437***	0.412***	0.372***	0.425***	0.534***
	(0.000)	(0. 013)	(0.027)	(0.013)	(0.014)
Panel B					
Dependence Measure (Expansion)	0.517	0.494	0.545	0.525	0.597
Dependence Measure (Contraction)	0.831***	0.627***	0.621***	0.667***	0.772***
	(5.429)	(5.841)	(3.948)	(6.193)	(5.041)

Notes: The table reports the copula estimates of different equity-paired copula models. Panel A reports the time-varying MJC copula estimates. Goodness of fit AIC and BIC statistics are presented for each of the copula models. The LR (d) test statistics test the null hypothesis that the time-invariant copula model is not rejected as one move from time-invariant to time-varying copula models, where (d) is the degrees of freedom of the LR test. The standard errors of the copula estimates and p-values of the LR tests are reported in the parentheses. Due to space constraint the estimates of the static model are not presented. They can be provided on request. Panel B reports the comparison for the whole period of the study (April 1997 to March 2013). The p- values are reported in the parenthesis. The MA processes of In/US, In/UK, In/G, In/F and In/C are 13, 15, 11, 9 and 14, respectively.

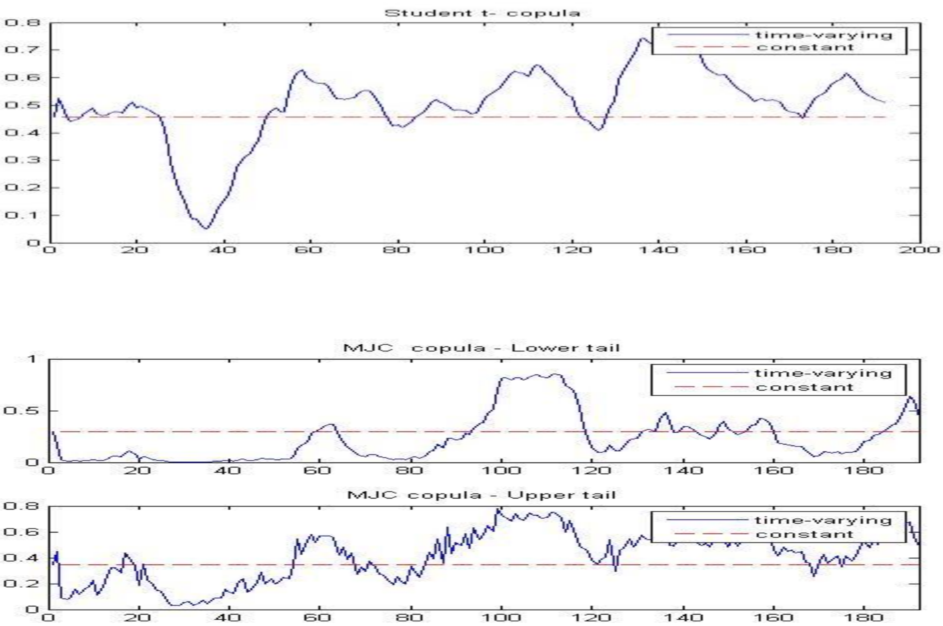
***, ** and * signifies rejection of the null hypothesis at 1, 5 and 10 percent levels, respectively.

Figure 9-1 presents the time path of the dependence structures of the five different combinations of the Indian and international equity return pairs. I present the lower and the upper tail dependence structures along with the time-varying conditional copula models for each pair. It is evident that for all the models the probability of extreme comovements in the upper tail is higher than the lower tail (see note of Figure 1). For instance, the average probability of extreme comovement in the upper tail is highest for Indian-Canadian equity pair, i.e. 0.534, and lowest for the Indian-German pair, i.e. 0.372 (see Panel E and Panel C of Figure 1). This indicates that there is a higher possibility of extreme comovements during the Canadian economic contraction regime than during the German economic decline regime. Thus, during economic decline regime Indian equity market provides a safer place for risk diversification for the German investors relative to the Canadian investors.

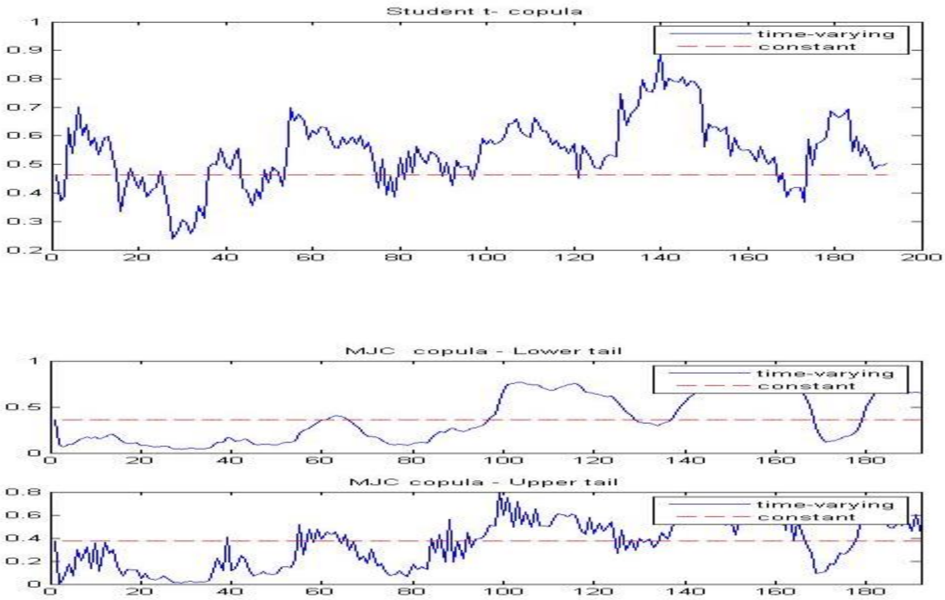
Figure 9-1: Time Path of Indian and Foreign Equity Dependence Structures



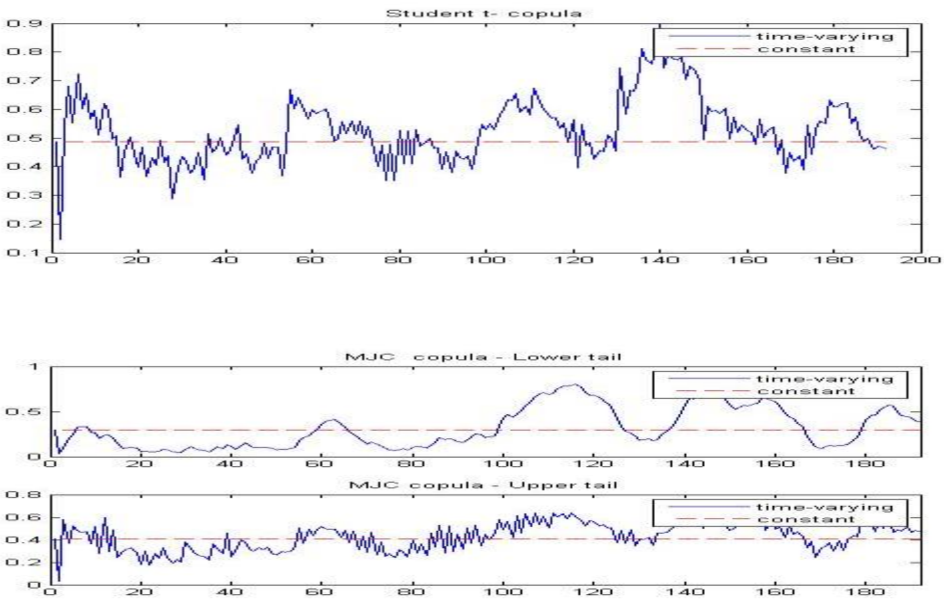
A: Dependence Structure of Indian Equity-US Equity Copula Pair



