Stock return, risk and asset pricing

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Author's Declaration

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Diana Nawwash Abed El-Hafeth Abu Ghunmi

Abstract

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This thesis attempts to address a number of issues that have been identified in the asset pricing literature as essential for shaping stock returns. These issues include the need to uncover the link between the macroeconomic variables and stock returns. In addition to this, is the need to decide, in light of the findings of the literature, whether to advise investors to include idiosyncratic risk and downside risk as risk factors in their asset pricing models. The results presented here suggest, consistent with other previous studies, that stock returns are a function of a number of previously identified risk factors along with the wider set of macroeconomic variables. These macroeconomic variables could be represented by a number of estimated macro factors. However, only one of these estimated factors emerged as significant in explaining the cross-section of stock returns. Nevertheless, it is important to note that the size (SMB) and value (HML) factors remain important factors in explaining the cross sectional returns on UK stocks, even with the existence of the other risk factors. This finding of inability of the examined macroeconomic variables to capture the pricing power of the SMB and the HML may cast doubt on the possibility of finding more macroeconomic factors that are able to account for these two factors in the cross section of returns in the UK. Interestingly, this conclusion seems to contradict previous authors' findings of potential links in the UK market. The results also support past studies that find that downside risk is an important risk factor and by allowing the downside risk premium to vary with business cycle conditions, downside risk might be a better measure of risk than market risk. Nevertheless, this thesis shows that although this finding is applicable in times of economic expansion, during recession, there is no conclusive relationship between downside risk and stock returns. Furthermore, this thesis supports the studies which find that idiosyncratic risk is not significant in pricing stocks. However in contrast to other studies, it reveals this by showing that time-varying risk could be the reason behind the

potentially illusive findings of idiosyncratic risk effect. This thesis confirms that, for London Stock Exchange investors, macroeconomic variables should never be overlooked when estimating stock returns and downside risk could be an influential risk factor.

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Chapter 1 Introduction

1.1 Introduction

"Theorists develop models with testable predictions; empirical researchers document "puzzles"—stylized facts that fail to fit established theories—and this stimulates the development of new theories." (Campbell, 2000, p.1515)

This relationship between the theories and the empirical data is what this thesis attempts to study. It examines, in the light of the recent issues and developments in the area of asset pricing to what extent stock returns are explained by the theory. It also aims to study what findings are spurious and what puzzles remain and therefore how much support can be offered to the current literature. The relationship between stock returns and risk is of particular interest not only for researchers but also because it is at the very heart of all investment decisions. Therefore, this research is not only important from a theoretical point of view but it also matters to investment decision makers.

No researcher in finance can deny that the theoretical models of Sharpe (1964), Merton (1973), Ross (1976) and Breeden (1979) are important. However, Schwert (2003, p.964) notes "Many people have developed extensions of theoretical asset-pricing models that include multiple factors ......, although none of these models match closely with the empirical Fama–French model". Despite the fact that Schwert's (2003) statement looks like good news for Fama and French's (1993) three-factor model, the asset pricing models, which Campbell (2000) describes as being concerned with the determinants of the risk premium, are facing challenges ahead. These challenges are posited by Campbell

(2000) and Cochrane (2006) as being the requirement to unearth the association between the macroeconomic variables and stock returns.

1.2 Macroeconomic Factors and Fama and French Asset Pricing Model

The capital asset pricing model (CAPM) of Sharpe (1964) has been questioned in terms of its underlying assumptions as well as its empirical application as pointed out by Merton (1973) and Fama and French (2004). Roll (1977) points out that providing that the theoretical market portfolio has not been identified the model could not be assessed empirically. Fortunately, APT of Ross (1976) overcomes this problem as indicated by Roll and Ross (1980). Roll and Ross (1980) point out that the APT does not need the market portfolio and is empirically testable. Burmeister and McElroy (1988) state that the risk factors in the APT could be either statistically based or macroeconomic factors. They also point out that the latter has the benefit of relating stock returns to the wider economy. Furthermore, Priestley (1996) argues that the first route lacks economic meaning[1].

As mentioned earlier, Merton (1973) refers to the theoretical shorcomings of the CAPM and points out that its static nature is not realistic. Merton (1973) developed an intertemporal capital asset pricing (ICAPM) model and indicates that it is important as it accounts for the future investment opportunities' shifts that are ignored by the CAPM.

[1] For the statistically based factors (see (Roll and Ross (1980), Connor and Korajczyk (1986, 1988) and Jones (2001)) and for the macroeconomic factors (see Chen et al., (1986), Priestley (1996) and Antoniou et al, (1998)).

However, Breeden (1979) points out that while this intertemporal aspect of the ICAPM is crucial, the model's applicability is questionable as it measures risk with multi-betas that are associated with unknown state variables. He developed the consumption asset pricing model. And he argues that this model overcomes the ambiguity regarding the risk factors as it replaces the multi-betas with a single consumption beta. The standing of this model is described by Cochrane (2001, Ch (2)) who points out that although the consumption asset pricing model is perfect theoretically, its poor empirical performance prompts the need for other models. Nevertheless, Cochrane (1996) states that the consumption based model performs unsatisfactorily in the empirical applications and this could be caused by, among other things, problems with consumption data. Campbell (1993) also points to consumption data problem.

On the empirical side, Campbell (2000) indicates that the empirical financial anomalies that defy the CAPM include the small size, value and momentum effects. He points out that that potential causes for such findings that have been put forward in the literature to date include the failure of market proxy, spurious findings, mistakes and psychological biases. He comments further that these findings could also be explained in a rational multifactor model such Fama and French (1993) three-factor model or the ICAPM of Merton (1973).

Fama and French (1993) developed a three- factor model that includes in addition to market portfolio, the HML and SMB as risk factors. Despite the fact that they report a strong performance for their model in describing the changes in stock price they admit that there are problems. Fama and French (1993) state that as these two factors are selected empirically and with the lack of a theory to support them, any explanation will never be ultimate.

Furthermore, Fama and French (1995) point out that they support the rational story behind the size and value factors as these factors are associated with profitability. However, they indicate that the state variables behind these factors still need to be established. Furthermore, Fama and French (1996) point out that they support that Fama and French's (1993) factors are factors in the line of ICAPM model but the state variables need to be known concretely. Cochrane (2006) states that the economic drivers of the marginal value of wealth and the returns on the Fama and French size and value factors need to be known. He further points out that this could be achieved only through macroeconomic models. Among the studies that meet such a challenge is Petkova (2006) who suggests a model that includes excess market return and innovations to dividend yield, term spread, default spread and one month interest rate. She reports that her selected state variables capture Fama and French's (1993) SMB and HML in the context of the ICAPM and her model outperforms the Fama and French's (1993) three-factor model and the SMB and HML influence on stock returns disappear when she adds them in her model.

However, Petkova (2006) points out that the variables she chooses are not the only variables in the information set of investors and there could be other useful risk factors. Therefore her model leaves open the possibility that other macroeconomic factors are ignored in the analysis even though they are important. Fortunately, the dynamic factor model method of Stock and Watson (2002a, b) opens the opportunity for asset pricing to exploit many macroeconomic variables to help answer the challenges that are posited by Campbell (2000) and Cochrane (2006) who stress that those macroeconomic variables which are responsible for the behavior of stock returns must be understood. Furthermore, as cited earlier, Cochrane (2006) points out nothing other than macroeconomic models can give understanding to the performance of Fama and French's (1993) factors. Studying this relationship between the economic forces and Fama and French's (1993) factors is the first objective of this thesis.

On the dynamic factor approach applications in asset pricing side, Mönch (2004) points out that he uses the dynamic factor model method of Stock and Watson (1998, 2002a) on large macroeconomic variables to employ the resulting estimated factors as risk factors which he describes as a new approach for uncovering the risk factors. He indicates that he compares his model with Fama and French's (1993) three-factor and Campbell's (1996) models and also augments the latter model with the estimated factors to test if the estimated factor adds additional information. However he does not provide an answer to whether these estimated factors capture Fama and French's (1993) factors. In addition he uses the estimated factors while this thesis employs the innovations in the estimated factors. Furthermore, Ludvigson and Ng (2007) points out they employ the dynamic factor models with large dataset to provide a solution for the omitted risk factors in the conditional information set.

1.3 Idiosyncratic Risk and Time Varying Betas

Another important recent topic in asset pricing is idiosyncratic risk. In developing his CAPM model Sharpe (1964) states that as a result of diversification the unsystematic part of the total risk does not affect the asset's return. In spite of this, Merton (1987) develops a model in which stock return depends positively on its systematic risk as well as its specific risk in a market where information is incomplete. Furthermore, Malkiel and Xu (2006) point out they derive a model that includes the undiversified idiosyncratic risk as a potential risk factor because in a world of no market portfolio, undiversified idiosyncratic risk is a priced factor.

Empirically, Malkiel and Xu (2006), Spiegel and Wang (2005), Chua, Goh and Zhang (2007) and Fu (2007) report a positive relationship between stock returns and idiosyncratic risk, while Ang, Hodrick, Xing and Zhang (2006, 2008) report a negative idiosyncratic risk effect on stock returns. Ang, Hodrick, Xing and Zhang (2008) point out that this is a puzzling global finding whose sources need to be studied. On the other hand, Huang et al. (2006) indicate that there is no cross sectional idiosyncratic risk influence on the stock returns and the negative effect arises from the return reversal. Furthermore, Bali and Cakici (2008) state that because of these confusing findings their objective is to study whether idiosyncratic risk effect is genuine. They report that it is not robust and it is a matter of differences in applied methods used by these studies.

From another perspective, Chen and Keown (1981) point out that when time-variation in beta is not accounted for then residual risk from OLS will not be pure as it will reflect this variability and will be heteroskedastic. Ang and Chen (2007) also refer to this issue and they call the part that is due to time-varying beta and appears in the residuals an omitted variable. Furthermore, Malkiel and Xu (2006) point out that the residuals from any pricing model could be representative of omitted factors and other effects. Therefore, the second objective of this thesis is to attempt to contribute to idiosyncratic risk literature by examining whether accounting for time-variation in betas by applying Avramov and Chordia's (2006) conditional model and methodology could explain the mystery of idiosyncratic risk in the cross section of returns and hence support Bali and Cakici (2008) and others who provide evidence that idiosyncratic risk is not significant.

1.4 Downside Risk and Business Cycle

Sharpe (1964) points out that the mean variance model might be inadequate for some circumstances and he argues that Markowitz indicates that semivariance based model could be favoured. However, Bawa and Lindenberg (1977) develop a model which they call the mean - lower partial CAPM that uses the lower partial moment instead of the variance. They point out that their model implies the CAPM when stock returns are normally distributed.

More recently, Ang Chen and Xang (2006) propose a downside risk model with disappointment aversion utility maximizers. They point out that these investors are anxious about the downside changes of stock prices. They report a significant cross-sectional price for downside risk. In addition, Post and Vliet (2005) report that they find downside beta, conditionally and unconditionally, is a superior cross sectional risk factor to market beta. They report that they find the superiority of mean-semivariance CAPM occurs, in particular, when the economy in its bad states but it is not that strong over Ang Chen and Xing's (published later as Ang Chen and Xing (2006)) sample period. Post and Vliet (2005) point out that the latter study's downside risk measure is questionable and it does not use conditional tests of downside risk. Therefore, the third objective of this thesis is to examine the effect of a time-varying (conditional) risk premium in Ang Chen and Xing's (2006) downside risk model, over the business cycle on the relationship between downside risk and stock returns.

1.5 Issues and Contribution

The above cited literature demonstrates the current standing of asset pricing models and highlights the unresolved issues that remain to be addressed. Based on this, the objectives of the chapters of this thesis are outlined below.

Chapter (2) starts by reviewing the relevant literature related to asset pricing models and dynamic factor models. Based on this and motivated by Campbell's (2000) and Cochrane's (2006) demand for understanding of the relationship between the macroeconomic variables and stock returns and Fama and French's (1993) SMB and HML, the second chapter examines if the macroeconomic variables are able to explain the cross section of UK stock returns and whether they can capture Fama and French's

(1993) SMB and HML. Therefore, this chapter applies Petkova's (2006) model that includes excess market returns, innovations to dividend yield, term spread, default spread and one month interest as well her model that includes, in addition to these five variables, the HML and SMB. Then instead of confining the analysis to a small number of macro factors, it moves to augment Petkova's (2006) model (keeping only factors that are found significant in the UK) with innovations to factors estimated from a large panel of macroeconomic variables by the dynamic factor model method of Stock and Watson (2002a, b).

The results show that innovations in dividend yield, term spread and one estimated factor (relates to unemployment and term spread) and the HML and SMB are significant factors in the UK market. However, this chapter finds no association between the first three factors and the Fama and French's (1993) SMB and HML. This chapter contributes to the literature by using innovations in estimated factors from large macro variables to examine whether they can capture the HML and SMB. The results cast doubt on the possibility of finding further macro factors that can replace the HML and SMB in the UK. As mentioned earlier, Mönch (2004) uses estimated factors from a large set of macro variables and augments Campbell's (1996) model with these estimated factors, but this chapter differs in using the innovations to estimated factors and attempts to link them to the HML and SMB.

Chapter (3) starts by reviewing the relevant literature related to idiosyncratic risk and stock returns and time-varying betas to establish the importance of studying idiosyncratic risk. Based on this and motivated by the indecisive findings regarding idiosyncratic risk ability to explain stock returns. This chapter examines idiosyncratic risk in the cross-section of UK stock returns. Bali and Cakici's (2008) attribute idiosyncratic risk effect to methodological issues and conclude that idiosyncratic risk is insignificant. Furthermore, there are findings that idiosyncratic risk effect is significant in the UK as found by studies such as Angelidis and Tessaromatis (2008a), Ang, Hodrick, Xing and Zhang (2008) and Fletcher (2007). This chapter examines idiosyncratic risk in the UK market by following mainly Ang, Hodrick, Xing and Zhang (2006, 2008) and Spiegel and Wang (2005). Then it examines whether accounting for time-variation in beta by applying Avramov and Chordia's (2006) conditional model and methodology can capture the effect of idiosyncratic risk. Avramov and Chordia (2006) point out that what distinguishes their methodology is that they model beta explicitly.

These results show, consistent with the literature, confusing findings regarding the significance of the relationship between idiosyncratic risk and stock returns. However when Avramov and Chordia's (2006) conditional model and methodology are applied, the results show idiosyncratic risk is insignificant in explaining the cross sectional returns in the UK market. This conclusion is consistent with Bali and Cakici (2008). This chapter contributes to the literature of idiosyncratic risk by supporting those who stress the importance of time-varying beta as a potential explanation to the confusing evidence about idiosyncratic risk effect. It shows that this confusing evidence could be attributed to not using time-varying beta modelled explicitly as in Avramov and Chordia's (2006) conditional model. This chapter however does not study the effect of time-varying beta on idiosyncratic risk which is calculated using daily returns following Ang, Hodrick, Xing and Zhang (2006, 2008).

Chapter (4) similarly commences by reviewing the relevant literature related to downside risk and time varying risk over the business cycle. The fourth chapter is motivated by the encouraging downside risk findings of Ang Chen and Xing (2006) and Post and Vliet (2005) and the criticisms the latter study made concerning Ang Chen and Xing' (later published as Ang Chen and Xing (2006)) methodology, which is in line with the importance of time-varying risk. Added to this, are the findings of Pedersen and Hwang (2007) and Olmo (2007) regarding the potential importance of downside risk in UK. Therefore, the fourth chapter examines if the significant role of downside risk of Ang Chen and Xing (2006) is also important in the UK cross section of returns and whether these findings are strengthened or weakened by allowing for downside risk – return relationship to vary over the business cycle. More specifically, it studies whether their findings hold only over particular phases of the business cycle, as argued by Post and Vliet (2005), rather than all over the business cycle. Consequently, this chapter first applies Ang Chen and Xing's (2006) study to the UK market. Then it follows Post and Vliet's (2005) conditional test approach which includes dividing the full sample period into recession and expansion and then reapplying Ang Chen and Xing's (2006) model and methodology over the recession and expansion periods one by one. The Economic Research Cycle Institute's dates of the business cycle are used to divide the sample into recession and expansion following Antoniou et al., (2007).

The results show that Ang Chen and Xing's (2006) downside beta is priced in the UK market, although it has a problem pricing the riskiest stocks. Furthermore, downside beta and CAPM beta show, to a large extent, similar performance unconditionally. However, when Ang Chen and Xing's (2006) downside risk model and methodology are applied separately over the expansion and recession periods rather than over the full sample period as before, the results show downside beta excels over CAPM beta in explaining the cross sectional changes in stock prices over expansion, but both measures of risk have inconclusive results over the recession period. Also the findings show some support for Pedersen and Hwang's (2007) and Olmo's (2007) studies.

Chapter 2 Macroeconomic Factors and Fama and French Asset Pricing Model

2.1 Introduction

> "In sum, the program of understanding the real, macroeconomic risks that drive asset prices (or the proof that they do not do so at all) is not some weird branch of finance; it is the trunk of the tree. As frustratingly slow as progress is, this is the only way to answer the central questions of financial economics"(Cochrane, 2006, p.6).

This chapter addresses this issue by examining the link between macroeconomic factors and stocks prices, the importance of which is stressed by Cochrane (2006) and Campbell (2000). The keystone asset pricing models in the asset pricing literature are the capital asset pricing model (CAPM) of Sharpe (1964), the arbitrate pricing theory (APT) of Ross (1976), the intertemporal capital asset pricing model (ICAPM) of Merton (1973), the consumption-based asset pricing model (C-CAPM) of Breeden (1979), and then Fama and French (1993) developed their three factor model.

Unfortunately the situation of the latter model compared with first four models is summarized by Cochrane's (1999, p.40) statement "In general, empirical success varies inversely with theoretical purity". Fama and French (1993) admit that as the additional two factors in their model; the size (SMB) and the book-to-market (HML) were chosen empirically, with no theoretical support, the interpretation of such factors is debatable. In fact connecting SMB and HML to macroeconomy is one of the most important issues in current research in this area (Cochrane, 2006) and one of the motivations behind this chapter.

In an attempt to legitimatize their model as a rational asset pricing model, Fama and French (1996) argue that the SMB and HML factors could be interpreted as proxies for multifactor-minimum-variance portfolios in a two-state ICAPM of Merton (1973), that could be related to relative distress. In addition, they reported that the three-factor model is able to explain variation in portfolios' returns constructed from sorting stocks on a number of firm characteristics, but it fails the Jegadeesh and Titman's (1993) momentum effect. Despite this success they point out that they have not yet discovered, unquestionably, the ICAPM's state variables or the APT's factors that would support their findings in the context of Merton's (1973) model or Ross's (1976) model, and hence a number of explanations is still feasible. This is also stressed by Lewellen (1999) who points out that the risks factors that underlie the size and book-to-market portfolios must be known for a complete rational explanation to be attained and Hahn and Lee (2006) indicate that the above statement of Lewellen (1999) is still valid. Furthermore, Lettau and Ludvigson (2001) argue that Fama and French's (1993, 1995) interpretation that the three-factor model captures common risk factors, is debatable as the association between the macroeconomic risk factors and the size and book-to-market factors is still to be clarified.

A way to resolve the controversy surrounding the HML and SMB was suggested by Cochrane (2006). He points out that asset pricing models that use portfolios as risk factors can do the job of pricing stocks but cannot explain why portfolios of SMB and HML are so priced and only macroeconomic models can come up with the explanation. Liew and Vassalou (2000) reported that the HML and SMB are related to future economic growth and argue that these findings support Fama and French's (1992, 1993, 1995, 1998) risk story that these variables proxy for the ICAPM's state variables of Merton's (1973). Lettau and Ludvigson (2001) reported that the higher nondiversifiable risk of value portfolios can, in part, explain the value premium. Recently, Petkova (2006) reported that these debatable Fama and French's (1993) HML (book-to-market) and SMB (size) portfolios are proxies for risk factors which are the innovations to aggregate dividend yield, term spread, default spread and the one-month Treasury-Bill. She points out that these four[2] variables predict future changes in the investment opportunity set. Furthermore, Hahn and Lee (2006) report support to the risk story as well.

However, these studies have used only a subset of the potential actual information set that is available to investors. Therefore it keeps open the question of whether the employed risk factors are the only priced factors or if there are missing macroeconomic risk variables that are able to capture the variation in stock returns that need to be considered and whether these missing variables are able to capture the HML and SMB performance. In fact, Lettau and Ludvigson (2001) address this issue of potential missing variables. They point out that the information set observed by the researcher is only part of the set used by the investor. They indicate that they overcome this problem by choosing a conditioning factor that captures the expectations in the market. Furthermore, Ludvigson and Ng (2007) point to what they call a problem of omitted-information in the context of the conditioning information, and indicate that they overcome this problem by employing a large panel of data using the dynamic factor models. Additionally, Mönch (2006) employs the dynamic factor models with large set of data and reports that the

[2] Petkova (2006) suggests a model that includes excess market returns and innovations to aggregate dividend yield, term spread, default spread and the one-month Treasury-Bill.

estimated factors account for the information used by investors. Mönch (2004) points out that he uses the factors estimated using the dynamic factor model method of Stock and Watson (1998, 2002a) on large set of macro variables as potential risk factors and also points out that he augments Campbell's (1996) model with the priced estimated factors to emphasize the added information by these factors.

This chapter contributes to the literature of asset pricing by providing another investigation of this potential problem. This problem has arisen because the potential existence of risk factors that are important for explaining the returns on stocks are missed when only a few sets of standard risk factors that are used extensively in the literature are chosen. Chen (2003) points out that this potential problem (i.e. missing risk factors) could be behind his model's rejection to the rational explanation for the book-to-market effect. This is important as the objective of this chapter is first to respond to Campbell's (2000) and Cochrane's (2006) demand to find the macroeconomic variables that are responsible for stock's risk premia. The second aim is to respond to Cochrane's (2006) challenge to find the macroeconomic factors that are tracked by Fama and French's (1993) HML and SMB factors.

A recent paper that takes on these challenges is Petkova (2006). She suggests a model that includes market excess returns and innovations to variables that are state variables in the context of the ICAPM of Merton (1973) and examines if Fama and French's (1993) factors fall within ICAPM interpretation by relating them to the surprises to the four state variables. Furthermore, Petkova (2006) mentions that in response to the fishing license criticism of the ICAPM that is made by Cochrane (2001) and Fama

(1991), she selects as state variables those that have the ability to predict the future investment opportunity set. Also she points out that Cochrane (2001) criticize studies that do not check the predictive ability of their factors. Therefore, this chapter starts by applying Petkova's (2006) study and methodology to the UK market. This provides an out-of-sample test for her study.

However, Petkova's (2006) study does not rule out the potential existence of other macroeconomic risk factors that are valuable for pricing stocks and these need to be taken into account in order to respond satisfactorily to the challenges put forward by Cochrane (2006) and Campbell (2000). Indeed Petkova (2006) acknowledges this shortcoming and states that there could be other useful information that is used by market participants to predict the changes in the investment opportunity set. But she concludes that based on her findings the state variables that she has employed appear to be appropriate pricing variables.

This chapter overcomes this shortcoming and augments her model with other possible predictive macroeconomic variables to examine if there are missing risk factors that are not captured by her chosen state variables and/ or if other factors are required to capture the returns on the HML and SMB. In extending the possible set of state variables, care needs be taken regarding the variables chosen as additional potential risk factors. Fama (1991) accuses the asset pricing models with multiple factors of being licenses to look for factors explaining the stock returns that already have been found. However, Cochrane (2001, Ch (9)) points out that ICAPM is not exactly such a license as state variables have to be predictive factors. He states they are those variables that have the ability to predict stock returns or economic variables. In addition, Cochrane (2006) indicates that for the state variables in the ICAPM model to affect stock's return, they have to be able to forecast the return on the market and consumption.

Therefore, in order not to fulfill Fama's (1991) fears regarding the multifactor models, the dynamic factors model of Stock and Watson (2002a, 2002b) is utilized in this chapter. The relevance of this model to the objective of this chapter comes clear from understanding what it does. Stock and Watson (2002a) employ the method to forecast macroeconomic series. They point out rather than choosing a few potential predictive variables to forecast macroeconomic variables, the approximate factor model summarizes the information contained in a large set of variables in a few factors that are estimated by method of the principal component analysis. They reported that a great deal of the variability in the examined large set of macro variables is captured by few estimated factors. Therefore this chapter examines if such estimated factors that are found to forecast the macroeconomic activity can be additional risk factors in the context of the ICAPM and if they bear any relation to the Fama and French's (1993) HML and SMB. In sum, this chapter aims at addressing the challenges to asst pricing models, that have been stressed and discussed by Campbell (2000) and Cochrane (2001, 1999, 2006) to relate the macroeconomic forces to stock returns and Fama and French's (1993) factors in the UK.

On the estimated macro factors as potential risk factors front, Mönch (2004) pointed out that he studied whether a few factors estimated from a large dataset of macroeconomic variables could explain the cross-sectional returns on Fama and French's (1993) 25 size and book-to-market portfolios. He indicated that he developed a model, that he calls the "diffusion index pricing model", which employs the common factors estimated from a large macroeconomic dataset, using the method of Stock and Watson (1998, 2002a) as risk factors. He states that his motivation is examining whether the common factors that drive the macroeconomy also drive stock returns. Mönch (2004) points out that he compares his model with a number of models including Campbell (1996) and Fama and French (1993) three-factor model. Furthermore, he points out that to test for additional information provided by these estimated factors, he augments Campbell's (1996) model with the estimated factors. However this chapter differs from his in number of ways. First, he developed a theoretical framework for his model, while this chapter makes no assumptions but rather uses the innovations to the estimated common factors as potential risk factors. In contrast he uses the estimated common factors themselves as risk factors. This is important as Merton (1973) states that in the ICAPM world, stock return is determined by market risk and the risk that arises from the changes in the investment opportunities where the latter could be described by at least one state variable which is the changes in the interest rate. Furthermore, Brennan et al (2004) emphasize this nature of the ICAPM and indicate that the risk factors in the ICAPM are innovations to state variables that describe the investments set and not only factors that are related to stock returns. Second, this chapter examines whether the innovations to these estimated factors are able to absorb the explanatory power of the Fama and French's (1993) HML and SMB, while he merely compared the performances of the two models, despite the fact that capturing the effect of the HML and SMB is one of the main issues in asset pricing that needs to be solved as discussed by Cochrane (2001, 1999, 2006) among others. Third, this chapter is applied to the UK whereas he applied his study to the USA. Furthermore, while Mönch (2004) treated the risk factors as possible state variables, this chapter treats the innovations in the estimated factors as potential state variables, and as in his study it uses Stock and Watson's (2002a, 2002b) dynamic factor model and methodology to estimate the common factors.

The second contribution of this chapter is providing an out-of-sample test of Petkova's[3] (2006) study. Fletcher (2007) applies Petkova's (2006) model to the UK. He points out that he uses Petkova's (2006) and Fama and French's (1993) three-factor model among other models to compare their pricing ability of idiosyncratic and systematic risks on two set of UK stocks return; industry portfolios and cluster portfolios. However, the aim of this chapter is to examine whether the risk factors in Petkova's (2006) model that she found to be priced risk factors in the US market and are able to capture the value and size premium of the Fama and French's (1993) HML and SMB factors, deliver similar results in the UK market; i.e. to be priced as risk factors and capture the Fama and French's (1993) HML and SMB in the UK. This is important as Griffin (2002) reported that a version of the Fama and French's (1993) three-factor model that includes country-specific factors is better at explaining the cross section of returns than its global version counterpart. In addition he reported that the correlation between the US market excess returns and the UK market excess returns is 0.68 and the correlation between the US SMB (US HML) and UK SMB (UK HML) are 0.15 and 0.27 respectively. Griffin (2002) pointed out these low correlations opposed with what was expected under the assumption of similar state variables underlie the HML and SMB portfolios across integrated markets. Therefore it is important for the objective of this

[3] Cochrane (2006) pointed out that Campbell (1996) is among few studies that ensured that their selected risk variables are along the line of the ICAPM of Merton (1973). Also Cochrane (2006) pointed in this regard to Petkova (2006) as well.

chapter to examine the wider set of macroeconomic variables and not restrict the analysis to a few selected potential risk factors.

The rest of the chapter is organized as follows: section 2.2 includes a review of the relevant literature, section 2.3 states the hypotheses, section 2.4 discusses the data and the methodology, section 2.5 presents the results and discusses the empirical findings and finally section 2.6 concludes.

2.2 Literature Review

At the millennium, Campbell (2000) argued that understanding what economic forces drive the reward for risk is the challenge that is facing asset pricing. Also Cochrane (2006) pointed out that understanding those macroeconomic factors that drive the price of risk and the premiums on the size and value portfolios is the challenge. Inspired by these, the current chapter studies the macroeconomic determinants of stocks prices in general and the Fama -French HML and SMB in particular.