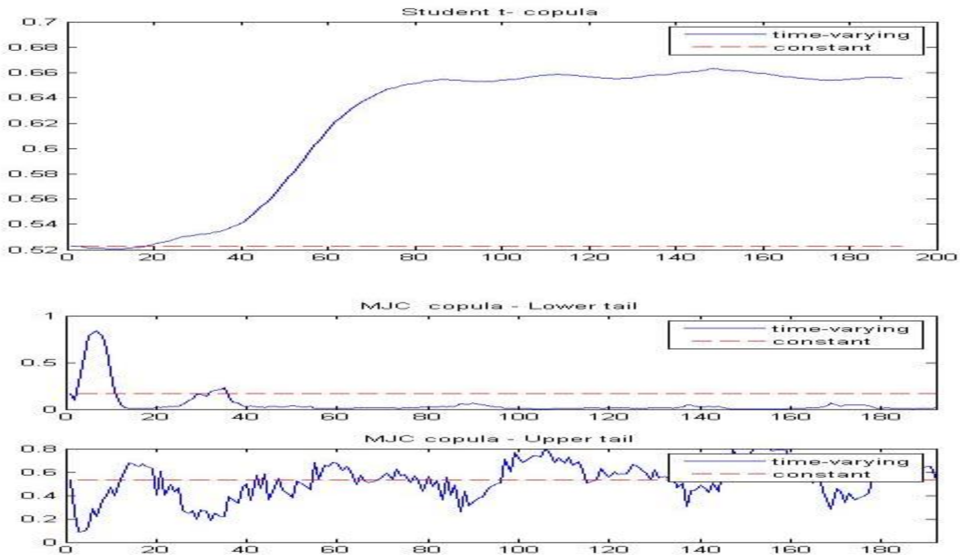
B: Dependence Structure of Indian Equity-UK Equity Copula Pair



C: Dependence Structure of Indian Equity-German Equity Copula Pair



D: Dependence Structure of Indian Equity-French Equity Copula Pair



E: Dependence Structure of Indian Equity-Canadian Equity Copula Pair

Notes: In the figure, Panels A to E show the time path of the time-varying dependence structure of Indian and the foreign equity return-pairs. The average dependence measures for the period 1987 to 2012 of the different asset pairs are: In/US = 0.524, In/UK = 0.504, In/G = 0.545, In/F = 0.528 and In/C = 0.619. The lower tail corresponds to the extreme movements in the economic expansionary phase and the upper tail corresponds to the extreme movements in the economic contractionary phase.

9.4.3 Economic Factor Contributions

Thus far, we have the overall picture of how the stock returns move in tandem. In this subsection, I examine the factors that drive the forward-looking dependence structure during the economic expansion and contraction phases using MSSV model as illustrated earlier. Specifically, this research explores whether Indian-international equity market linkages are related to financial market development indicator, country specific macroeconomic variables and associated stock market measures. Existing literature reports that financial market development is closely related to market integration. In particular, previous studies show that financial market development measures (proxied by equity market capitalization to GDP, equity market turnover ratio) have significant association with stock market integration (Bekaert and Harvey, 2000; Carrieri, Errunza and Hogan, 2007; Panchenko and Wu, 2009). Thus, in line with De Jong and De Roon (2005) I consider a measure of Indian equity Market Openness (MO) as a proxy for financial development measure. MO is computed as the total market capitalization of the S&P Investable Index over the S&P Global Index. To account for macroeconomic variables, I rely on existing literature that identifies specific macroeconomic factors that significantly influence stock return dynamics. Chui and Yang (2012) show that federal rates and Producer Price Index (PPI) have significant influence on the US, the UK and the German capital markets. Consistent with the Modigliani-Cohn hypothesis, Campbell and Vuolteenaho (2004) show that inflation significantly affects stock markets. Based on the previous studies this work, therefore, include three macroeconomic factors: i) PPI, ii) interest rate (IR), i.e. three month Treasury bill rate, and iii) inflation uncertainty (IU). Inflation is measured (i_t measured as (π)) as the log difference of the Consumer Price Index for all items for all urban consumers. To estimate Expected Inflation (π_e) Treasury Inflation Protected note is subtracted from ten-year Treasury note. Inflation Uncertainty (iu_t is meaasured as (π_u)) is estimated as the fractional uncertainty measure of inflation $\left[\frac{\pi_e - \pi}{\pi}\right]$. Increase in IU has detrimental effect on the stock markets. Further, inflationary pressures impact the stock prices through the discounted cash flow framework. Likewise, Interest rate (IR) is expected to have significant influence in both the economic contractionary and the expansionary phase. During the economic expansion phase the rightward shift of the aggregate demand raises the real income and inflation. This leads to a demand-pull inflation which is counter-balanced by an increase in the real interest rate by the central bank. Whereas, during the economic contractionary phase, the government increases spending through expansionary fiscal policy. With rising interest rate, investments tend to fall subjected to high cost of borrowing. This crowding effect hampers the economic growth and has an unfavourable impact on the equity markets. Similarly, since higher than expected price inflation has a bearish effect of the stock markets, an increase in the level of PPI is viewed unfavourable by the investors. Thus, inclusion of these variables will reveal key insights on the dynamics of the macroeconomic factors affecting the asset market linkages.

To account for stock market uncertainty, I use VIX and DVAX as the proxies for stock market uncertainties in the India, US, Canada and the European nations, respectively. Fama and French (1988) and Kalay (1982) highlight the influence of dividend yield on expected stock returns and variances in stock prices. Further, Panchenko and Wu (2009) report significant influence of dividend yield and price to earnings ratio on concordance of asset returns in emerging capital markets. I, thus, include two stock market indicators, i.e. dividend yields (DY) and price to earnings ratio (PE). To mitigate the issues related to omitted variable bias in examining the influence of Indian factors on the dependence structure, a control variable, i.e. stock traded turnover ratio (TR), is included. Further, to take into consideration the existing literature on capital market linkages (Panchenko and Wu, 2009), I also include market capitalization (MC) as a stock market indicator. An increase in market capitalization value suggests improved market sentiments. Inclusion of these variables helps us to ascertain additional explanatory powers of the factors that influence the dependence structure of return comovements. But most importantly, this study includes the key fundamental variables established in the asset return dynamics and asset market linkages by Bakeart and Harvey (2000), Scruggs Glabanidis (2003), Panchenko and Wu (2009) and Chui and Yang (2012) amongst other to investigate the determinants of the return comovements during the extremes.

Table 9-3 presents the impact of Indian and international factors on the stock return comovements. The findings show evidence of two regimes of the dependence structure, i.e. Regimes (1) and (2), corresponding to economic contraction (EC) phase and economic expansion (EE) phase, respectively. Here, it is important to remind that these economic phases relate to the developed markets. The findings reveal several interesting insights. The findings show that market openness (MO) is positive and statistically significant in both the phases of the economy for all the international markets. This suggests that increase in stock market openness increases the likelihood of extreme comovements across Indian and international equity market returns. The significant effect of MO on stock market linkages can be explained by De Jong and De Roon’s (2005) segmentation risk premia phenomenon. A high segmentation risk premia is priced into the risk premium of an emerging market’s stocks when the emerging market is loosely connected with the rest of the international financial markets. However, as the emerging market loosens up, the segmentation risk premia declines, decreasing the equity risk premia of the emerging market’s stocks. This happens because of the greater risk sharing between domestic and international investors, which increase the concordance between domestic and foreign stock markets. The positive and significant influence of MO also implies that increased equity market integration post Indian liberalization has contributed to the phenomenon of financial contagion. Consistent with the existing literature on market linkages of emerging markets (Bekaert and Harvey, 2000; Carrieri, Errunza and Hogan, 2007), it is evident that the Indian financial market development control variable, i.e. stock traded turnover ratio (TR) is significant.