Stochastic discount factor, multifactor models and the macroeconomic variables are linked together as shown by Campbell (2000) and Cochrane (2001, 1999). Campbell (2000) indicates that the stochastic discount factor (SDF) is useful for understanding the multifactor pricing models. He writes the asset pricing equation as (Campbell, 2000, p.1517, Eq.1):

$$p_{it} = E_t[m_{t+1}X_{i,t+1}] \tag{1}$$

Equation (1) above is in Campbell's (2000) notations. He defines the notations in the above equation as follows; p_{it} is stock's i price at t time, E_t is the operator for conditional expectations, m_{t+1} is the SDF[4] and $X_{i,t+1}$ is stock's i random payoff at $t+1$.

He derives the risk premium on stock i as (Campbell, 2000, p. 1520, Eq.5):

$$E_t(R_{i,t+1} - R_{f,t+1}) = \frac{-\operatorname{cov}_t(m_{t+1}, R_{i,t+1} - R_{f,t+1})}{E_t m_{t+1}} \tag{2}$$

Equation (2) above is in Campbell's (2000) notations. He points out that this equation means that the risk premium on risky stock is calculated by the negative co-variance of its excess returns $(R_{i,t+1} - R_{f,t+1})$ with the m_{t+1} divided by risk-free asset's price ($E_t m_{t+1}$). He explained this as stocks that produce low returns in bad states of the economy, when investors have high marginal utility must be rewarded with high risk premiums.

Cochrane (2001, Ch (9)) argues that the consumption-based model is a theoretically sound asset pricing model but does not produce good empirical performance, hence, searches have been made to link the stochastic discount factor with other variables, such as in the factor pricing models. He shows clearly the link between the SDF equation and the CAPM, APT, and ICAPM. Furthermore, Cochrane (2001, Ch (9)) points out that the variables that should be employed in the SDF as risk factors need to be searched for. He further indicates that asset pricing models seek risk factors that signal the incidence of the bad times of the economy. Cochrane (1999) identified such factors as those that are

[4] Cochrane (2001, Ch(1)) pointed out that other names for the SDF includes the marginal rate of substitution and pricing kernel.

associated with consumption which include; market return (CAPM), state variables and events of eroded noninvestment-based income, and fourth group is portfolio returns which could be seen as proxies for one of these three groups. Nevertheless, he stated that theory and empirics are in disagreement. He indicated that the Fama and French's (1993) SMB and HML factors are examples of such portfolios, but he acknowledges that it is not entirely obvious what macroeconomic risks are behind these two factors.

In summary, Cochrane (2001, 1999, 2006) and Campbell (2000) have summarized the challenges that asset pricing faces which are establishing the link between the macroeconomic risks and stock returns and Fama and French's (1993) SMB and HML. This chapter attempts to address these issues, but first its reviews the relevant literature that matters to this study.

2.2.1 Fama and French's (1993) Three-Factor Model

Fama and French (1992) examined the ability of a number of variables along with the CAPM beta to explain the cross sectional returns on stocks. They pointed out that these chosen variables constitute a challenge to the CAPM and include the size, the book-to-market ratio, the leverage, and the earnings to price ratio. They reported that their findings could be interpreted as size and book-to-market[5] are potential proxies for risk factors. More specifically, they reported that beta fails to explain the cross-sectional variation in stock returns while size and book-to-market succeed in this task and even

[5] Chen (2003) points out that there is a recent support to the risk story. However, he reports, based on his model, a rejection for such an explanation to be underlying the book-to-market value effect. Nevertheless, he points out that other state variables that may be used by investors need to be considered.

more they drive out the leverage and earnings to price ratio which are both found to be individually significant. Fama and French (1993) developed a three-factor model which includes market portfolio, size portfolio - SMB (the difference in return between small and large stocks' portfolios) and book-to-market portfolio - HML (the difference in return between value and growth stocks' portfolios). They pointed out because they aim to examine if the SMB and HML are able to explain the cross sectional returns on stocks that are associated with size and book-to-market characteristics, therefore, they constructed 25 portfolios of stocks according to their size and book-to-market values to be the testing assets. They reported that their three-factor model is able to explain the variation in stock returns and pointed out that these two factors are proxies for non-diversifiable risk factors.

Fama and French (1996) reported that the three-factor model is able to explain the variation in the cross section of portfolios' average returns that are constructed by sorting stocks on other firm characteristics, but it does not succeed in capturing the momentum effect of Jegadeesh and Titman (1993). They state that their results regarding the ability of HML and SMB to explain returns on stocks, are in line with a rational asset pricing's story such as the ICAPM of Merton (1973) or the APT of Ross (1976), however they acknowledged that other stories are still possible.

Ferson, et al., (1999) questioned the reliability of pricing factors that were constructed on the basis of attributes that are found to explain the cross sectional variation in returns on an empirical ground as the SMB and HML of Fama and French

(1993, 1996)[6]. They pointed out that such portfolios would have power to explain changes in stock prices even if they might not be connected to risk. Ferson and Harvey (1999) reported that, using lagged predictive variables, a conditional Fama-French's (1993) three-factor model is rejected and argued that their findings send a strong warning to the use of this model in the risk-returns calculations. Brennan, et al., (1998) studied the individual stocks rather than portfolios and stressed that this was vital in light of Roll's (1977) and Lo and MacKinlay's (1990) criticism of the use of portfolios. They reported that non-risk variables are able to explain stock returns, even though the Fama and French's (1993) HML and SMB factors are accounted for, these include the trading volume (a liquidity proxy) and momentum, while the book-to-market and size variables are weakened.

Davis, et al., (2000) studied the value premium and states that four widespread interpretations were put forward to this phenomenon[7] including: (1) it is a reward for risk in agreement with the ICAPM of Merton (1973) or APT of Ross (1976), (2) it is a chance and possibly to disappear in other samples, (3) it is a result of overreaction by investors, or (4) it captures the characteristics rather than the risk aspect of the value effect. They studied the last explanation and reported that no matter what the book-to-market value characteristics is, the loading on the HML is what explains returns, and Fama and French (1993) model performs better in capturing the value premium than the characteristics model. They explained that the reason for Daniel and Titman's (1997) findings that

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[6] Ferson, et al., (1999), in their footnote (2), summarize the potential explanations for the HML and SMB performance. In addition, Fama and French (1998) provide summery of the potential explanations for the value premium.

[7] See Davis, et al., (2000), for more details on the relevant literature relate to these issues.

support the characteristics model is that these are peculiar to the short sample period of their study.

Liew and Vassalou (2000) pointed out that their findings, based on data of ten countries[8], is consistent with the risk-explanation story of the HML and SMB in line with ICAPM of Merton (1973). They reported that these two factors link positively to the future economic growth, a finding that is sustained in the existence of business cycle variables (short-term interest rate, dividend yield, term spread and industrial production). They argued that this finding could be explained as when high growth in the economy is predicted, small and value stocks outperform large and growth stocks in term of prosperity. In addition they reported the HML and SMB carry information that is different from that of the market portfolio. However, they commented that the results suggest the country plays a role in deciding the relationship between the HML and SMB and the future economy which they justified as due to the differences in size, accounting standard and market capitalization between these countries.

Kelly (2003) reported that Fama and French's (1993) factors are related to macroeconomic variables (shocks) and hence are state variables in line with the ICAPM. He pointed out that he builds on Liew and Vassalou's (2000) study by decomposing the nominal economy's growth into real growth and inflation. He indicated that this permits studying the relationship between the HML and SMB and these two parts; inflation and

[8] Liew and Vassalou's (2000) study sample's includes United States, United Kingdom, Netherlands, Germany, France, Switzerland, Italy, Canada, Australia and Japan.

real growth. He reported that generally, using data from 18 countries[9], there is a negative (positive) relationship between the SMB and unexpected inflation (real growth) and positive relationship between the HML and the future real growth. Hanhardt and Ansotegui (2008) also reported that their findings lend support to the HML and SMB as risk-based factors consistent with the ICAPM for the Eurozone area. Furthermore, they pointed out this consistent with Liew and Vassalou (2000), the Fama and French (1993) factors are predictors of future growth, in particular, the SMB factor.

Other evidence that supports the risk story behind the HML and SMB is provided by Lettau and Ludvigson (2001). They reported a conditional consumption CAPM, in which the consumption risk factor is scaled by the conditioning variable (log consumption –wealth ratio) capture the value premium. They pointed out that value stocks are riskier in times of high risk premium (bad states of the economy) and therefore have higher returns. They indicated that for Fama and French's (1993) factors to be interpreted as capturing macroeconomic risk then the average cross sectional returns of these factors should be accounted for by macroeconomic factors. They stated that their findings propose that the Fama and French's (1993) SMB and HML factors could be proxies for risk variables that have risk premia that are time-varying.

In addition, Petkova and Zhang (2005) reported a positive (negative) covariation between betas of value (growth) stocks and expected excess return on the market which they interpreted as helping toward explaining the value premium. They stated that their

[9] Kelly's (2003) study sample includes, United States, Canada, United Kingdom, Netherlands, Germany, France, Switzerland, Austria, Italy, Sweden, Spain, Denmark, Finland, Belgium, Norway, South Korea, Japan and Australia.

ability to find such results when earlier studies failed the task is that they use the expected rather than realized returns. They pointed out that the value premium seems to be explained by the time variation in risk but nevertheless, the conditional CAPM is not able to completely capture the value premium's magnitude.

Furthermore, Petkova (2006) pointed out that the explanation of Fama and French's (1993) SMB and HML are in line with risk story of the ICAPM of Merton's (1973). She reported the HML portfolio is positively related to the innovations in term spread and innovations in default spread while it is negatively related to the innovations in the dividend yield, she stated that, hence HML could be a proxy for duration risk. Furthermore, she reported that the SMB portfolio is negatively related to the innovations in the default spread and pointed out that SMB could be a proxy for distress risk.

Although the above studies examine the possible explanation of the HML and SMB in the ICAPM of Merton (1973), by attempting to connect them with the macroeconomic variables, the risk story behind the performance of these factors could be supported using other sources as Anderson and Garcia-Feijóo (2006) do. They explained that the investment activities of the firm that precedes forming the portfolios, can explain the returns of value stocks and growth stocks. They pointed out that before portfolio formation, growth (value) stocks increase (decrease) their investments, lower (increase) their book-to-market value and experience low (high) return in the following period. They pointed out that their findings support the risk explanation behind the size and book-to-market characteristics.

Fama and French (1996) described their interpretation of the HML and SMB portfolios as state variables in the ICAPM of Merton (1973) or risk factors in the APT of Ross (1976) as aggressive. However, in light of the above mentioned promising literature, this chapter is interested in this interpretation of the Fama and French's (1993) HML and SMB as state variables in the ICAPM of Merton (1973). To shed more light on the ICAPM of Merton (1973) as an asset pricing model the chapter will proceed to discuss the literature related to this model in the next sub-section.

2.2.2 Intertemporal Capital Asset Pricing Model

Merton (1973) developed the intertemporal capital asset pricing model (ICAPM) and explained that the single-period capital asset pricing model is a special case of the ICAPM when the investment opportunities are assumed constant. He pointed out that, however, the interest rate is stochastic, which is a component of the investment opportunities, and hence the constant set assumption is implausible. He developed an equilibrium model in which the expected return is a function of the exposure to the market risk and the other risks that arise from the changes in the future investment opportunities and stressed that an important feature of this model relative to the CAPM is that an asset's expected excess return will not be zero if it has zero market risk.

Cochrane (2001, Ch (9))[10] wrote the ICAPM equation in the SDF framework where he indicates that the state variables proxy for the consumption. However, Cochrane (2001, Ch (9)) points out because the ICAPM model does not specify what are these state

[10] This is from Cochrane (2001) chapter 9.

variables, researchers exploit this model as a justification to the ad hoc factors that they employ in their studies as Fama (1991) accused them. He comments further that ICAPM is not an open tool as the factors in the context of the ICAPM should be forecasting the future investment opportunity set. Cochrane[11] (2006) points out that Campbell (1996) (and those who built on his work including Petkova (2006)), Ferson and Harvey (1999) and Brennan et al, (2005) are the only papers that have ensured that their employed factors predict returns on the market.

Chen, Roll and Ross (1986) examined if shocks (surprise) to a number of macroeconomic variables (state variables) are priced in the cross-section of returns. They pointed out that the use of macro variables as potential risk factors is consistent with ICAPM of Merton (1973) and APT of Ross (1976). They reported shocks (innovations) to the risk premia (difference in return on low-grade and high-grade (governmental) bonds), industrial production, term structure (difference between long-term and short-term governmental interest rates) and unexpected and expected inflation are risk factors as they are able to capture the returns on the stocks. They acknowledged that they have not studied all the potentially priced macroeconomic variables but they argued that their variables seem to be important compared with others. Shanken and Weinstein (2006) challenged the findings of Chen Roll and Ross (1986). They examined the relation between these same five variables and stock returns. They reported that only one factor

[11] Cochrane (2006) cite Brennan et al (2005) and in his reference appears "Brennan, Michael J., Yihong Xia, and AshleyWang 2005, "Estimation and Test of a Simple Model of Intertemporal Asset Pricing," Journal of Finance 59, 1743-1776". I found Brennan, M., Wang, A., and Xia, Y., (2004), "Estimation and Test of a Simple Model of Intertemporal Capital Asset Pricing", Journal of Finance, 59, pp.1743–1775. This is obviously the same paper that Cochrane refers to.

remains significant, which is the industrial production while the other variables are not. They indicated that this change in the significance of the macro variables compared with Chen, Roll and Ross's (1986) findings is a result of the macro variables' factor loadings in their study are estimated using portfolio's returns after ranking dates whilst Chen, Roll and Ross (1986) estimated the factor loadings using portfolio's returns before the ranking dates.

Asprem (1989) reported, using data from different European countries[12], a number of macro variables are related to market returns and stated that these macro factors could be state variables in the context of the ICAPM. More specifically, he reported that there is, among other variables, a negative reaction of stock prices to employment, interest rates and inflation. Chen (1991) reported an association between the state variables' predictability of the returns on the market and their predictability of the macroeconomy. He pointed out whilst the current growth in the economy is tracked by the dividend yield and the default spread, it relates negatively to expected returns. Furthermore he stated that whereas the future growth is tracked by the term structure, the Treasury-Bill and the past growth of the industrial production, it relates positively to the expected returns.

Campbell (1996) developed a model in which he described that asset return as function of innovations in a three set of factors; (1) market return, (2) predictors of future returns on the market and (3) predictors of future human capital's returns. He pointed out that the second set of factors (2 above) is the state variables of Merton. He reported that

[12]Asprem's (1989) study sample includes; United Kingdom, Germany, France, Netherlands, Switzerland, Sweden, Denmark, Norway, Finland, and Italy

the overriding pricing factor is market risk and stated that the value of the intertemporal view of asset pricing theory comes from its ability to give an explanation for the importance of the market return as a risk factor in asset returns. He clarified that this importance stems form the market return's association with other two factors (2 and 3 above) and not just being part of the investor's wealth.

Furthermore, Ferson and Harvey (1999) pointed out that the ICAPM is one of the likely successors to the empirically failed CAPM, although the empirical findings are disappointing. They reported that a number of lagged macro variables which include the dividend yield, term spread, default spread and a measure related to short-term interest rate, are able to capture the stock returns' variation. Vassalou (2003) reported that the GDP future news is important for pricing stocks and captures the HML and SMB pricing power. She pointed out that a pricing model, which includes proxy for future GDP's news and market returns as risk factors, is consistent with the ICAPM in which investors are hedging against the state variable's risk.

Supporting the importance of the macroeconomy to stock returns, Flannery and Protopapadakis (2002) indicated that risk factors, in context of Merton (1973), Ross (1976) and Breeden (1979) could be powerfully proxied by macro variables, although, they have not received the expected support on empirical ground. They examined the importance of the announcements on 17 macroeconomic variables for stock market and pointed out that this is the largest set ever used in this context. They pointed out that they found six variables are potentially important risk factors. More specifically they reported that they uncovered new evidence of the influential role of employment, housing starts and the balance of trade on the conditional variance of stock returns. Furthermore, they reported the market returns is influenced by CPI and PPI, and whilst money supply influences the level and the conditional variance of returns, the industrial production and GNP are not significant.

Brennan, Wang and Xia (2004) indicated Merton's (1973) ICAPM has an important feature which is, its state variables are innovations in predictive factors of the investment opportunities and not merely any factor. They developed an ICAPM model in which the state variables are the Sharpe ratio and the real interest rate. They reported that these state variables are priced in the cross section of returns and that their ICAPM model outperformed the Fama and French (1993) three-factor model and the CAPM model in a number of exercises.

Petkova (2006) proposes a model that includes excess market returns and innovation to dividend yield, term spread, default spread and short term interest rate as a model in the context of the ICAPM of Merton (1973). She pointed out that these four potential state variables describe the conditional returns and the yield curve components of the investment set. She reported that her model outperforms the Fama and French's (1993) model. Furthermore, she reported that her ICAPM specification succeeds as conditional model whereas the Fama and French (1993) three-factor model fails conditionally. In addition she examined a model that includes excess market returns and innovation to dividend yield, term spread, default spread, short term interest rate and Fama and French's (1993) HML and SMB. She reported the innovations in the four variables drive out the HML and SMB ability to explain stock returns.

The above studies employ a small number of macro variables compared with the large number of macroeconomic variables that are available publicly and may represent potential risk factors. This makes them vulnerable to the charge that they leave out other precious information for pricing stocks that is not accounted for (Lettau and Ludvigson (2001), Petkova (2006), Mönch (2004, 2006) and Ludvigson and Ng (2007)). Therefore, the main objective of this chapter is to attempt to fill this gap by augmenting the set of the proposed risk variables by Petkova's (2006) to include the whole set of macroeconomic variables available by utilizing the recent development in the dynamic factor models of Stock and Watson (2002a and 2002b). To shed more light on this topic the chapter present the related literature chapter in the next sub-section.

2.2.3 Dynamic Factors Models

Stock and Watson (1998, 2002a,b) introduce the dynamic factor model. Stock and Watson (2002a) point out that instead of choosing a limited set of predictive variables, the dynamic factors model can be used to reduce the large set of available data into a small set of factors that contain the information related to the common variation. They use the approximate dynamic factor model and the principal component analysis to model the macro variables to be predicted and to estimate the common factors from a large set of potentially useful predictors, respectively. They explained that the assumption is the macro variable of interest and to be forecasted (y_t) and the predictive set (X_t) follow a dynamic factor model. Stock and Watson (2002a) stated that assuming that the number of lags is finite they can express the dynamic factor by, what they call "the static representation of the dynamic factor model" and employ the principal components technique to estimate the factors. They write the static factor model as following (Stock and Watson, 2002a, p.148, Eq.2.3 and Eq.2.4. respectively)

$$y_{t+1} = \beta' F_t + \gamma(L) y_t + \varepsilon_{t+1} \tag{3}$$

$$X_t = \Lambda F_t + e_t \tag{4}$$

Equations (3) and (4) above are in Stock and Watson's (2002a) notations. They define the notations in the above equation as follow; F_t as r $\times 1$ vector of factors to be estimated and their lags, ε_{t+1} as an errors that they assume is uncorrelated with the factors, their lags, the lagged forecasted variable and its lags and the predictive variables and their lags, and e_t as N $\times 1$ vector of idiosyncratic errors. They used their model to forecast a number of macro variables and reported that a few estimated common factors required for capturing the common variation in the 215 macro variables used as predictive set. They pointed out that this means that the variability of the macroeconomy is driven by a few common factors. Stock and Watson (2002b) point out that they allow in this dynamic model for serial and cross sectional correlation in the idiosyncratic error. In addition they state that when the number of observations in the time series (T) and number of predictive variables (N) go to infinity; the estimated common factors will be consistent. Furthermore, they employ the model to forecast industrial production and report promising results in favor of the factor models against the more traditional forecasting methods (such as AR).

The factor models were also studied intensively by Forni et al., (2000) who developed the generalized dynamic factor models. Forni et al., (2000) point out that their model permits autoregressive reaction whilst the static model with lagged factors of

Stock and Watson (1998) does not. Furthermore, they state that on the other hand, the latter model takes account of time variation in the factor loading whereas their model does not. Indeed Forni et al., (2004) state that Forni et al's (2000) generalized dynamic factor model is a generalization of Stock and Watson's (2002a) model as well as other models. Forni et al., (2005) point out that they suggested a prediction method that overcomes the shortcoming of Forni et al's (2000) method. More specifically, they stated that Forni et al's (2000) method lacks the ability to predict whilst Stock and Watson's (2002a, b) method is appropriate for such task. They mentioned that their suggested method keeps the benefits of the former approach and reported that their method is superior to that of Stock and Watson.

An application of the factor model for forecasting in the UK is provided by Artis, Banerjee and Marcellino (2005). They use the dynamic factor model and the principal component analysis and reported that the factor models are superior to previously employed prediction methods. They stated that they compile a panel of 81 macroeconomic variables. They reported that half of the variation in these macroeconomic variables is captured by six estimated common factors which track, among other major variables, interest rates, employment, and monetary measures. Furthermore, Artis, Banerjee and Marcellino (2005) point out that as the factors estimated from a large set of macro variables are linked to vital macro variables, these estimated factors can be seen as the UK economy' drivers.

Forni et al., (2000) reported that they use generalized dynamic factor model to calculate an indicator of the business conditions. Inklaar, Jacobs and Ward (2003) indicated that they employed this latter model along with NBER approach to calculate a business cycle index. They point out that while the first method weights the constituent variables on statistical basis the second uses the judgment. They argued that a large set and a limited set of predictive variables can deliver similar performance, providing the limited set of variables is chosen carefully. In addition, Gillitzer, Kearns and Richards (2005) reported that the coincident index calculated using the dynamic factor models provide better description of the business cycle in Australia than the GDP. In addition they point out that their findings are consistent with Inklaar et al., (2003), in that the number of variables used in factor models need not be large as long as the variables are selected carefully.

Boivin and Ng (2006) examine whether a limited number of variables compared with a large dataset usually employed in the factor models hurts or helps. They point out that more variables may reduce the common variability and increases the correlation across the error components. They reported that a small set of variables delivered common components that either similar if not superior to their counterparts from a much larger set. They stated that the dataset's quality and not only its size what matter for a good estimation.

The above studies show factor models are useful in economics applications such as forecasting macroeconomic variables as in Stock and Watson (2002a, b) or the construction of a coincident index as in Forni et al (2000). However as this chapter studies the behavior of stock price, it turns attention to the next sub-section which cites the studies that apply factor models to asset pricing, even though they are limited so far.

2.2.4 Factor Models and Asset Pricing Models

A number of studies study the dynamic factor models, used for estimating factors from a large set of macroeconomic variables, in asset pricing. Among these is Mönch (2004) who argues that there could be common factors that drive all the macroeconomic variables that have been found by researchers to be priced risk factors in the stock returns. Therefore, he indicates that his goal is to examine if the estimated factors that account for the variation that is common across macroeconomic variables also drive stock returns. He points out that factors, estimated from a large set of macro variables using the dynamic factor model and the principal components analysis of Stock and Watson (1998, 2002a), are used as state variables in an asset pricing model. Mönch (2004) calls this model as "diffusion index pricing model". He reported that a pricing model with two estimated factors along with the market portfolio explains cross-sectionally the returns on the Fama and French's (1993) 25 size and book-to-market portfolios similarly to the Fama and French's (1993) three-factor model. He pointed out that one of these factors associates with business cycle (interest rates spread, unemployment and capacity utilization) and the other relates to the exchange rates. He points out that he augments Campbell (1996) model with these two priced estimated factors and reports this augmented model does much better than Campbell model while a little better than his diffusion index model. He reported results using cross sectional regression of Fama and MacBeth (1973) and GMM of Hansen (1982).

Mönch (2006) indicates that he uses the common factors estimated by applying the dynamic factor model of Stock and Watson (2002a, b) to a large group of macro variables as conditioning instrument in a conditional asset pricing models on the Fama and French's (1993) 25 size and book-to-market portfolios. He points out that investors have large set of information and replacing these with a small number of predictors is inadequate. He indicated that he overcame the problem of degrees of freedom, which is associated with the use of a many variables, by employing the dynamic factor models. He reported that the estimated factors, which are employed as conditioning instruments, contain additional information to the those contained in the widespread conditioning instruments (interest rates measures, term spread, dividend yield, default spread, labor income to consumption and log consumption to wealth ratios) and are better than them. He reported that these common factors are related to inflation, interest rates and housing variables.

Ludvigson and Ng (2007) point out that they use the dynamic factor model to overcome the problem of omitted information in studying the relationship of market return's conditional mean with its conditional volatility. Consequently, they reported a positive relationship between risk and return. They pointed out that they augmented the conditioning instruments set that include a number of widespread predictive variables, such as, among others, dividend price ratio, term spread and default spread with the common factors. They reported that two estimated factors from a financial dataset, which they call the risk premium factor and volatility factor, are important for conditioning the mean of stock market returns and one factor estimated from the macroeconomic dataset is important for conditional volatility. They reported that they find this latter factor is a real factor as it relates to output and employment. They pointed out that augmenting the conditional information set with common factors is important for uncovering the correct link between risk and return.

The above studies show the importance of the dynamic factor models in extracting information that may have not been utilized so far, by depending on using only the variables that have been identified in the literature as useful, for describing the behavior of the stock returns. Therefore, this chapter applies Stoc k and Watson's (2002a, b) dynamic factor model and principal component approach to estimate factors from a large set of macroeconomic variables and use these factors as inputs for possible risk factors.

2.3 Hypotheses

Therefore, building on the findings of the previous studies and the issues that they emphasize are important for asset pricing, this section develops the hypotheses of this chapter.

2.3.1. Fama and French's (1993) Model and UK Stock Market

A number of studies have examined the Fama and French's (1993) three-factor model in the UK. Fletcher (2001) reported that, using a sample periods span January-1982 to December -1996, the risk premium is insignificant for the SMB but significant for HML with positive sign. Fletcher and Kihanda (2005) reported that, for the period January -1975 to December 2001, the HML's and SMB's means are insignificant with positive and negative signs, respectively. On the other hand, Al-Horani, Pope and Stark

(2003) reported that, for the period 1990 - 1999, the SMB has significant mean with positive sign, while the HML has an insignificant average returns. Furthermore they reported that the Fama and French's (1993) three factor model has a good explanatory power. Hussain, Toms and Diacon (2002) pointed out that they follow Fama and French's (1996) study as closely as possible when apply it to the UK market. They reported positive means for the UK HML and SMB although the last is insignificant. Furthermore, they reported that these factors are significant factors and the Fama and French's (1993) three-factor model outperforms the CAPM in UK market, although none of them is a perfect model. In addition they pointed out the UK results are in line with that of US.

Therefore, this chapter first examines if Fama and French's (1993) three factor model in the UK stock returns over sample period from July 1981 to December 2005 by following Fama and French (1993). The first hypothesis is stated as follows

Hypothesis (1): The Fama-French's (1993) SMB and HML portfolios are priced risk factors in the UK cross sectional returns of the Fama and French's (1993) 25 size and book-to-market portfolios.

2.3.2 State Variables and Stock Returns

Cochrane (2001, 2006) emphasizes that the state variables of Merton's (ICAPM) must predict future returns. Cochrane (2006) praises Campbell (1996) and Petkova (2006), among few other studies, for applying this criterion. Petkova (2006) suggests a model that includes excess market return and innovations to dividend yield, term spread, default spread, and the short term interest rates. She pointed out that these four innovations capture the shifts in the investment opportunities. In light of this, this chapter applies Petkova's (2006) model to examine if the innovations to these state variables are priced in the UK market as she found them priced in the US. This provides an out-of-sample test of Petkova's (2006) study. Nevertheless, this is done not for the sake of replication but in response to Campbell's (2000) challenge. He points out that identifying the economic determinants of the risk premiums is the current challenge. Also Cochrane (2006) argues that it is crucial to identify the macroeconomic drivers of the price of risk. Therefore, the second hypothesis is stated as follows

Hypothesis (2): Innovations to dividend yield, term spread, default spread, and the short term interest rates are priced cross sectionally by the UK Fama and French's (1993) 25 size and book-to-market portfolios

2.3.3 Are Fama and French (1993) Factors tracked by macroeconomic forces in UK Stock Market?

As cited in the literature review section, Cochrane (2006) points out that the macroeconomic variables that are behind the size and value factors of Fama and French (1993) should be identified. Petkova (2006) reports that she finds for the US stock market, the Fama and French (1993) SMB and HML are driven by innovations to variables that are state variables in Merton's (1973) ICAPM. In fact her exercise is in line with Cochrane (2006) who points out that the macro models should be tested to whether they can explain the Fama and French three factors instead of the 25 portfolios.