Considering the Indian factors, the findings reveal significant and positive influence of inflation uncertainty (IU) during the economic expansion periods. This finding is however intuitive as increase in IU has detrimental effect on the stock markets. More interestingly, interest rate (IR) has a significantly negative influence in both the economic contractionary and the expansionary phases. This has significant economic significance. The negative influence of IR during the economic contraction phase possibly suggests that an increase in the Indian interest rate invites international capital flows that boost the Indian stock market while the international stock markets are still in a bearish phase. In contrast, the negative impact of IR in the economic expansion phase shows evidence of crowding effect in the Indian market. Similar to IR, Producer Price Index (PPI) has a negative influence in both the phases of the economy, though it is only significant for Indian-US and Indian-Canadian markets. Considering the stock market indicators, DY and PE have greater positive impact during the economic expansion phases. This suggests that higher DY and PE positively impact the Indian equity market, bringing in international capital flows and thereby increasing market linkages during periods of economic expansion. While similar findings are reported by some recent research on international market linkages (Aloui, Aïssa and Nguyen, 2011; Panchenko and Wu, 2009; Bracker, Docking and Koch, 1999), they do not specifically show the influence of the domestic and international factors on the dependence measure, especially during the various phases of the economy. The stock market indicator, market capitalization (MC), bears the same sign as the other market indicator TR. However, MC is not statistically significant. Finally, it is worth noting that Indian stock market volatility is only significant for the Indian-US market during the contraction phase. It bears a positive sign suggesting that an increase in Indian stock market volatility increases the dependence measure. Given the established linkage of increase in stock return volatility during periods of economic decline, this result is not surprising.

Moving on to the international factors, the results reveal several interesting insights. The inflation uncertainty (IU) variable shows a similar influence like the Indian IU factor, indicating that inflation uncertainty in the international markets triggers an increase in dependence measure. Though insignificant, the negative sign of inflation uncertainty can be attributed to the fact that stock market investors are subjected to inflation illusion (Modigliani and Cohn, 1979). The investors fail to understand the effect of inflation on nominal dividend growth, considering that the stock prices are undervalued when the inflation is high and may become over valued when inflation falls. What is more appealing is the influence of interest rates (IR) on the return comovements. In contrast to the Indian IR factor, the international IR variable has a positive impact. This has significant economic implications. The possibility of the increase in dependence measure due to an increase in international interest rates can be attributed to the reduction in investments as IR rises. This suggests that both international and Indian equity markets are adversely affected by the hike in international interest rates. However, while an increase in the Indian interest rates negatively affects its stock market, it has no impact on the international equity markets. The impact of DY varies across the regimes and is country specific. While, clearly, more research is accounted for in this area, it suggests that during periods of economic contraction high DY fails to uplift the investors' sentiments in the developed markets. Similar results are observed for the other stock market indicator, i.e. PE, during the economic contraction phase. More unexpected is the influence of stock volatility (SV) on the dependence measure. The impact is negative and is significant during the economic contraction regime. This suggests that increase in stock market volatility in the developed markets during the economic contraction phase does not adversely impact the Indian stock market returns. Finally, it is evident that the impact of international stock market indicator (MC) is negative. This indicates that high market capitalization reflects positive investor sentiments and hence contributes towards reduction in the dependence measure.

Table 9-3: Impact of Domestic and International Variables

Factors	Variables	Panel A: India-US		Panel B: India-UK		Panel C: India-Germany		Panel A: India-France		Panel A: India-Canada	
		Regime 1 (EC)	Regime 2 (EE)	Regime 1 (EC)	Regime 2 (EE)	Regime 1 (EC)	Regime 2 (EE)	Regime 1 (EC)	Regime 2 (EE)	Regime 1 (EC)	Regime 2 (EE)
Indian	MO	2.027***	3.237***	5.014***	6.897***	0.620***	0.683***	2.306***	2.603***	5.422***	16.130***
		(0.005)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
	IU	-0.228	0.207***	0.304	1.641***	0.583	0.676***	-0.330	0.780	-0.810	1.423***
		(0.713)	(0.000)	(0.492)	(0.0271)	(0.745)	(0.000)	(0.440)	(0.109)	(0.117)	(0.000)
	IR	-0.510***	-0.813***	-3.795***	-3.428***	-2.547**	-2.079***	-0.412	-0.523**	-0.660***	-3.717***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.035)	(0.009)	(0.798)	(0.020)	(0.000)	(0.000)
	PPI	-1.968***	-2.169***	-0.332	-0.202	-0.477	-0.331	0.020	-0.129	-0.344***	-0.839
		(0.037)	(0.005)	(0.672)	(0.110)	(0.781)	(0.853)	(0.745)	(0.938)	(0.000)	(0.842)
	DY	0.600	1.951***	0.138***	1.192***	0.061	1.745***	0.053	0.598***	0.784***	1.413***
		(0.3810)	(0.000)	(0.000)	(0.000)	(0.781)	(0.000)	(0.548)	(0.000)	(0.000)	(0.000)
	PE	0.064	0.033	0.133	0.192***	0.106	0.156	-0.422	0.134	-0.071	0.116***
		(0.981)	(0.757)	(0.446)	(0.000)	(0.259)	(0.457)	(0.673)	(0.503)	(0.556)	(0.018)
	SV	0.326**	0.009	-0.007	0.029	0.063	-0.023	-0.164	0.103	0.014	0.061
		(0.042)	(0.936)	(0.190)	(0.383)	(0.780)	(0.714)	(0.120)	(0.452)	(0.546)	(0.177)
	TR	-0.029***	-0.005	-0.006	-0.025**	-0.014	-0.030**	-0.041	-0.024	-0.008	-0.002

		(0.000)	(0.862)	(0.729)	(0.047)	(0.692)	(0.049)	(0.781)	(0.548)	(0.673)	(0.757)
	MC	-0.186	-0.076	-0.002	-0.017	0.059	-0.028	-0.208	-0.009	-0.009	-0.029
		(0.240)	(0.906)	(0.209)	(0.383)	(0.780)	(0.500)	(0.590)	(0.452)	(0.256)	(0.177)
International	IU	-0.188	3.941**	-1.129	2.413**	0.159	3.716***	-0.753	1.114	0.148	2.618***
		(0.710)	(0.019)	(0.031)	(0.046)	(0.550)	(0.000)	(0.201)	(0.462)	(0.308)	(0.000)
	IR	0.172	3.853**	1.193**	2.672**	0.528	5.816***	0.071	9.227**	0.096	1.596***
		(0.8722)	(0.015)	(0.038)	(0.045)	(0.503)	(0.000)	(0.431)	(0.019)	(0.741)	(0.000)
	PPI	-0.955**	-1.459	0.453	0.402	0.016	0.037	-1.340***	-0.391	-0.194**	0.051
		(0.0401)	(0.121)	(0.341)	(0.246)	(0.118)	(0.110)	(0.000)	(0.291)	(0.043)	(0.110)
	DY	2.123***	-1.450***	0.683**	-1.073***	1.269***	0.972***	0.891***	0.093	0.439**	-0.141
		(0.000)	(0.000)	(0.0462)	(0.000)	(0.000)	(0.000)	(0.000)	(0.329)	(0.0470)	(0.815)
	PE	0.008	0.007	0.190**	0.069	0.068	0.123**	-0.133	0.313	0.090**	0.042
		(0.613)	(0.209)	(0.036)	(0.741)	(0.256)	(0.038)	(0.778)	(0.500)	(0.031)	(0.719)
	SV	-0.117***	-0.008	-0.003	-0.099	-0.071	-0.070	-0.368**	-0.011	-0.025	-0.008
		(0.000)	(0.316)	(0.585)	(0.109)	(0.502)	(0.911)	(0.035)	(0.405)	(0.714)	(0.376)
	MC	-0.120***	-0.091	-0.064	0.019	0.060	-0.384***	-0.948***	-0.043	-0.020	-0.125
		(0.000)	(0.541)	(0.502)	(0.671)	(0.984)	(0.000)	(0.000)	(0.911)	(0.624)	(0.633)
Std. Dev. (Regime)		0.076***	0.098***	0.098***	0.027***	0.097***	0.065	0.085***	0.134***	0.030***	0.025
		[0.001]	[0.002]	[0.001]	[0.000]	[0.002]	[0.001]	[0.001]	[0.024]	[0.000]	[0.990]
Transition Prob.		0.99**	0.83**	0.88**	0.78**	0.98***	0.79**	0.97***	0.78**	0.82**	0.78**

	[0.860]	[0.840]	[0.190]	[0.220]	[0.420]	[0.560]	[0.810]	[0.320]	[0.140]	[0.320]
AIC	-406.490		-316.784		-368.634		-316.093		-476.874	

Note: The table reports the summary the parameter estimation results of the Markov switching stochastic volatility models of five explanatory variables for the various dependence structure. Regime 1 corresponds to expansion regime of the dependence measure and Regime 2 corresponds to the contraction regime of the dependence measure. The expansion regime of the dependence structure relates to economic contraction (EC) phase and the contraction regime of the dependence structure relates to economic expansion (EE) phase. The set of domestic (Indian) explanatory variables constitute Indian market openness (MO), inflation uncertainty (IU), interest rate (IR), producer price index (PPI), dividend yield (DY) price to earnings ratio (PE), stock volatility (SV)and market capitalization (MC). The Stock traded turnover ratio (TR) is the control variable. The set of international explanatory variables constitute inflation uncertainty (IU), interest rate (IR), producer price index (PPI), dividend yield (DY), price to earnings ratio (PE), stock volatility (SV) and market capitalization (MC). Std. Dev. (Regime) reports the standard deviation of the regime states. Transition Prob. (TP) corresponds to the transition probabilities of the two regimes. TP for Regime 1 refers to the probability of the dependence measure to stay in the expansion regime and TP for Regime 2 corresponds to the probability of the dependence measure to stay in contraction regime. The Standard errors are reported in brackets. The p-values of the factor coefficients are reported in parenthesis. The sample period is from April 1997 to March 2013.

** corresponds to 5 percent significance level and *** corresponds to one percent significance level.

9.4.4 Robustness Check: Panelled Quantile Regressions

Standard linear regression estimates the mean relationship between a dependent variable an independent variables based on a conditional mean function $E[y|X]$, where y is the endogenous variable and X is the set of exogenous variables. However, such an assumptions provides restricted analysis of the relationship between the regressors and the endogenous variable. However, greater insights can be obtained regarding the relationship between the dependent and the independent variables by examining the relationship at different points in the conditional distribution of the endogenous variable. Quantile regression enables us to conduct such an analysis. In reference to this study the different points in the conditional distribution of Y relates to the various quartiles of the return comovements that characterizes the cyclical changes of the economy. Hence, examining the impact of the regressors on the dependent variable using quantile regression allows me to conduct a robustness check of the results that I have obtained using regime switching framework.

Here, I estimate the quantile regression model to further investigate the factors that drive the forward-looking dependence structure during the extremes. Though this approach permits estimating various quantile regressions (Koenker and Bassett Jr, 1978), I rely on least absolute deviation regression to overcome the low-power problem of the ordinary least square regressions (see Connolly, 1989).

I estimate the coefficients of the quantile regression at θ (denotes the quartiles for which the relation between the dependence structures and the explanatory variables is estimated) from 0.10, 0.25, 0.05 and 0.75. I also include two additional extreme percentiles at 0.99 and 0.01 levels to observe the changes in the forward-looking dependence structure when large deviations are present. The statistical inferences from these regression models are drawn by bootstrapping method (Andrews and Buchinsky, 2000; Angelis, Hall and Young, 1993). Here, it is necessary to state that lower θ values indicate economic expansion phase and the higher θ values indicate economic contraction phase.

In Table 9-4 reports the regression results from the quantile methods that provide crucial support for the arguments as illustrated in the previous sub-section. Several interesting findings are apparent here. First, MO plays a more dominant role during periods of extreme economic expansion which is marked by low dependence measure. This has critical economic significance. During periods of economic expansion, increase in markets openness between Indian and international equity markets escalate the dependence measure which has detrimental impact during the economic contraction phase. Though, more research is required in the area of market openness and its differential effects during periods of economic expansion and contraction, some recent research gives credence to our argument that increase in market openness during economic expansion phase (which increase the dependence measure between the Indian and the international equity markets) contributes to financial contagion during periods of economic contraction (Poshakwale and Thapa, 2009). Importantly, the significantly positive impact of stock market openness indicates that it provides additional explanatory power over both domestic and international influences.

Second, concerning the Indian variables, IR and PPI show a significant negative influence. In contrast, inflation uncertainty has a positive influence only during periods of economic expansion. The negative influence of IR indicates that positive revisions to Indian interest rate reduce the current equity premium affecting the Indian equity returns. Further, the positive impact of DY during economic expansion phases suggests that they work to increase Indian stock market performance. In doing so, they influence capital flows to India. Interestingly, Indian stock market volatility is only positively significant during extreme periods of economic contraction. Third, considering the international factors, in particular, interest rate and dividend yield have a significant influence. More interestingly, in contrast to the factor exposure of the Indian IR variable, the international IR variable shows a positive significant influence during periods of extreme economic expansion and contraction. This suggests that with rising interest rates in international markets, investments tend to fall subjected to high cost of borrowing which also significantly affects the Indian market. Yet, another interesting observation is the coefficient exposure of DY. The signs are negative during the economic expansion phase (though only significant at 0.01 quantile) and positive during the economic contraction phase. This possibly suggests that even if firms pay dividends during economic recession signalling high level of earning potential in the future, they fail to significantly impact the investors' sentiments during economic turmoil.

Finally, it is worth nothing that both the Indian and the international stock market volatility factors are only significant during the extreme economic contraction phase. However, the impacts are different. While an increase in Indian stock market volatility increases the dependence measure, increase in international stock market volatility reduces the dependence measure. This indicates that while high stock volatility in Indian market reflects global economic downturn, high stock market volatility in international markets fails to severely impact the Indian stock markets during phases of extreme economic contraction.

Table 9-4: Quantile Regression Estimates Examining the Impact of Domestic and International variables

Factors	Variables	Quantile Regression (θ) 0.01	0.10	0.25	0.50	0.75	0.99	Pooled Regression
	C	-0.004	0.265***	0.450***	0.528***	0.562***	0.693***	0.464***
		(0.945)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Domestic	MO	1.028***	5.700***	2.721***	2.762***	3.084***	2.858**	3.338***
		(0.000)	(0.000)	(0.000)	(0.004)	(0.000)	(0.011)	(0.000)
	IU	1.264***	0.749***	0.627***	0.339**	0.161	0.142	0.543***
		(0.000)	(0.000)	(0.000)	(0.024)	(0.253)	(0.563)	(0.000)
	IR	-4.716***	-3.308***	-2.607***	-1.945***	-1.718***	-2.901***	-2.411***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	PPI	-5.083***	-2.005**	-0.156	0.415	-0.882*	-2.301**	-0.725
		(0.000)	(0.043)	(0.875)	(0.572)	(0.090)	(0.000)	(0.170)
	DY	1.721***	1.058***	0.506**	0.206	0.119	0.080	0.453***
		(0.000)	(0.000)	(0.000)	(0.149)	(0.345)	(0.718)	(0.000)
	PE	0.212***	0.128	0.084	0.018	0.020	0.117	0.056
		(0.000)	(0.295)	(0.193)	(0.727)	(0.697)	(0.112)	(0.212)
	SV	0.018	-0.028	0.031	0.014	0.049**	0.059***	0.030
		(0.653)	(0.540)	(0.539)	(0.777)	(0.049)	(0.000)	(0.217)