Therefore, if the Fama and French's (1993) size and book-to-market portfolios (hypothesis 1) and the innovations in the four variables chosen by Petkova (2006) which are innovations to dividend yield, term spread, default spread, and the short term interest rates (hypothesis 2) are priced in the UK, then the next hypothesis examines if the Fama and French's (1993) SMB's influence and HML's influence on stock returns are lost for macroeconomic factors as hypothesized and examined by Petkova (2006) for the US market. Therefore, the third hypothesis following Petkova (2006) is:

Hypothesis (3): The innovations to dividend yield, term spread, default spread, and the short term interest rates drive the Fama and French's (1993) SMB and HML factors.

Liew and Vassalou (2000) reported that the SMB and HML in the UK do relate to the future GDP growth and the significance of this association is preserved for the HML but is absorbed for the SMB by other variables related to business cycle (such as dividend yield, term spread and T-Bill). Furthermore, they point that these findings support that these two variables are in line with ICAPM of Merton (1973). Kelly (2003) reports that that the SMB and HML are linked to real GDP growth and the HML factor also relates to unexpected inflation in the UK. He points out that this is in agreement with ICAPM interpretation of SMB and HML. Furthermore, Kelly (2003) report that Fama and French's (1993) model outperforms the CAPM.

2.3.4 Large Panel of Macroeconomic Variables and Stock Returns

So far this chapter follows Petkova (2006) and applies her study and methodology to the UK, as she takes on the challenges of Cochrane (2006) and Campbell (2000) as mentioned earlier. However, Ludvigson and Ng (2007) pointed to an important problem of using a small set of variables. They reported that they augmented the conditional information set, in studying the risk and return relationship, with factors estimated from a large dataset using the dynamic factor model to overcome the problem of the omitted information. They pointed out that this problem arises from the fact that the information used by researchers is short of all the real information used by investors. Although Ludvigson and Ng (2007) use the estimated factors as conditioning variables, their argument applies to this chapter as well.

Furthermore, Mönch (2006) pointed out that the factors estimated using dynamic factor model with large macroeconomic variables captures the information used by investors. He examines whether factors estimated from a large set of economic variables, when used as conditioning variables in the asset pricing model, carry pricing information and whether these pricing information are additional information to those contained in the widespread conditioning variables. He points out that he uses the Fama and French's (1993) 25 size and book-to-market portfolios as his test assets. He reports that the estimated factors are important conditioning information and are better than the widespread conditioning information. Furthermore, he reports that these estimated factors carry additional information over those contained in the widespread conditioning variables which includes, among others, dividend yield, term spread, default spread, one month interest rate and difference between three and one month rates. Also Chen (2003) refers to potential missing state variables in the empirical research that is used by investors.

On the other hand, Flannery and Protopapadakis (2002) pointed out that the Chen, Roll, and Ross's (1986) statement of the lack of knowledge about the economic sources of risk is valid. Although Flannery and Protopapadakis (2002) employs 17 macro variables, the dynamic factor models can utilize much larger set of variables.

Given the above, it is natural for the next step in this chapter to be the examination whether a few common factors estimated from a large set of macroeconomic variables following Stock and Watson's (2002a, b) dynamic factor model method are priced in the UK stock market. This is done by replacing the innovations in the state variables in Petkova's (2006) model that includes innovations in dividend yield, term spread, default spread and one month T-Bill with the innovation to the estimated factors. The fourth hypotheses is stated as follows

Hypothesis (4)A: Innovations to factors that are estimated from a large panel of macroeconomic variables are priced cross sectionally by the Fama and French's (1993) 25 size and book-to-market portfolios

Mönch (2004) applies the dynamic factor models to estimate the factors, which he then uses as state variables (see the above literature review section (Factor Models and Asset Pricing Models)). However, this chapter differs in that its uses the innovations to the estimated factors, which follows the application of the innovations to the four variables chosen by Petkova (2006)), while Mönch (2004) uses the estimated factors themselves.

Hypothesis (4)B: The innovations to estimated common components drive the Fama and French's (1993) SMB and HML factors.

We believe this chapter could be the first study to use the innovations in factors estimated form a large panel of macro variables as potential drivers of the Fama and French's (1993) SMB and HML. Hypothesis (4B) becomes important, in particular, if the innovations to the four state variables in Petkova' (2006) model (in Hypothesis (3)) do not capture the effects of the size and value portfolios of Fama and French (1993).

2.3.5 Other Estimation Methods

Priestley (1996) suggested the Kalman filter based method to produce the innovations. He pointed out that this method ensures that the learning process is reflected in the investor's expectations, as well as the produced surprises are real innovations. He reported that this method delivered better results for the APT than the autoregressive and rate of change methods. On the other hand, Shanken (1992) pointed out that the coefficients in the Fama and MacBeth's (1973) second step regression suffers from the problem of the error-in-variable, because of the generated regressors. He pointed out that the standard errors of the risk premiums under the Fama and MacBeth's (1973) method are understated. Jagannathan and Wang (1998) pointed out that when the conditional distribution of returns is not homoskedastic, the standard errors are not inevitably understated by the Fama and MacBeth (1973) method. Jagannathan and Wang (2002) point out that the reason the generalized methods of moments (GMM) of Hansen (1982) gains its status as it overcomes all the problems by allowing for non-normality, heteroskedasticity and serial dependence.

Therefore as a robustness check for the chapter's results, different innovation estimation techniques and model estimation method are used; VAR and Fama and MacBeth (1973) following Petkova (2006), then the VAR based innovations are replaced by Priestley's (1996) Kalman Filter based innovations. In addition this chapter replaces the Fama and MacBeth (1973) method with the GMM on beta representation following Jagannathan and Wang (2002). Petkova (2006) noted that she also used the GMM method. However, she applied the GMM to the stochastic discount factor representation, while this chapter follows Jagannathan and Wang (2002) in applying the GMM to the beta representation.

2.4 Data and Methodology

2.4.1. Data

2.4.1.1 Stock returns

The sample consists of all the UK common stocks traded on the London Stock Exchange (LSE), excluding foreign stocks, for the period of June 1981 to December 2005 obtained from the Datastream. This includes both active and dead (de-listed) stocks.

Actives stocks are those that were still being traded until December, 2005 while the de-listed stocks are those that happened to be traded some time between 1981 and 2005 and then de-listed. Financial firms are excluded from the dataset. Fama and French (1992) pointed out that they excluded them as they have different leverage than non financial stocks. In addition, Griffin (2002) indicated that he used non financial firms and market-to-book ratio's inverse downloaded from Datastream. Additionally, Fletcher (2001) pointed out that he formed the Fama and French's (1993) six portfolios for UK using non-financial stocks. Following them, this chapter excludes financial stocks from the analysis. The final database that is available for analysis before applying any more criteria constitutes of 3706 non-financial stocks. The database has not been checked for the illiquid and very small stocks and therefore it could contain a large number of highly illiquid and very small stocks that are not frequently traded. These could severely affect the results and some of the findings may be affected by the presence of such stocks. The beginning of the period is determined based on the availability of book value data from the Datastream. This chapter uses the monthly frequency.

Professor Krishna Paudyal has supplied this chapter with the Fama and French's (1993) SMB and HML for the UK from July – 1981 up to December - 2003 which are constructed following the methods explained in Fama and French (1993, 1996). For the rest of the sample period; 2004 and 2005, the Fama and French's (1993) SMB and HML for the UK are constructed in this chapter following Fama and French (1993) closely, which is the same method used by Professor Paudyal. Fama and French (1993) pointed out December's (t-1) price, June's (t) price and year (t-1)'s fiscal year end book value should be available for each stock to be used. Fama and French (1993) describe how they construct the HML and SMB, as follows; in June, year (t), (1) common stocks are divided into small size portfolio and big size portfolio, using the median size of NYSE as breakpoints, (2) stocks are divided independently into three; low (30%), medium (40%) and high (30%) book-to-market portfolios, using NYSE book-to-market values after ranking as breakpoints. They pointed out that they measure size as shares multiplied by their individual price, market value as its value at end of December of year (*t-1*), and book-value as of its value at the end of the stock's fiscal year occurred in the previous year (*t-1*). They pointed out that they exclude stocks with negative book values from the breakpoints' computation and portfolios' constructing. They pointed out that they form, by intersecting the above size and book-to-market portfolios, six portfolios and compute these portfolios' monthly returns from July (*t*) to June (*t+1*) as the value-weighted returns. They pointed out that this is to ensure the used book value is already publicly available. They pointed out that this process is repeated every June. They pointed out that they construct, for each month, the SMB as the spread between the three small portfolios' average returns and the three large portfolios' average return, and the HML as the spread between the two high portfolios' average returns and the two low portfolios' average returns, where high and low in terms of their book-to-market values. Furthermore, Fama and French (1993) pointed out that they use the constituent stocks of the six portfolios and the stocks with negative book value to form the market portfolios. They pointed out that return on this portfolio is the value-weighted returns minus the risk free-rate.

This chapter replicates Fama and French's (1993) procedure for constructing the SMB an d H ML for 2004 and 2005 for the UK. In addition it replicates Fama and French's (1993) procedure for constructing the market portfolio for the UK for the whole sample period, but it uses the median size of the LSE to divide the LSE stocks into size portfolios and the LSE' ranked book-to-market values to divide the LSE stocks into book-to-market portfolios. Indeed, Hussain, Toms and Diacon (2002) point out that they use the median size of LSE and the LSE (30%, 40% and 30%) ranked book-to-market values to divide LSE stocks into size and book-to-market portfolios, respectively and then to form the HML and SMB for UK market.

This chapter employs as test assets, the UK Fama and French's (1993) 25 size and book-to-market value portfolios. The reason for choosing these portfolios is that Petkova (2006) uses these portfolios as test assets, and as the first objective of this chapter is to provide an out-of-sample test for her study on the UK market, this means that this chapter has to use them as test assets. In addition to this Petkova (2006) points out these test assets are benchmark. Furthermore, Fama and French (1993) point out that in order to examine the ability of the HML and SMB to explain the size and value returns, they employ these 25 portfolios. This chapter forms the Fama and French (1993) 25 portfolios by closely following Fama and French (1993). They point out that they form the 25 portfolios by similar to the six portfolios, with the difference is, five size portfolios are constructed using the breakpoints of NYSE and independently five book-to-market portfolios also constructed, using the breakpoints of NYSE and then the 25 size and book-to-market portfolios is the result of the intersection between these size quintile portfolios and book-to-market quintile portfolios. They pointed out the monthly value weighted excess (of risk free rate) returns of the 25 portfolios are computed from July (*t*) to June (*t-1*) to become the test assets.

This chapter replicates Fama and French's (1993) method for forming the 25 size and book-to-market portfolios for the UK stocks, but again this chapter use the LSE's breakpoints for the quintiles to divide the stocks of LSE into quintile portfolios. Hussain, Toms and Diacon (2002) also point out that they use LSE's breakpoints for the quintiles to divide the stocks of LSE and form the 25 size and book-to-market portfolios.

Table (2.1) shows the number of firms available after applying the criteria of Fama and French (1993) for stock's selection. Nagel (2001) points out that the data from Datastream has the problem of selection bias that existed until the 1970's end as high book-to-market value stocks as well as small stocks are missed from the Datastream. In agreement, Table (2.1) shows the number of available stocks with book values is small until the late eighties.

Table (2.2) presents the average returns on the UK Fama and French (1993) SMB, HML and market excess return for the period July-1981 to December-2005. It shows the average return on the HML portfolio is positive and significant at 1% while the average return on the SMB portfolio is negative and significant at 10%. This is not surprising as it is consistent with Dimson, Nagel and Quigley (2003). They reported that there is a bigger, in magnitude, and more significant value premium in UK relative to the smaller, in magnitude, and insignificant size premium. However while this chapter finds negatively significant size premium they reported positively insignificant size premium over the period from 1955-2001. Dimson, Nagel and Quigley (2003) depict the yearly returns of each portfolio (SMB and HML) over time. Dimson, Nagel and Quigley (2003) point out that they find the behavior of the SMB premium is consistent with Dimson and

Marsh (1999), it is volatile and exists before 1989, then it reverses before it recovers in 1999. In addition, Dimson, Nagel and Quigley (2003) report the HML portfolio had high and stable returns during the first part of their sample period, but since the nineties it has become more volatile and the highest value premium magnitudes happened in this recent period. To compare the premiums of Fama and French's (1993) factors used in this chapter with theirs (i.e. with Dimson, Nagel and Quigley (2003)), following them, it depicts each portfolio's (SMB and HML) return for the sample period July-1981 to December-2005 in Figure (2.1), however it uses monthly instead of yearly frequency. Panel (A) shows the HML's monthly returns and Panel (B) shows the SMB's monthly return. The figures show similar behavior for the size and value premium as those reported by Dimson, Nagel and Quigley (2003) over the overlapping period, this is despite the fact that the there are slight differences between this chapter and theirs in relation to forming the SMB and HML.

2.4.1.2 State Variables - Petkova's (2006) Chosen Variables

Two sets of candidate state variables are employed by this chapter; (1) the state variables selected by Petkova's (2006) and (2) the factors estimated from a large set of macroeconomic variables using the dynamic factor model and principal component analysis of Stock and Watson (2002a,b). Petkova (2006) uses innovations to four variables as candidate states variables. She defines these four variables as follow; (1) dividend yield on the CRSP portfolio (the ratio of total dividends calculated over the past 12 months to the index level), (2) the term spread (the spread in yields between ten- year government bond and one- year government bond), (3) default spread (the difference in the yields between corporate-Baa and government bonds, both long term bonds) and (4) one-month T-Bill yield. She states that these variables capture the shifts in the investment opportunities, where the second (2) and fourth (4) variables model the changes in yield curve and the first (1), third (3) and fourth (4) variables stock returns' conditional distribution. As the first step of this chapter is to apply Petkova's (2006) study and methodology to the UK, it follows her and employs the UK counterpart variables. The purpose is to examine whether her chosen set of variables are priced in the UK in a step toward responding to the challenges of Campbell (2000) and Cochrane (2006). These variables are;

1- dividend yield of FTSE all share,

2- term spread; the spread on 5-year central government securities over that of the three-month Treasury bill,

3- default spread; the spread of the UK FTA Debenture and Loan Stock Redemption Yield (25 years) over that of the UK 20-year central government bonds from July – 1981 to October – 1995, then the spread of the Corporate Bond Yield over that of the UK 20-year central government bonds from November- 1995 to December-2005,

4- one-month T-Bill yield

These UK variables were also used by Antoniou et al., (2007) in their study of momentum in the UK (in p.959). This chapter follows their definitions of the dividend yield and default spread but it uses the five-year government bonds while they use the 20 year government bonds in the term spread definition. The five year government bonds is used in measuring the term spread and not the 20 year bonds because when the term spread is measured based on the 20 year government bonds, the innovations to the term spread is found to be insignificant.