	TR	-0.034***	-0.016**	-0.004	-0.005	-0.012**	-0.002	-0.012
		(0.000)	(0.045)	(0.630)	(0.632)	(0.034)	(0.665)	(0.084)
	MC	-0.031	-0.049	-0.083	0.012	-0.050	-0.044	-0.057
		(0.737)	(0.525)	(0.262)	(0.832)	(0.279)	(0.347)	(0.191)
International	IU	2.049***	0.186	0.278	-0.013	-0.453	0.206	0.480
		(0.000)	(0.720)	(0.569)	(0.981)	(0.358)	(0.735)	(0.174)
	IR	3.157***	1.124***	0.351	0.471	0.942*	1.385**	0.684**
		(0.000)	(0.000)	(0.320)	(0.300)	(0.082)	(0.041)	(0.035)
	PPI	1.325	-0.535	-1.509	-1.697**	-1.158**	-0.170	-1.209**
		(0.360)	(0.728)	(0.313)	(0.014)	(0.015)	(0.760)	(0.040)
	DY	-2.017***	-0.296	-0.099	0.836	2.245***	3.229***	1.031**
		(0.000)	(0.616)	(0.877)	(0.254)	(0.000)	(0.000)	(0.015)
	PE	0.208	0.304***	0.108	0.142**	0.142***	-0.001	0.136***
		(0.165)	(0.000)	(0.180)	(0.011)	(0.000)	(0.965)	(0.000)
	SV	-0.013	0.017	-0.009	-0.008	-0.022	-0.121***	-0.017
		(0.667)	(0.577)	(0.716)	(0.720)	(0.302)	(0.000)	(0.344)
	MC	-0.241	-0.113	0.040	-0.099	-0.156**	-0.210**	-0.054
		(0.168)	(0.338)	(0.725)	(0.263)	(0.034)	(0.022)	(0.412)
R2		0.480	0.261	0.147	0.139	0.229	0.389	0.354
Mean		0.166	0.435	0.502	0.550	0.618	0.801	0.551

Note: the coefficients of the quantile regression Note: The table reports quantile regression estimates at θ (denotes the quartiles for which the relation between the dependence structures and the explanatory variables is estimated). The lower θ values represent economic expansion regime and the higher θ values represent expansion regime. The set of domestic (Indian) explanatory variables constitute Indian market openness (MO), inflation uncertainty (IU), interest rate (IR), producer price index (PPI), dividend yield (DY) price to earnings ratio (PE), stock volatility (SV)and market capitalization (MC). Stock traded turnover ratio (TR) is the control variable. The set of international explanatory variables constitute inflation uncertainty (IU), interest rate (IR), producer price index (PPI), dividend yield (DY), price to earnings ratio (PE), stock volatility (SV) and market capitalization (MC). The p-values of the factor coefficients are reported in parenthesis. The sample period is from April 1997 to March 2013.

* corresponds to 10 percent significance level, ** corresponds to 5 percent significance level and *** corresponds to one percent significance level.

9.5 Summary

This study examines the drivers of time-varying equity return comovements during economic expansion and contraction regimes. Using equity market index data from April 1997 to March 2013 for India and five major developed economies (the US, the UK, Germany, France and Canada), I examine the regime switching behaviour of the extreme return comovements and identify the factors which drive these comovements. Robust estimation of tail dependence structures during economic contraction and expansion periods has important implications for the international portfolio investors seeking diversification of risk by investing in emerging markets like India. Further, understanding of the factors which drive international equity market linkages would provide greater insights for international investors.

The study reports several interesting findings. The findings show that the probability of extreme comovements in the economic contractionary phase is relatively higher than in the expansionary phase. This has profound implications for international portfolio diversification since historically one of the attractions of investing in the emerging markets was their relatively low correlations with the developed markets which offered international investors opportunities to diversify risk. Further, it is evident that both Indian and international inflation uncertainty are likely to adversely affect the risk diversification potential of the Indian market since they positively impact the return comovements. Similarly, international interest rates also positively impact the return comovements which imply that both international and Indian equity markets are adversely affected by these developments. On the contrary, while an increase in the Indian interest rates negatively affects its stock market, it has no impact on the international equity markets. Interestingly, the study finds that increase in stock market volatility in the developed markets during the economic contraction phase does not adversely impact the Indian stock market returns. Finally, the findings show that Indian dividend yield (DY) and price-to-earnings (PE) ratios seem to have a greater positive impact on return comovements during the economic expansion phase as compared to the economic contraction phase. However an increase in international dividend yield during the economic contraction phase increases the return comovements suggesting that it fails to improve the investors' sentiments in both the Indian and the international equity markets.

Findings reported in the paper have significant implications for both the policy makers in emerging economies like India and the international investors seeking to diversify portfolio risk. First, for the policy makers the impact of interest rates and inflation on return comovements could be used for anticipating financial contagion and/or spill over effects. For international investors, reliable and accurate estimation of the dependence structure of the equity returns comovements will enable them to achieve better asset allocation and greater risk diversification. This is particularly critical since during extreme market conditions, the tail dependence structure can potentially reveal critical information for active portfolio management.

9.6 Appendix

Copula Estimation

I obtain the dependence parameter of the Student-t and modified Joe-Clayton (MJC) using maximum likelihood (ML) method. Referring to equation (9-1) I have $C(u,v;\delta)=C((F_{X|K}(x\,|\,k;\theta_1),F_{Y|K}(y\,|\,k;\theta_2);\delta)$, where θ_1 and θ_2 are the coefficients of the conditioning vector k. Therefore, the joint density of an instance (x_t, y_t) is written as

$$c(x_t, y_t;\delta)=\frac{\partial^2 C(u_t, v_t;\delta)}{\partial u_t \partial v_t}\cdot\frac{\partial u_t}{\partial x_t}\cdot\frac{\partial v_t}{\partial y_t}$$
$$\Rightarrow c(x_t, y_t;\delta)=c(u_t, v_t;\delta).f_{X\,|k}(x_t\,|\,k;\theta_1).f_{Y\,|k}(y_t\,|\,k;\theta_2) \qquad \text{(A-1)}$$

From the above equation, the log-likelihood of the sample $(x_{1,t}, y_{1,t})$ written as

$$L(\Phi)=\sum_{t=1}^{T}\ln\left[c(u_t, v_t;\delta).f_{X\,|k}(x_t\,|\,k;\theta_1).f_{Y\,|k}(y_t\,|\,k;\theta_2)\right] \qquad \text{(A-2)}$$
$$\Rightarrow L(\Phi)=\sum_{t=1}^{T}\ln\left[c\left(F_{X|k}(x_t\,|\,k;\theta_1\delta)\times F_{Y|k}(y_t\,|\,k;\theta_2\delta)\right)f_{X\,|k}(x_t\,|\,k;\theta_1).f_{Y\,|k}(y_t\,|\,k;\theta_2)\right]$$
$$\Rightarrow L(\Phi)=L_C+L_X+L_Y$$

As noted by Jondeau and Rockinger (2006), the ML estimation may be difficult to compute if the number of unknown parameters is large, in which case only numerical gradients can be computed instead of having an analytical expression of the likelihood gradients. This leads to considerable slowing down of the numerical estimation. I, therefore, compute the ML estimation using Inverse Function of Margins (Joe and Xu 1996). This is a two-step estimation process. First, the marginal distribution parameters are estimated employing an ARMA (p, q)-EGARCH (1, 1)-t process as discussed above.

I also capture the time variation of the dependence structure which further increases the number of unknown parameters to be estimated. The following estimation equation is used for computing the values of $\hat{\theta}_1$ and $\hat{\theta}_2$.

$$\hat{\theta}_K = \arg \underset{\theta}{Max}\, L_{XY}\left(x_t, y_t; \theta_1, \theta_2\right);\ fork = 1,2 \tag{A- 3}$$

Next, I estimate the copula parameter $(\hat{\delta})$ using the following equation.

$$\hat{\delta} = \arg \underset{\delta}{Max}\, L_C\left(x_t, y_t; \delta, \hat{\theta}_1, \hat{\theta}_2\right) \tag{A- 4}$$

In this second step the marginal densities do not influence the copula estimation parameter as the marginal parameters are computed using equation (A- 3). Therefore, the second remains unchanged and computes asymptotically efficient and normal estimates of the copula parameter (Cherubini, Luciano and Vecchiato 2004; Joe 1997).

Estimation filter for the MSSV model

The Kalman filter employed for projection is an iterative process. It forecasts the state variable at $'t+1'$ period and updates it when z_t is observable in the equation (9-8). For deriving the filtering equations I denote:

$g_{t|t-1}^{(m,n)} = E\left[g_t \middle| S_t = m, S_{t-1} = n, \psi_{t-1}\right]$, $p_{t|t-1}^{m,n} = E\left[(g_t - g_{t|t-1}^{m,n}) \middle| S_t = m, S_{t-1} = n, \psi_{t-1}\right]$,

$g_{t|t-1}^{m} = E\left[g_t \middle| S_t = m, \psi_{t-1}\right]$ and $p_{t|t-1}^{m} = E\left[(g_t - g_{t|t-1}^{m})^2 \middle| S_t = m, \psi_{t-1}\right]$.

Following Smith (2002), I first forecast log-volatility and then update the previous forecasted estimate. The sequential steps are:

Step 1: The log-volatility is forecast using:

$$g_{t|t-1}^{m,n} = \omega_m + \varphi_m g_{t-1|t-1}^{n} \tag{B- 1}$$

$$p_{t|t-1}^{m,n} = \varphi_m^2 p_{t-1|t-1}^{n} + \sigma_{\eta n}^2 \tag{B- 2}$$

Step 2: The forecasted estimate is updated using

$$g_{t|t}^{m.n} = g_{t|t-1}^{m.n} + p_{t|t-1}^{m,n}\left(p_{t|t-1}^{m,n} + \frac{\pi^2}{2}\right)^{-1}\left(z_t - z_{t|t-1}^{m,n}\right) \tag{B- 3}$$

$$p_{t|t}^{m.n} = p_{t|t-1}^{m.n} - p_{t|t-1}^{m,n}\left(p_{t|t-1}^{m,n} + \frac{\pi^2}{2}\right)^{-1} p_{t|t-1}^{m,n} \tag{B- 4}$$

The conditional densities are computed using the following equation

$$f\left(z_t \middle| S_t = m, S_{t-1} = n, \psi_{t-1}\right) = \frac{1}{\sqrt{2\pi\left(p_{t|t-1}^{m,n} + \frac{\pi^2}{2}\right)}} - \exp\left(\frac{-\left(z_t - z_{t|t-1}^{m,n}\right)^2}{2\left(p_{t|t-1}^{m,n} + \frac{\pi^2}{2}\right)}\right)^{-1} p_{t|t-1}^{m,n} \tag{B- 5}$$

It can be noted that the above procedures makes our process exclusively path dependent. Hence, to remove the path dependence I rely on Kim(1994) as stated in Smith (2002). I compute the conditional expectation of the log-volatility forecast by taking the weighted average output of the previous iteration using the formulations stated below.

$$g_{t|t}^{m} = \frac{\sum_{n=1}^{N} \Pr\left[S_t = m, S_{t-1} = n \middle| \psi_t\right] g_{t|t}^{m,n}}{\Pr\left[S_t = m \middle| \psi_t\right]} \tag{B- 6}$$

$$p_{t|t}^{m} = \frac{\sum_{n=1}^{N} \Pr\left[S_t = m, S_{t-1} = n \middle| \psi_t\right] \left(p_{t|t}^{m,n} + (g_{t|t}^{n} - g_{t|t}^{m,n})^2 \right)}{\Pr\left[S_t = m \middle| \psi_t\right]} \tag{B- 7}$$

The regime probabilities are calculated based on Smith's (2002) modification of Hamilton's (1989) filter. First, wI estimate the regime probabilities using

$$\Pr\left[S_t = m, S_{t-1} = n \middle| \psi_{t-1}\right] = \Pr\left[S_t = m \middle| S_{t-1} = n\right] \times \Pr\left[S_{t-1} = m \middle| \psi_{t-1}\right] \tag{B- 8}$$

The term $\Pr\left[S_{t-1} = m \middle| \psi_{t-1}\right]$ in the equation (B- 8) is the previous iteration filter output. Next I calibrate the joint density using

$$f\left(z_t, S_t = m, S_{t-1} = n \middle| \psi_{t-1}\right) = f\left(z_t \middle| S_t = m, S_{t-1} = n, \psi_{t-1}\right) \times \Pr\left[S_{t-1} = m \middle| \psi_{t-1}\right] \tag{B- 9}$$

where $f\left(z_t, S_t = m, S_{t-1} = n \middle| \psi_{t-1}\right)$ is defined previously in equation (B- 5). In step three I integrate the regimes to calculate the unconditional density as given in equation (B- 10) and then we update the probability of the regimes in state $'t'$ using equation (B- 11).

$$f\left(z_t \middle| \psi_{t-1}\right) = \sum_{m=1}^{M} \sum_{n=1}^{N} f\left(z_t \middle| S_t = m, S_{t-1} = n, \psi_{t-1}\right) \tag{B- 10}$$

$$\Pr\left[S_t = m, S_{t-1} = m \middle| \psi_{t-1}\right] = \frac{f\left(z_t \middle| S_t = m, S_{t-1} = n, \psi_{t-1}\right)}{f\left(z_t, \middle| \psi_{t-1}\right)} \tag{B- 11}$$

Turning Points in the Economic Cycle

Table 9 (A-1): Turning Points of Economic Expansion and Contraction phases

Turning Point	Date	Expansion (E)/Contraction (C)	Months in Phase
Panel A: US			
0	4/1997	E1	47
1	3/2001	C1	8
2	11/2001	E2	73
3	12/2007	C2	18
4	6/2009	E3	46
Panel B: UK			
0	4/1997	E1	133
1	5/2008	C1	20
2	1/2010	E2	7
3	8/2010	C2	18
4	2/2012	E3	14
Panel C: Germany			
0	4/1997	E1	45
1	1/2001	C1	31
2	8/2003	E2	56
3	4/2008	C2	9
4	1/2009	E3	51
Panel D: France			
0	4/1997	E1	64
1	8/2002	C1	9
2	5/2003	E2	57
3	2/2008	C2	12
4	2/2009	E3	50

Panel E: Canada			
Turning Point	Date	Expansion (E)/Contraction (C)	Months in Phase
0	4/1997	E1	129
1	1/2008	C1	18
2	7/2009	E2	45

Notes: The turning points of the economic cycle are based on the National Bureau of Economic Research (NBER) official dates of troughs and peaks the United States and the Economic Cycle Research Institute (ECRI) for the United Kingdom, Germany, France and Canada. (ECRI 2014; NBER 2012). The sample period is from April 1997 to March 2013, yielding 192 monthly observations. Each month in the sample is divided into either an expansionary phase or a contractionary phase based on the turning point.

Regime Classification Statistic

An ideal switching model should classify the regimes sharply, i.e. the regime transition probabilities (p_{mn}) should be as close to 0 or 1. Based on Ang and Bakaert (2002) I construct the regime classification statistic (RCS) for M states as

$$RCS(M) = 100M^2 \frac{1}{T} \sum_{t=1}^{T} \left(\prod_{m=1}^{M} p_{mt} \right)$$

where $p_{mt} = Pr\,(S_t = m|I_T)$ indicate the regime transition probabilities and $100M^2$ serves as a normalizing constant to keep the statistic between 0 and 100. A value of 0 signifies perfect regime classification, whereas a value of 100 implies that the regimes are not capable of distinguishing the behaviour of the data, i.e. dependence structure, across the defined regimes and hence they are irrelevant.

CHAPTER 10

Summary and Conclusion

10.1 Introduction

Considerable time variation in the asset return comovements has been of key interest to portfolio managers and academic researchers. Much of the research in this area has been restricted to the conventional financial assets, i.e. stocks and bonds. There is little research on the impact of changes in the real economy and non-macro factors on the return dynamics of assets comprising financial, commodity and real estate. Extant research on the comovements of assets other than stock and bonds also does not explicitly consider the factors that might influence the dependence structures of their return comovements (Case et al., 2012; Chan et al., 2011; Liow and Yang, 2005). Further, dependence measure has prime importance in analyzing financial contagion. Studies in the past have dealt this issue considering linear correlation as an estimate of the comovement between two random variables. Though this measure of association is easy and convenient to calibrate, it might yield highly biased results in case of non-normal distribution of the sample data. In particular, the linear correlation measure fails to provide an appropriate estimate of the dependence structure when dealing with multivariate distributions exhibiting complex dynamic and asymmetric characteristics. Since, literature confirms the presence of asymmetric dependence among various asset returns (Barsky, 1989; Reboredo, 2011), it is fair to say that linear measure of association leads to inefficient estimation of return comovements especially when analysing periods of economic expansion and contraction.