2.4.1.3 State Variables - Large Panel of Macroeconomic Variables

As mentioned earlier in the chapter, the problem, in choosing a limited number of potential risk variables, is that they may not be representative to the information set used by the investors, as pointed out by Ludvigson and Ng (2007) and Petkova (2006) among others. To overcome this problem, Ludvigson and Ng (2007) and Mönch (2006) use the dynamic factors models. For the same reason as well as to avoid the pitfall of using any variable that is pointed out by Fama (1991), this chapter chooses variables that are suggested by Cochrane (2001). He points out that the factors in the ICAPM are those variables that have predictive ability of stock returns or have predictive ability of macroeconomic variables. Stock and Watson (2002a) used factors estimated from a large dataset of macroeconomic variables to forecast macro variables therefore this chapter estimates factors from a large dataset of macroeconomic variables using Stock and Watson's (2002a, b) method. Then this chapter uses the innovations to these estimated factors as candidate state variables. Therefore, it selects variables in line with the ICAPM of Merton (1973) as suggest by Cochrane (2001), i.e. those that predict macroeconomic variables.

Laganà and Mountford (2005) point out that VAR model has the problem that it uses a limited set of variables that may not reflect the reality and hence it could be misspecified. They point out that they use factor –augmented vector autoregression model to study the interest rates in the UK. They point out that they construct a large balanced panel of macroeconomic variables (105) for the UK for the purpose of using them to estimate factors using Stock and Watson's (1998, 2002a) method and add then them to VAR model. Laganà and Mountford (2005) also point out that Boivin and Ng (later published as Boivin and Ng (2006)) indicate that increasing the number of variables may be harmful. In addition, Laganà and Mountford (2005) point out that they chose variables and categories similar to Bernanke et al., (2005) and Stock and Watson (2002a) from Datastream. Furthermore, Artis, Banerjee and Marcellino (2005) point out that they build a balanced large set of macroeconomic variables (81), from Datastream and the OECD, for the UK economy which they use with the dynamic factor model to forecast macro variables.

Therefore this chapter downloads from the Datastream as much as it finds of the variables that are used by Laganà and Mountford (2005) and some of those used by Artis, Banerjee and Marcellino (2005) and Kapetanios, Labhard, and Price (2006). However it does not retrieve any financial variables that are used by these studies as its studies the macroeconomic variables.

In this chapter, a balanced dataset containing 78 monthly macroeconomic variables for the UK, from July- 1981 to December – 2005 is collected from the Datastream. These variables are (1) those used by Laganà and Mountford[13] (2005) covering their macroeconomic categories. However, this chapter does not manage to retrieve the entire

[13] Laganà and Mountford (2005) use the following categories "employment; government finance; output; housing starts and vehicles; consumer and retail confidence; prices; money and loans; interest rates; composite leading indicator; and stock prices and exchange rates". See their Appendix (Laganà and Mountford (2005, p.94-97)

105 variable used by them for its balanced dataset over the period July – 1981 to December 2005; (2) Additional few variables are obtained similar to those used by Artis, Banerjee and Marcellino (2005); (3) Additional few variables are obtained similar to those of Kapetanios, Labhard, and Price (2006); and (4) variables of default spread which are also similar to Ludvigson and Ng (2007) are also included in the chapter dataset. See Appendix (A).

2.4.2 Methodology

2.4.2.1 Petkova's (2006) Model of the ICAPM

This chapter applies Petkova's (2006) model. She states that she assumes a discrete and unconditional version of Merton's (1973) ICAPM. Before proceeding, it is important to understand the context of the unconditional form of the ICAPM model. For this purpose this chapter cites Constantinides's (1989) study. Constantinides (1989) points out that in the unconditional ICAPM that he derives from the conditional ICAPM, stock returns co-vary not just with the state variables but also with the vector of information set (ϕ^{t-1}) and the variables that have been found are able to predict stock returns are candidates for this vector.

Petkova (2006, p.583, Eq.1) assumes the following ICAPM for each i:

$$E(R_i) = \gamma_M \beta_{i,M} + \sum (\gamma_{u^K}) \beta_{i,u^K} \tag{5}$$

Equation (5) above is in Petkova's (2006) notations, she defines the notations in the above equation as follow; $E(R_i)$ is stock i excess return , γ_M and γ_{u^K} are risk premiums on the market and innovations in K state variable, respectively. $\beta_{i,M}, \beta_{i,u^K}$ are obtained from time series regression, (Petkova, 2006, p.584, Eq.2)

$$R_{i,t} = \alpha_i + \beta_{i,M} R_{M,t} + \sum (\beta_{i,u^K}) u_t^K + \varepsilon_{i,t} \quad (6)$$

Equation (6) above is in Petkova's (2006) notations. She defines the notations in the above equation as follow; $R_{M,t}$ is the market's excess return and u_t^K's are the state variables' innovation, all measured at the end of time t.

To estimate the innovations from the state variables, Petkova (2006) uses the vector autoregressive approach of Campbell (1996). She assumes the following first-order autoregressive model (VAR), (Petkova, 2006, p.584, Eq.3)

$$\mathrm{z}_t = \mathrm{A}\mathrm{z}_{t-1} + u_t \quad (7)$$

Equation (7) above is in Petkova's (2006) notations. She points out that she inserts as the first element in the demeaned[14] state variables vector (z_t), the excess market return followed by the other state variables. She states that the model presented by the above cross-sectional, time-series and VAR models has an advantage. She points out that Campbell (1996) points such model reduces the possibility of uncovering spurious relationships.

2.4.2.2 VAR Innovations

This chapter uses VAR following Petkova (2006). As mentioned earlier Petkova (2006) estimates the vector of innovations to the state variables (u_t) from the VAR (equation (7) above). She indicates the first variable to enter the VAR is the excess

[14] Campbell (1996) points out that this assumption is for simplicity.

market returns, then it is followed by (in her order) the dividend yield, term spread, default spread, risk-free rate, Fama and French's (1993) HML and SMB where all the variables are demeaned. She points out that in this specification the HML and SMB are considered as possible state variables.

The VAR lag length is decided as suggested by Hall (1991). He points out that there are two methods to determine the order of the VAR. However, he points out the preferable approach is the one that begins by a high order and then reduces down the lags' length and then uses the likelihood ratio restriction's test. In additions, he indicates that when the OLS is used to estimate the VAR model, the log likelihood ratio still can be computed.

Petkova (2006) points out that Campbell (1996) indicates for the VAR's estimation results to have a meaning, there is a need to orthogonalize the factors and scale them. Petkova (2006) points out that she follows Campbell in trianagularizing the VAR system and leaves unaffected the innovation to the excess return on the market (the first variable to enter) and calculates the orthogonalized innovations to the second variable in the system as its part which is orthogonal to the first unaffected variables etc. In addition, Petkova (2006) points out that again she follows Campbell (1996) and scales the innovations to the variables so that their variances will be equal to variance of the innovation to excess market return. Therefore, this chapter follows Petkova (2006) in triangularizing and scaling the innovations in the state variables[15].

[15] See Hamiltcn (1994), *Time Series Analysis*, for illustration of the technical procedure of the triangularization.

This chapter follows Petkova (2006) exactly in her application of VAR system (including the order of the variables inserted) to estimate the innovations to the dividend yield, term spread, default spread, one-month interest rate, Fama and French's (1993) HML and SMB. Furthermore, this chapter also applies her VAR system in similar way to the factors estimated from a large set of macroeconomic variables where the latter replace the above Petkova's (2006) chosen state variables. Including factors estimated from a large step of macroeconomic variables into VAR model is similar to Laganà and Mountford (2005) who augment the VAR model with factors estimated using the dynamic factor model. Laganà and Mountford (2005) point out that they follow Bernanke et al. (2005) and include factors estimated from a large set of macroeconomic variables into the VAR model to study the monetary policy, where the factors estimated using the dynamic factor approach of Stock and Watson (1998, 2002a).

2.4.2.3 Kalman Filter Innovations

In addition to using the VAR to calculate the innovations to the potential state variables as in Petkova's (2006), this chapter uses the Kalman filter of Priestley (1996) as an alternative technique to produce these innovations. Petkova (2006) points out that she uses AR (1) as an alternative method to estimate the innovations and points out that the results are not different from the VAR's. However Priestley (1996) studies the APT of Ross (1976) and points out that a problem with the autoregressive model is that it does not entail the learning process by the investors. He points out that a method based on the Kalman filter overcomes this problem.

Priestley (1996) models the risk factor, as (Priestley, 1996, p.873, Eq.4 and Eq.5, respectively)

$$X_t = X^{\bullet}_t + u_t \tag{8}$$

$$X^{\bullet}_t = X^{\bullet}_{t-1} + \gamma_{t-1} + \zeta_t$$

$$\gamma_t = \gamma_{t-1} + \omega_t \tag{9}$$

Equations (8) and (9) above are in Priestley's (1996) notations, he defines Equations (8) and (9) as the measurement and transition equations, respectively. In addition he defines the notations in the above equations as follow, $X^{\bullet}_t$ is the expected value of the risk factor (X_t), γ_{t-1} is a parameter, and u_t , ζ_t ω_t are white noises. He indicates if the above model produces non-serially correlated residuals then these will be the innovations to be used as risk factors, otherwise, X_t is modeled as (Priestley, 1996, p.873, Eq.6 and Eq.7, respectively p.873)

$$X_t = \delta_{it} X_{t-i} + \varepsilon_t \tag{10}$$

$$\delta_{it} = \delta_{it-1} + \omega_{it} \tag{11}$$

Equations (10) and (11) above are in Priestley's (1996) notations. Priestley (1996) defines equations (10) and (11) as the measurement and transition equations respectively. He points out that that X_t is here modeled as an autoregressive process in which the parameters are time-varying.

2.4.2.4 Dynamic Factor Model of Stock and Watson (2002a, b): Their Static Representation

This chapter follows Stock and Watson (2002a, b) static representation of dynamic factor model and principal components analysis which they use to estimate factors from a large set of macroeconomic variables.

Stock and Watson (2002a, p.148, Eq.2.3 and Eq.2.4. respectively) assumes

$$X_t = \Lambda F_t + e_t \tag{4}$$

Equations (4) above is in Stock and Watson's (2002a) notations (see section 2.2.3 Dynamic Factors Models in the literature review above). Following Stock and Watson's (2002a, b) this chapter assumes the macroeconomic variables follow equation (4) and uses their principal component approach to estimates the factors (F_t). Then it uses innovations in these estimated factors as potential risk factors. Stock and Watson (2002a, b) include these estimated factors in a second step regression to predict a number of macroeconomic variables (see Equation (3) in section 2.2.3 Dynamic Factors Model in the literature review above.

Stock and Watson (2002a) point out[16] that as under the dynamic factor the macroeconomic series should be I(0), these series may need to be (1) transformed, (2) first differenced and (3) undergone outliers screening. Artis, Banerjee and Marcellino (2005) point out that they follow Marcellino, Stock and Watson (2003) in this regard. For

[16] As mentioned earlier in the chapter, Mönch (2004) uses the factors estimated, using the method of Stock and Watson, from a large set of US macro variables, as potential state variable, however, this chapter is different from his study as it uses the innovations in these estimated factors as potential state variables while he used these estimated factors themselves as state variables.

convenience, as Marcellino, Stock and Watson (2003) describe these processes in details this chapter also follows Marcellino, Stock and Watson (2003). They point out that, all non-negative, non-rates and non-percentage series, are transformed by taking logarithms and the general rule is to apply same transformation and differencing degree to the group of variables. They indicate that the next step is that all the series under study undergo seasonal adjustment process of two-step which includes Wallis's (1974) adjustment and in the final step all the series are screened for outliers. They define the outliers as those observations that 6 times more than the interquartile range. They point out that the outliers are treated as missing observations and all the series are transformed so that they have zero and one unit of mean and variance, respectively.

This chapter follows Marcellino, Stock and Watson (2003) in these steps. However, firstly, for the first step Stock and Watson (2002a) point out that unit root tests are undertaken as a part of the process to deicide whether to take differencing. Therefore, the Augmented Dickey Fuller test for unit root is performed for all the series as described and explained by Harris and Sollis (2003, Chapter (3))[17]. Furthermore this chapter applies Perron's (1997) test for break points in the series. Marcellino, Stock and Watson (2003) point out that they use two sets of transformed data, however, this chapter follows Laganà and Mountford (2005) and Stock and Watson (2002a) in that using one set of transformed variables. Secondly, for seasonal adjustment, this chapter simply uses the X-11 procedure in SAS version (9.0) for seasonal adjustment. Finally, instead of treating the outliers as missing observations, this chapter replaces the outliers as follow; each outlier observation is replaced by the maximum value (after removing all the outliers) if the original

[17] As preliminary test, this chapter applies Dickey Fuller test as in Harris and Sollis (2003, Chapter (3)).

observation is positive and the minimum value if the original observation is negative. Schneider and Spitzer (2004) pointed out that they replaced the outlier by an interpolation, and hence it is not necessarily to treat the outliers as missing observations.

2.4.2.5 Fama and MacBeth's (1973) Cross Sectional Regressions

The next step is estimating Petkova's (2006) models with her different specifications following Petkova (2006) as explained below. She uses the Fama and MacBeth (1973) methodology to estimate the time-series and cross-sectional equations of the model as follows: she indicates that in the first she runs for each stock the time-series regressions to estimate the betas as (Petkova (2006, p.587, Eq.5):

$$R_{i,t} = \alpha_i + \beta_{i,M} R_{M,t} + \sum(\beta_{i,\hat{u}^K})\hat{u}_t^K + \varepsilon_{i,t} \tag{12}$$

Equation (12) above is in Petkova's (2006) notations, although she specifies $\sum(\beta_{i,\hat{u}^K})\hat{u}_t^K$. Then she states the next second step is estimating the monthly cross-sectional regression as (Petkova, 2006, p.587, Eq.6):

$$E(R_i) = \gamma_o + \gamma_M \hat{\beta}_{i,M} + \sum(\gamma_{\hat{u}^K})\hat{\beta}_{i,\hat{u}^K} + e_{i,t} \tag{13}$$

Equation (13) above is in Petkova's (2006) notations, although she specifies $\sum(\gamma_{\hat{u}^K})\hat{\beta}_{i,\hat{u}^K}$. She specifies $\sum(\beta_{i,\hat{u}^K})\hat{u}_t^K$ and $\sum(\gamma_{\hat{u}^K})\hat{\beta}_{i,\hat{u}^K}$ in the above equations (12 and 13) for her most general model which includes as factors the market excess returns, innovations to dividend yield, innovations to term spread, innovations to default spread, innovations to one-month interest rate, innovations to HML and innovations to SMB. In addition Petkova (2006) examines the Fama and French's (1993) three-factor model and her other model that includes the market excess returns, innovations to dividend yield, innovations to term spread, innovations to default spread, and innovations to one-month interest rate. Petkova (2006) points out that she proposes this last model (that includes the market excess returns, innovations to dividend yield, innovations to term spread, innovations to default spread, and innovations to one-month interest rate) as a superior ICAPM model.