Thus, to address these research gaps in the existing literature, this study explores the differential impact of the various macro and non-macroeconomic factors on the dependence structure of asset return comovements using two stage Markov switching stochastic volatility framework. This work uses an alternative method to estimate the dependence structure of the asset return comovements based on the theory of copula. The prime motivation to employ copula is that it enables to examine scale-free dependence structure, which is preserved during simulation. Further, there is no restriction on the distribution of the data set, unlike other parametric methods.

This study provides critical insights on the behaviour of return comovements of three different asset classes. These findings have strong implications for researchers, practitioners and policy makers. Below, I present the summary of the key contributions to the existing Literature.

10.2 Contributions to the existing literature

10.2.1 Modelling the dependence structure of asset return comovements

In this study, I use copula models to examine the return comovement of five assets belonging to three different asset classes: financial assets (equities and bonds), real estate (housing) and commodities (gold and oil) for the US market. The period of study is from the fourth quarter 1987 to the fourth quarter 2012. I examine the bivariate and the multivariate dependence structures using static and time-varying elliptical and non-elliptical copulas. Based on my examination, the most important conclusions are as follows:

First, the Student-t copula provides superior estimation for dependence structure for all the combinations of the asset pairs across the three different asset classes. Second, concerning the bivariate copula approach: i) the Student-t copulas dominate in both the static case with constant dependence structure and the time varying case with the dependence structures following evolutionary ARMA processes, ii) in case of non-elliptical copulas the Clayton copulas show the best fit statistics followed by MJC. Yet, it should be noted that only in the case of B/RE and E/RE the time-varying Clayton copula dominates over Student t-copula. This is because of the asymptotic joint distribution of B/RE and E/RE. Third, the LR test statistics of the time-varying copulas rejects the null for all the copula pairs. This specifies that the dynamics of the dependence structure are well captured by the evolutionary process of the time-varying copula models. Consistent with this finding, I also observe that the static dependence measure overestimates the correlation of the asset returns during the expansion phase and underestimates the correlation measure in the contraction phase. Fourth, for the multivariate copula models, the Student-t copula dominates over the Gaussian copula. Results also show an increase in the dependence measure of the return comovements for the combination of all the assets since the August 2007subprime crisis. This suggests a reduction in diversification benefits due to high measure of return comovement.

10.2.2 The dynamics and the determinants of bivariate asset return comovements

Employing two stage Markov switching stochastic volatility framework and using the US data from 1987 to 2012 for three different asset classes and several macro and non-macro variables, I report a number of significant findings. First, I confirm that the dependence structures of asset return comovements of all asset pairs show significant regime-switching behaviour both in terms of statistical and economic significance. Two regimes are identified which corresponds to economic expansion and economic contraction phases. Specifically, the Dependence structure Low State (DSLS) corresponds to the economic expansion phase and the Dependence Structure High State (DSHS) corresponds to the economic contraction phase. Second, examining the factor contributions, it is evident that the model fit worsens considerably when the non-macro factors are dropped for the equity-bond and equity-oil pairs. Third, the results indicate that interest rate and inflation have significant effect on the dependence structure during the economic contraction regime, whilst risk aversion plays a significant in the economic expansion regime. Among the non-macro factors output uncertainty, bond illiquidity measure and depth of recession contribute significantly in explaining the variations of the dependence structures. Fourth, the findings reveal that real estate-oil dependence structure is influenced only by macroeconomic developments. Finally, the study shows that the dependence structure regimes are asset return comovement specific. This suggests that macroeconomic and non-macro variables affect different asset return comovements differently. These findings are robust to the alternative regime switching MGARCH framework.

10.2.3 The dynamics and the determinants of joint asset return comovements

This study examines the macroeconomic and the non-macroeconomic factors that influence the Joint Dependence Structure (JDS) of asset returns of three different asset classes using the US data from 1987 to 2012. The empirical work reports several novel insights. First, the findings indicate that the joint dependence structures of asset return comovements show significant regime-switching behaviour both in terms of statistical and economic significance. The two regimes identified correspond to economic expansion and economic contraction phases. Second, the findings state that among the macroeconomic variables, inflation plays a central role (positive influence) during both the phases of the economy. Also, risk aversion is positively significant during the economic contraction phase, whereas risk free rate negatively affects the JDS during the economic expansion phase. Third, among the non-macroeconomic variables, the uncertainty and illiquidity variables play a dominant role in both the phases of the economy. The findings also reveal that the input uncertainty and bond illiquidity factors have the highest coefficient values. Fourth, examining the factor contributions, I confirm that the model fit worsens considerably when the non-macro factors are dropped. Thus, it is fair to say that the non-macroeconomic factors play a critical role in explaining the variations in the JDS. The findings of this study are also conclusive from the quartile regressions, which are estimated for robustness check.

10.2.4 The dynamics and the determinants of the Indian and the developed equity market linkages

This study also examines the economic sources of stock return comovements of the emerging Indian equity market and the developed equity markets of US, UK, Germany, France, and Canada during periods of economic expansion and economic contraction for the sample period April 1997 to March 2013.

The study reports several novel findings. The findings show that the probability of extreme comovements in the economic contractionary phase is relatively higher than in the expansionary phase. This has profound implications for international portfolio diversification since historically one of the attractions of investing in the emerging markets was their relatively low correlations with the developed markets which offered international investors opportunities to diversify risk. Further, it is evident that both Indian and international inflation uncertainty are likely to adversely affect the risk diversification potential of the Indian market since they positively impact the return comovements. Similarly, international interest rates also positively impact the return comovements which imply that both international and Indian equity markets are adversely affected by these developments. On the contrary, while an increase in the Indian interest rates negatively affects its stock market, it has no impact on the international equity markets. Interestingly, the study finds that increase in stock market volatility in the developed markets during the economic contraction phase does not adversely impact the Indian stock market returns. Finally, the findings show that Indian dividend yield (DY) and price-to-earnings (PE) ratios seem to have a greater positive impact on return comovements during the economic expansion phase as compared to the economic contraction phase. However an increase in international dividend yield during the economic contraction phase increases the return comovements suggesting that it fails to improve the investors' sentiments in both the Indian and the international equity markets.

10.3 Contributions to practice

The findings of this work have important implications for portfolio diversification and asset allocation. For instance, if the dependence structure of the asset returns comovements is accurately estimated, dynamic asset allocation techniques can be adopted for rebalancing the multi-asset portfolio. Analysing the tails of the dependence structure reveals critical information for active portfolio management, specifically during extreme market conditions. In particular, the findings of the lower tails favour: i) investments in gold over bond during economic contraction phase to maximize risk diversification and ii) investment in bonds provide superior hedge for oil.

Even if the dependence structure of the asset return comovements might not be perfectly predicted especially during periods of economic crisis, these findings still hold important implications for portfolio diversification and hedging. In phases of economic contraction, the primary concern of the investors is to minimize losses. Time path of the dependence structure reveal that there is evidence of financial contagion between all assets, yet the probability of joint extreme events is significantly less for the gold-paired copulas. This implies that in order to hedge financial risks during when it is most needed, investors should hold a component of gold in their portfolio. The lower tails provide evidence that all the other assets provide limited financial diversification during crisis period.

Overall, the regime switching analysis of the dependence structure has two key implications for asset allocation and portfolio diversification. First, since there are two regimes for each of the asset pair returns comovements, the asset allocation strategies must be aligned with the regime-switching behaviour of the dependence structure. Second, the dependence structure of all asset pairs is higher during the economic decline phase than during economic expansion phase, except for equity-gold and bond-oil pairs. This implies that investment in gold provides diversification for equity-based portfolio, while bond provides a good hedge for oil.