Petkova (2006) points out that she estimates the factor loadings in the time series regression by running multiple regressions over the full-sample period as in Lettau and Ludvigson (2001) and also by using Fama and MacBeth's (1973) rolling multiple regressions over five-year window. This chapter follows Petkova (2006) in using Fama and MacBeth (1973) regressions with multiple regressions over the full sample period for estimating the betas.

Petkova (2006) calculates Fama and MacBeth's (1973 t-statistics for the estimated coefficients but because of the problem of the errors-in-variables, Petkova (2006) points out that she also uses the Shanken (1992) correction to correct for this problem. This chapter does the same and applies Shanken's (1992) correction. Shanken (1992, p.13, Eq.11) derives it as:

$$(1+\hat{c})[\hat{W}-\hat{\Sigma}_{F}^{*}]+\hat{\Sigma}_{\bar{F}}^{*} \qquad (14)$$

Equation (14) above is in Shanken's (1992) notations, he defines the notations in the above equation as; $\hat{c}=\hat{\Gamma}_{12}'\hat{\Sigma}_{F}^{-1}\hat{\Gamma}_{12}$, $\hat{W}$ is the covariance matrix of $\hat{\Gamma}_{t}$, where the latter is a vector of the cross-sectional regression estimates, $\hat{\Sigma}_{F}^{*}$ is bordered version of the covariance matrix of the factors ($\hat{\Sigma}_F$). He points out under the assumption of serially independent factors, then $\hat{\Sigma}^*_F = \hat{\Sigma}^*_{\bar{F}}$.

Petkova (2006, p.599, Eq.13) computes the cross sectional R^2 as:

$$R^2 = \frac{\sigma^2_C(\bar{R}) - \sigma^2_C(\bar{e})}{\sigma^2_C(\bar{R})} \tag{15}$$

Equation (15) above is in Petkova's (2006) notations, she defines the notations in the above equation as; σ^2_C, $\bar{e}$ and $\bar{R}$ as the cross-sectional variance, vectors of average residuals and average excess returns, respectively. She points out that Lettau and Ludvigson (2001) as well as Jagannathan and Wang (1996) use this measure. She also calculates the adjusted cross-sectional R^2. Furthermore, she depicts the performance of the models visually, she points that this is useful for comparison. This chapter follows Petkova's (2006) in calculating both cross-sectional R^2 and depicting the models' performance visually. However, she points out because the R^2 has a problem of assigning similar weights to the test assets regardless of how much they are correlated, she calculates the composite pricing errors (test of jointly zero pricing errors). Similarly Lettau and Ludvigson (2001) point out that they test the hypothesis of jointly zero pricing errors using the Wald test (χ^2 test) as (Lettau and Ludvigson, 2001,p.1265, footnote 28)

$$(1+\lambda'\Sigma_f^{-1}\lambda)^{-1}\hat{\alpha}'_{FM}Cov(\hat{\alpha}_{FM})^{-1}\hat{\alpha}_{FM} \quad \sim \chi^2{}_{N-K} \tag{16}$$

Equation (16) above is in Lettau and Ludvigson's (2001) notations. They define the notations in the above equation as follows Σ_f; the factors' covariance matrix, $\hat{\alpha}'_{FM}$; the vector of Fama and MacBeth's pricing errors, K and N; number of factors and portfolios, respectively, and $1+\lambda'\Sigma_f^{-1}\lambda$ is Shanken's (1992) correction. This chapter follows Petkova (2006) in calculating the test of jointly zero pricing errors. However it applies as in Lettau and Ludvigson (2001) which differs from Petkova (2006) in that she takes a transformation of the above statistic.

Note that $1+\lambda'\Sigma_f^{-1}\lambda$ in Equation (16) is equivalent to $1+\hat{c}$ in Equation (14)

2.4.2.6 Generalized Methods of Moments (GMM)

Jagannathan and Wang (1998) indicate that Fama and MacBeth's (1973) method does not inevitably underestimate the standard errors if the factors and returns are not homoskedastic. In addition, Jagannathan and Wang (2002) point out that the generalized method of moments (GMM) allows for the violations of homoskedasticity and serial independence and because of that they use it on their beta representation asset pricing model. Petkova (2006) points out that she uses GMM estimation but on the stochastic discount factor model form of the ICAPM. However, this chapter adopts Jagannathan and Wang's (2002) method of applying the GMM on the beta representation of the asset pricing model. They call it the beta method.

Jagannathan and Wang (2002) write the beta representation of an asset pricing model as follow (Jagannathan and Wang, 2002, p.2339, Eq.1)

$$E[r_t]=\delta\beta \tag{17}$$

Equation (17) above is in Jagannathan and Wang's (2002) notations, they define the notations in the above equation as r_t is a n-vector of stocks excess returns, δ , β are the factor price's of risk and factor loading, respectively. They point out that the above beta representation results in the following factor model (Jagannathan and Wang, 2002, p.2340, Eq.2)[18]

$$r_t = (\delta - \mu + f_t)\beta + \varepsilon_t \tag{18}$$

Equation (18) above is in Jagannathan and Wang's (2002) notations, they define the notations in the above equation as follow; μ is the mean of risk factor f_t, ε_t is the residuals. In addition they point out that f_t could be (1) a traded factor, in this case there is a restriction that $\mu = \delta$ which implies the factor's mean is used as its risk premium's estimate, or (2) non-traded factor. Furthermore, Jagannathan and Wang (2002) point out that in the case of non-traded factors, the moments restrictions of the model (18) above are (Jagannathan and Wang, 2002, p.2341, Eq.3, Eq.4, Eq.5 and Eq.6, respectively)

$$E(r_t - (\delta - \mu + f_t)\beta) = 0_{n\times 1} \tag{19}$$

$$E[(r_t - (\delta - \mu + f_t)\beta)]f_t = 0_{n\times 1} \tag{20}$$

$$E[f_t - \mu] = 0 \tag{21}$$

$$E[(f_t - \mu)^2 - \sigma^2] = 0 \tag{22}$$

Equations (19), (20), (21) and (22) above are in Jagannathan and Wang's (2002) notations. They define the notations in the above equations as $0_{n\times 1}$ is the n-vector of zeros, $\theta = (\delta, \beta', \mu, \sigma^2)'$ is vector of parameters to be estimated, σ^2 is the factor's variance. They point that they assume Hansen's (1982) regulatory conditions are fulfilled. Furthermore, they point out that they test the model specification using Hansen's J-statistic which under linearity and large number of time series' observation

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[18] See Jagannathan and Wang (2002), for more details.

assumptions converges to χ^2. Jagannathan and Wang (2002) point out that when the factor is traded then the moments restrictions are (Jagannathan and Wang, 2002, p.2341, footnote 2)

$$E[r_t - f_t\beta] = 0_{n\times 1} \tag{23}$$

$$E[r_t - \beta f_t]f_t = 0_{n\times 1} \tag{24}$$

Equations (23) and (24) above are in Jagannathan and Wang's (2002) notations. They point out that in such case β can be calculated using (Eq.23 and Eq. 24) and μ and σ^2 can be estimated separately from (21 and 22), where μ is the risk premium. To keep consistency across equations' notations that appear above in the other sections of the methodology, δ (risk premium) is equivalent to γ and f_t (risk factor) is equivalent to u_t^K.

This chapter follows Jagannathan and Wang (2002) and estimates all various Petkova's (2006) models - which are estimated in the previous section using Fama and MacBeth (1973) methods following Petkova (2006) - using GMM with the moments Eq.19, Eq.20, Eq.21 and Eq.22. In a model which includes traded factors only or traded factors and non-traded factors the model is estimated using the moments from Eq.19 to Eq.22 and a test of the equivalency between the estimated risk premium and the mean of the factor is conducted as in Jahankhani (1976). Furthermore, Fama and French's (1993) model is also estimated using Eq.23 and Eq.24 and separately Eq.21 and Eq.22.

Fama and MacBeth (1973) points out that in the CAPM the estimated market risk premium should equal the average market excess return. They point out that to test statistically the difference in magnitude between the two is in fact equivalent to the test of the difference between the estimated intercept and the average risk free-rate. They calculate the t-statistics for the difference by dividing the difference between the estimated coefficient and its average by the standard error of the estimated coefficient. Similarly, Jahankhani (1976) points out that he tests if the estimated risk premium is equal to the corresponding factor's average excess return using the following statistics (Jahankhani, 1976, p.520)

$$t(R_m) = \frac{\gamma_{1t} - (\overline{R}_{mt} - \overline{R}_{ft})}{s(\hat{\gamma}_{1t})} \tag{25}$$

Equation (25) above is in Jahankhani's (1976) notations. Eq.(25) could be written, using the above Jagannathan and Wang's (2002) notations to keep the consistency, as

$$t(f_t) = \frac{\delta - \mu}{s\tan dard\_error(\delta)}$$

Lewellen, Nagel and Shanken (2006) point out that the fact that many models are found to have power to capture the value and size effects while they are not related to each other is confusing. They point out that the restriction on the slopes' magnitudes from the cross sectional regression; i.e. the estimated risk premium should be equal to the average of its risk factor, should be tested. This chapter applies the test as in Jahankhani (1976) for the equivalence between the estimated risk premium and the average return to traded factors where the Fama and MacBeth (1973) or GMM on the beta representation following Jagannathan and Wang (2002) are used to estimate the model as Jagannathan and Wang (2002) point out that the traded factor imposes restriction on its estimated risk premium to be equal to its mean. Black, Jensen and Scholes (1972) also point out that the pricing theory entails the estimated risk premium in the cross sectional regression equals the average market excess return. They also show and calculate the above *t*- static for testing the equivalency between the two values. Furthermore, Brennan, Wang and Xia (2004) also use two-step cross sectional regression and examine if the average return on each of the Fama and French (1993) three factors is equal to its corresponding estimated risk premiums.

2.5 Results

2.5.1 Fama-French's (1993) Three-Factor Model in the UK-LSE

This chapter starts by testing the first hypothesis which examines if the Fama-French's (1993) SMB and HML portfolios are priced in the LSE using the Fama and French's (1993) 25 portfolios' excess returns. Panel (A) of Table (2.3) shows the coefficients estimated from the Fama and MacBeth (1973) second-step cross-sectional regression. It is apparent that excess market returns is insignificant, while the SMB and HML are statistically significant at 5% and 1%, respectively using Fama and MacBeth's (1973) t-statistics. However, when Shanken's (1992) corrected standard errors are calculated, only the SMB and HML are found to be significant. However, and despite the fact that the estimated intercept is not significant, the hypothesis of jointly zero-pricing errors is rejected as χ^2 shows. Nevertheless, the hypothesis that the risk premiums on the market portfolio and SMB are equivalent to their corresponding average returns is accepted while rejected for the HML at 10%.

Panel (B) of Table (2.3) shows the results of estimating the model using the GMM on the beta representation following Jagannathan and Wang (2002). As pointed out by the latter study paper when the factors are traded factors then there are restrictions that the average returns on the factors are equal to their corresponding risk premiums. The results in Panel (B) show the risk premiums estimated using the four moments restrictions (Eq.19-Eq.22), i.e. the factors are treated as non-traded factors and then the final column presents the test of the equivalency between the risk premium and its corresponding factor's mean. When the model is estimated by treating the candidate risk portfolios as traded factors, using the moments (Eq.23 and Eq.24) and then separately the moments (Eq.21 and Eq.22) as mentioned above, it produces similar J-statistic for the model restrictions.

The results from the GMM estimation are qualitatively similar to Fama and MacBeth's (1993) method results using the Shanken (1992) corrected standard errors. The SMB and HML are priced significantly with negative and positive risk premiums, respectively, while the market factor is not significantly priced. However, while the magnitude of the SMB premium is similar under the two methods, the risk premiums of the market portfolio and the HML are smaller under the GMM and the hypothesis that factor's mean equal to its estimated risk premium is accepted for the three factors; market excess return, SMB and HML. This is not surprising for the HML as its estimated risk premium under the GMM estimation is much closer to its average return. Finally the specification test is accepted as the Hansen's J – statistic shows.

The first hypothesis, which states that the Fama-French's (1993) SMB and HML are priced factors in the cross sectional returns on the UK Fama and French's (1993) 25 size and book-to-market portfolios, is accepted. Although the Fama and French's (1993) three-factor model's pricing errors hypothesis is rejected under the Fama and MacBeth's (1973) methodology, the model specification is accepted under the GMM. In addition, while the SMB premium is negative and significant, the HML premium is positive and significant. This finding is expected as it is shown in Table (2.2) that the average return on the SMB portfolio is negative and significant at 10% over the sample period from July-1981 to December -2005. Furthermore the performance of SMB is consistent with Dimson, Nagel and Quigley's (2003) study although the sample of the latter study ends in 2001. Petkova (2006) reported that the application of the Fama and French's (1993) three factor model resulted in a SMB premium that is positive but insignificant and a significant and positive risk premium associated with HML for the US market. Furthermore she reports that the risk premium of the market portfolio is negative but insignificant and the jointly zero pricing error hypothesis is rejected for the Fama and French's (1993) three-factor model

2.5.2 Petkova's (2006) Model that includes Excess Market Return and Innovations to Four Variables

This subsection shows the results of the testing of the second hypothesis which applies Petkova's (2006) model of the ICAPM, which includes the excess market return, and innovations to dividend yield, term spread, default spread and one-month T-Bill, to the UK market to examine whether it is priced in the UK cross sectional average returns on stocks.

Panel (A) of Table (2.4) shows the results of estimating the model using Fama-MacBeth's (1973) methodology. The Fama and MacBeth's (1973) t-statistic show that all the risk premiums are significant including the intercept. However when Shanken's (1992) corrected standard errors are calculated, it is found that only the innovations to dividend yield is priced with significant negative risk premium. The hypothesis of jointly –zero pricing errors is also rejected.