Considering the examination on Indian and the developed economies equity market linkages – the findings have significant implications for both the policy makers in Indian emerging market and the international investors seeking to diversify portfolio risk. First, for the policy makers the impact of interest rates and inflation on return comovements could be used for anticipating financial contagion and/or spillover effects. For international investors, reliable and accurate estimation of the dependence structure of the equity returns comovements will enable them to achieve better asset allocation and greater risk diversification. This is particularly critical since during extreme market conditions, the tail dependence structure can potentially reveal critical information for active portfolio management.

An additional contribution of this thesis relates to the examination of the practical applications of modelling and examining the determinants of asset return comovements. The findings imply that single-regime models provide inaccurate estimates of asset return comovements during regimes of high volatility which is more profound during periods of economic contraction. Alternatively, the MSSV framework enhances the flexibility in the model accommodating the persistence of volatility shocks. Moreover, the Markov switching model is able to capture the 'pressure smoothening' effects of those shocks that are not persistent and are followed by low volatility regimes. Considering economic significance - the findings show that significant economic value is generated when comovements are more precisely forecasted. Overall, the findings indicate that the dynamic strategy outperforms a multivariate conditional covariance strategy. This, therefore, justifies that understanding the dynamics and the influence of macroeconomic and non-macroeconomic factors on asset return comovements enhances asset allocation decisions.

10.4 Limitations and Scope for Future Research

Positivists dominate social science research in finance. Herein lies a paradox, which I acknowledge in this section. The repressive nature of capital market research and the process in which it is disseminated lacks multidimensional perspectives. Furthermore, assumptions and ideologies of empirical financial research are based on unidimensional, neoclassical economic models. Thus, the deterministic view of quantitative financial research is similar that of statistical mechanics. Alternatively, viewing subjectively, the things are quite different. First, the appearance of certainty in measuring correctness of a theory is comforting, even though we neglect the disturbing ambiguity about objects that are neither correct nor false. In my case measuring the significance of a measure of association between asset returns suggests underlying interdependence between different assets, thus neglecting the influence of human interference in making financial investment decisions. Second, I consider the relationship between asset returns as a single dimensional universally identical object, strictly governed by laws. Yet, human beings contrive to define institutions and customs that govern social interactions. The rules of the society are thus not static and they change both undesirably and unlikely. In my view of this quantitative research, I do not distinguish myself from this unpredictable pattern of human behaviour, assuming independent asset risks. The independence assumption is obviously not realistic. In sum, financial activities can be viewed as inelastic interactions between human beings. They tend to be more subjective which stands in contrast to the objective assumptions of the positivist paradigm, which underpins the limitations of my research study.

However, it should be acknowledges that quantitative studies in capital markets dominate finance and it has certainly led to the creation and better understanding of market behaviour and predictions. Capital market researchers have influenced market regulatory policies and development of new financial instruments. Hence, they are recognized for their notable accomplishments. In view of these recompenses, it manifests to a scholar in finance like me to pursue research in similar veins.

Future research may overcome some of these limitations and produce more robust findings. Future avenues of empirical work in this field lies in improving the macro models. While the New Keynesian model puts useful restrictions on the macro-dynamics, if monetary policy switches through time, it generates a number of significant macroeconomic issues regarding the stability and determinacy of the rational expectations equilibrium. Thus, future research can be undertaken to overcome two particular limitations: i) parameter instability and ii) the rational expectation assumption that constraints the ability of the current macro models to fully characterize the macro dynamics. While this study overcomes the former limitation by incorporating regime switching behaviour in the models, future studies can employ generalized methods of moments technique to potentially resolve the second limitation. Further, survey-based expectations can be used to identify the parameters of a dynamic stochastic general equilibrium model that aims to capture the macro dynamics. Unlike real expectations, survey-based expectations are not conditioned to model specifications and reflect varied perception of the economic agents.

DISSEMINATION OF THE PHD RESEARCH

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Global Finance Conference (2014), 30th march – 2nd April, Dubai, "A New Look at the Return Comovements: Evidence from the Emerging Indian Equity Market"
(Along with Prof. Poshakwale) – This article is based on Chapter 9.

Multinational Financial Conference (2014), 4-5 April, Larnaca, Cyprus 'What drives Asset Market Linkages?'
(Along with Prof. Poshakwale) – This article is based on Chapters 4-8

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GLOSSARY

Arbitrage Pricing Theory	A theory that states expected return of a financial asset is a function of various risk factors. In particular, the theory predicts a relation between the returns of an asset and a linear combination of macro-economic factors and/or market indices.
Asset Allocation	The process of distribution an investor's wealth among various asset classes for portfolio construction.
Asset Class	Securities that are grouped together based on similar risk and return relations and attributes.
Beta	An estimate of non-diversifiable (systematic) risk as a function of asset's sensitivity to market portfolio.
Bond	A bond is a financial security in which an investor receives a variable or a fixed interest rate by lending money to a corporate or a government entity.
Brownian Motion	A stochastic process where the change in the underlying variable at an infinitesimally small period follows a normal distribution with mean and variance proportional to the length of that period.
Capital Asset Pricing Model (CAPM)	A theory that derives expected return of an asset based on non-diversifiable (systematic) risk and risk-free rate of return.
Copula	A techniques to measure correlation between variables with identifiable distributions
Correlation Coefficient	A statistic that measures the relationship between two variables. It varies from (-) one to (+) one.
Diversification	A process of allocating capital in various financial assets with the aim of minimizing risk in a portfolio.
Economic Index	A statistical measure of changes of an economic state variable.
Efficient Frontier	The loci of portfolios that have the maximum payoffs for a particular level of risk.
Flight to Liquidity	Relates to the situation when investors move their investments from more less liquid assets to more liquid assets.

GARCH Model	A technique employed to forecasts volatility. In these type of models the variances follow a mean-reverting process. One of the kay advantage of the GARCH models is that it can accommodate volatility clustering, i.e. periods of high volatility are followed by high volatility and periods of low volatility are followed by low volatility.
Hedging	An investment process or a trading strategy undertaken to eliminate a particular source of risk.
Idiosyncratic Volatility	The volatility caused due to unique characteristics of a specific financial instrument.
Investment	A commitment of fund by an investor for a specific period of time in order to derive expected returns that compensate investor's opportunity cost for that period.
Marginal Risks	Rate of change of risk with respect to a small variation in a particular variable.
Markov Chain	A stochastic process where the next change of an event depends on the present state and not on the preceding sequence of events.
Maximum Likelihood Function	A technique that estimates the parameters of a model by maximizing the probability of occurrence of an observed variable.
Mutual Fund Theorem	A theorem stating that investor's portfolio should hold a combination of risky and risk free assets depending on the risk preference of the investor.
Optimal Portfolio	The investor specific highest utility portfolio on the efficient frontier.
Portfolio Management	Managing a group of investments that have different payoff patterns over time.
Portfolio Optimization	A technique that maximizes portfolio returns subjected to equation of constraints. These are ideally based on risk and applicability of short selling.
Portfolio Return	The expected return of a group of investments over a specific period of time.
Principal Component Analysis	An analysis to determine the factors that explain most of the variations in a group of correlated variables.

Quadratic Programming	It relates to optimization of a quadratic function subjected to equation of constraints.
Regime-switching Model	A time-series model where parameters take a specific value for some defined regimes.
Regression Analysis	A technique used to determine the relationship of a dependent variable as a function of a number of independent variables.
Return	The expected payoff an investor estimates by holding an investment for a specific period of time.
Risk	The volatility of future returns that is influenced by various economic factors, market factors and firm performance.
Risk Premium	The compensation an investor seeks because of investment uncertainty.
Stochastic Process	A model defining the probabilistic behavior of a variable, which has an uncertain future outcome.
Separation Theorem	The former employs investment in the market portfolio and the latter is based on specific investor's risk preference.
Stationary Process	A stochastic process where the statistical properties of a variable are time-independent.
Stocks	Generally refers to common stocks that are equity investment stating ownership of a firm.
Tail Dependency	It relates to the degree of correlation in the tail of two variables in the same probability space.
Utility Function	A locus that represents preference of economic entities based on risk and expected return of an investment.
Variance	A statistic to measure variability across the mean. It is equal to sum of the squared differences from the mean divided by the total number of observations.