When the model is estimated using the GMM on the beta representation following Jagannathan and Wang's (2002), the results in Panel (B) reveal that in addition to the innovations to dividend yield, the innovations to term spread also significantly priced with negative risk premium, but the innovations to the default spread and T-Bill are not significant. A point to be mentioned here is that although the risk premiums of the market excess returns and innovations to default spread are not significant, their signs change under the GMM estimation compared with Fama and MacBeth's (1993) estimation. Finally the model specification is accepted by Hansen's J-statistic.

The innovations in the potential state variables in Table (2.4) are estimated as Petkova (2006) from a VAR system. To check the robustness of the results to the technique used to produce the innovations of the candidate risk factors, Table (2.5) reports results when the innovations are estimated based on Kalman Filter technique that is suggested by Priestley (1996) to replace the VAR innovations in Table (2.4). Panel (A) shows the results from Fama and MacBeth's (1973) cross-sectional regression. It is clear that the final conclusion is qualitatively close to its VAR counterpart in Panel (A) of Table (2.4). However, using the Kalman filter-based innovations, it is found that only the innovations to dividend yield and terms spread are priced risk factors under the Fama and MacBeth's (1973) t-statistics and when Shanken's (1992) corrected standard error is calculated, only the innovations to dividend yield is priced. A significant difference between the results based on VAR innovations and those based on Kalman filter innovations is the hypothesis of jointly-zero pricing errors is accepted for the latter innovations, this may imply that Kalman filter innovations are potentially superior estimates of the risk factors than VAR innovations.

Panel (B) of Table (2.5) shows the estimation using the GMM method. The results support those reported in Panel (A) using Fama and MacBeth's (1973) cross-sectional regression. Nevertheless, the innovations to the T-Bill is significant with positive risk premium. The positive sign of the risk premium of the innovations to the T-Bill is surprising given it was negative in all the previous estimations although insignificant. This may cast doubt on the importance of the short-term interest rate as a useful risk factor in the cross section of the UK stock returns.

Given the above, it could be concluded that innovations to the dividend yield and term spread are priced risk factors in the UK, a result that is robust to the innovation estimation technique and the model estimation method. In addition, the Fama and French's (1993) model, when applied to UK stock return, is rejected under the hypothesis of jointly-zero pricing error when the model is estimated using Fama and MacBeth's

(1973) methodology, while Petkova's (2006) model with market return and innovations to dividend yield, term spread, default spread and T-Bill is accepted for the UK market when the innovations are estimated using the Kalman filter-based technique. These results may be interpreted to mean that the latter model is a better description of the cross-sectional returns on the Fama and French's (1993) 25 size and book-to-market portfolios in the UK market. This is despite the fact that the adjusted R^2 is higher for the Fama and French's (1993) model.

In comparison, Petkova (2006) reports that the innovations to term spread and innovations to T-Bill are significantly priced in the US market. She reports the risk premium of the innovations to term spread is positive for the US while this chapter finds a negative risk premium for the UK market. Chen et al., (1986) report the risk premium associated with the shocks to the term spread is negative. However Chen et al., (1986) pointed out this is should be read in the light of the fact that inflation is already accounted for. Antoniou et al., (1998) report a positive but insignificant risk premium for the Kalman filter- based shocks to term spread and a positive and significant risk premium for the market portfolio for the UK in the context of APT of Ross (1976). Furthermore, they report that a number of shocks to macroeconomic factors have significant risk premium in the UK market, including, among others, default spread. However they report that its risk premium is not stable. Clare and Thomas (1994) also study the shocks to a number of macroeconomic variables as potential risk factors in the UK. They report, among the priced macroeconomic variables is, the default spread with positive risk premium. However they report insignificant risk premiums for the unemployment and term spread (both non stable sign). In addition, Petkova (2006) reports that the jointly zero pricing error hypothesis is rejected for the Fama and French's (1993) model but accepted for her mod el with the following state variables; market excess return and innovations to dividend yield, term spread, default spread and short term T-Bill is accepted. Note that Petkova (2006) reports the zero error for her model with innovation estimated from the VAR system while in this chapter her model is accepted on this basis, when the Kalman filter innovations replace VAR innovations while the model with the latter innovations is rejected in the UK.

2.5.3 Fama and French's (1993) Factors and State Variables; Do they Relate?

Having found (1) that Fama and French's (1993) model is able to explain the cross sectional UK stock returns and (2) Petkova's (2006) model with market excess return and innovations to dividend yield, term spread, default spread and T-Bill does well in pricing the Fama and French's (1993) 25 size and book-to-market portfolios, the next step is to test hypothesis (3) which also follows Petkova (2006) and examines if the innovations in her selected state variables can drive the Fama and French's (1993) SMB and HML factors. Therefore, this section uses Petkova's (2006) model with market excess return, innovations to dividend yield, term spread, default-spread, one-month interest rate and Fama-French's (1993) HML and SMB as risk factors.

Table (2.6) presents the results of Petkova's (2006) model with market excess return, innovations to dividend yield, term spread, default-spread, one-month interest rate and Fama-French's (1993) HML and SMB as risk factors. Panel (A) reports the estimates using Fama-MacBeth's (1973) cross-sectional regression. It is clear that the HML is still highly significant with positive risk premium, while the SMB becomes insignificant. In addition, it is found that only the innovations to dividend yield is significant as before while the innovations to term spread is insignificant. The adjusted R^2 is high although the hypothesis of jointly zero pricing errors is rejected.

Panel (B) of Table (2.6) shows the results form estimating the model as has been done for the models in the above sections of the results using the GMM on the beta representation following Jagannathan and Wang (2002). The results show that Fama and French's (1993) SMB and HML do not lose their influence on stock returns in the existence of the other risk factors. They are still significant with positive risk premium for the HML and negative risk premium for the SMB. In addition, the innovations to term spread and the innovations to dividend yield are also significant, even more the innovations to T-Bill is significantly priced with negative sign. The model specification is accepted as shown by Hansen's J-statistics.

Panel (A) of Table (2.7) presents the results when the Kalman filter innovations replace the VAR innovations in Table (2.6) and with HML and SMB real returns replace the innovations to HML and SMB. Panel (A) shows the results for Fama and MacBeth's (1973) cross-sectional regression. The results are qualitatively similar to those with VAR innovations in Panel (A) of Table (2.6), although the SMB is found to be negatively priced. The hypothesis of jointly-zero pricing errors is rejected but the test statistic is slightly smaller than in the case of the VAR innovations. Remember that in Table (2.5), when the model has only the market excess returns with innovations to the four variables, the jointly zero pricing errors is accepted for the Kalman-based innovations. Taken together, this may suggest that adding the HML and SMB to the model increases the deviations of the 25 Fama and French (1993) size and book-to-market expected returns from their actual values, despite the fact that the R^2 is much higher when the HML and SMB exist.

Panel (B) of Table (2.7) shows the results from the GMM estimation. They support the results from Panel (A) however, now, as in the case of the VAR innovations when the model is estimated with the GMM, the term spread is significant, even more the T-Bill is also significantly priced, though it differs from its VAR counterpart in the sign as the risk premium is now positive. But this positive T-Bill risk premium is consistent with the sign in Table (2.5). It seems that the one-month T-Bill risk premium is not stable; it is negative under the VAR innovations while positive under the Kalman Filter innovations.

Jagannathan and Wang (2002) point out that when the factor is traded then the restriction of the equivalency of the risk premiums of the factors to their corresponding average returns applies. This hypothesis is accepted for the HML and SMB, while it is marginally rejected for the market portfolio at 10% significance level. For the GMM estimates the hypothesis that each of the market, HML and SMB risk premium estimate is equal to its corresponding return average, is accepted.

It could be concluded that innovations to dividend yield, term spread, HML and SMB are important risk factors that drive the cross-sectional returns on the UK Fama and French's (1993) 25 size and book-to-market value portfolios. However, the HML and SMB continue to be significant factors in the existence of the other variables. This suggests that, in the UK, SMB and HML do not share the information captured by the innovations to the dividend yield, term spread, default spread and one month interest rate. Hence the best description of the UK returns is a model that contains excess market return, innovations to dividend yield, term spread, HML and SMB. This is unlike Petkova's (2006) findings for the US. She reports that her findings accept the hypothesis of the HML and SMB lose their influence to explain stock returns cross sectionally to the innovations to dividend yield, term spread, default spread and T-Bill, where the last four factors capture the information in these two factors.

2.5.4 The Common Macro Factors and the Stock Returns

The results of the previous section show that the UK Fama and French's (1993) SMB and HML are not explained by the innovations to Petkova's (2006) selected state variables. This does not answer the challenge that is posited by Cochrane (2006) which is to find the economic factors that are tracked by the SMB and HML portfolios. Therefore, these findings point at the possibility of the problem of omitted information as pointed out by Ludvigson and Ng (2007) and they point out that dynamic factor models solve such a problem. Therefore, this section applies the testing procedures, that are applied so far in the chapter, to factors estimated from large set of macroeconomic variables utilizing the dynamic factor models and principal components analysis of Stock and Watson (2002a, b), in an attempt to uncover these potential economic risk factors. Mönch (2004, 2006) also apply the dynamic factor models of Stock and Watson (2002a, b) in asset pricing as well.

2.5.4.1 Are the Common Macro Factors Pricing Factors?

To test the Hypothesis (4A) that the innovations to factors estimated from a large macro set are potential risk factors, six factors are estimated from a set of 78 UK macroeconomic variables using the dynamic factor models and principal components analysis of Stock and Watson (2002a, b). Petkova (2006) uses VAR to estimate the innovations of the state variables by including the market excess return as the first variable in the VAR model followed by the rest of the state variables. Following her, this section estimates the innovations to the estimated six factors from the VAR by including the market excess return first, followed by the six estimated factors. As mentioned earlier, adding estimated factors into the VAR this is also similar to Laganà and Mountford (2005) who point out that they add factors estimated from a large set of macro variables into the VAR. In addition, innovations in the estimated factors are estimated using the Kalman filter based method following Priestley (1996). The reason for choosing to estimate six factors is based on Artis, Banerjee and Marcellino (2005). They report that they found that half of the variation in their 81 UK macroeconomic variables could be accounted for by six common factors.

Table (2.8) reports the results of estimating the model in which the innovations in the six estimated factors replace the innovations in the four state variables in Petkova's (2006) model that includes excess market returns and innovations to dividend yield, term spread, default spread and one month interest rate. Panel (A) shows the results of Fama and MacBeth's (1973) cross-sectional regression. Based on their t-statistics, four factors are found priced; the innovations to the first, the second, the fifth and the sixth factors.

However, when Shanken's (1992) corrected standard errors are calculated, none of the innovations to these factors are significant. Although R^2 is very low, the zero pricing errors are accepted. Panel (B) of Table (2.8) shows the results of the GMM estimation following Jagannathan and Wang (2002). These results support the significance of the first and the sixth factors which are found to be priced by the Fama and French's (1993) 25 size and book-to-market portfolios. In addition, the model specification is accepted.

Table (2.9) reports the results for the same model in Table (2.8) but with Kalman Filter based- in novations substituting VAR-based innovations. The results from both Fama and MacBeth's (1973) cross-sectional regression (Panel (A)) and the GMM estimation (Panel (B)) support the above findings that the innovations to the first and the sixth estimated factors are potentially priced risk factors. Similarly as in the VAR-based innovations the jointly zero-pricing errors and Hansen *J*-statistic are accepted however R^2 is much higher. A point to be mentioned is that innovations based on the Kalman filter seem to be more robust than those from the VAR.

The finding that not all the common factors are significant risk factors is not surprising as Ludvigson and Ng (2007) point out not all the estimated factors are necessarily useful for forecasting the conditional mean of returns. Their argument applies to here as well. Indeed this is what should occur as Cochrane (2006) points out that the degrees of freedom are 3 and not 25 in Fama and French's portfolios. Cochrane (2006) points out further that this is Lewellen, Nagel, and Shanken's (2006) and Daniel and Titman's (2005) essential point.

Furthermore, Mönch (2004) reports that his model which includes market returns and two diffusion indexes (estimated factors) which relate to business cycle and foreign exchange risk does better than Campbell (1996) model and as well as Fama and French's (1993) model on the Fama and French's (1993) 25 portfolios.

2.5.4.2 Do the Priced Common Macro Factors Relate to HML and SMB?

Given that Hypothesis (4A) is accepted as it is found that innovations to at least two estimated factors are priced by the Fama and French's (1993) 25 size and book-to-market portfolios, this section turns its attention to testing Hypothesis (4B) which examines whether the Fama-French's (1993) S MB and HML share similar information to the innovations in the estimated common factors. Hypothesis (4B) is equivalent to Hypothesis (3). Therefore this section uses Petkova's (2006) model with excess market returns and innovations to dividend yield, term spread, default spread, one month interest rate, HML and SMB where the innovations in the estimated factors replace the innovations to dividend yield, term spread, default spread, and one month interest rate. The innovations in the estimated factors that are used include the innovations to the above four potentially priced estimated factors; the first, the second, the fifth and the sixth factors. Furthermore, the HML and SMB real returns are used rather than the innovations. Table (2.10) presents the results.

Panel (A) of Table (2.10) reports the results of estimating the model using the Fama and MacBeth's (1973) method. It shows that only the HML is significantly and positively priced and the SMB coefficient is marginally insignificant at conventional levels. In addition is it found that the market and SMB estimated risk premiums are equal to their corresponding averages, while the hypothesis that the HML risk premium is equal to its average is rejected at 5%. Panel (B) reports the results from the GMM on the beta representation following Jagannathan and Wang's (2002). It shows that innovations to the second factor is priced as well as the HML and SMB. Note that the risk premium associated with the innovations in the second factor is negative while previously in Table (2.8) (without HML and SMB) the sign is found to be positive. Again the hypotheses that the market and SMB estimated risk premiums are equal to their corresponding averages are accepted while it is rejected for the HML at 10%.

Panels (C and D) report the results when the insignificant estimated factors from above results; i.e. the innovations to five estimated factors except the innovations to the second factor, are excluded. The results support the importance of the innovations in the second estimated factor along with HML and SMB as potential risk factors. Furthermore, the jointly-zero pricing errors is marginally rejected at 10%, and the model specification measured by Hansen *J*-statistics is accepted. In addition, it is found that market and SMB estimated risk premiums are equal to their corresponding averages, while the hypothesis for the HML premium is rejected at 5%. However, under the GMM estimation, the hypothesis that the estimated risk premium is equal to its corresponding average returns is accepted for all the factors; the market, HML and SMB risk premiums.

Table (2.11) presents the results when the VAR innovations in Table (2.10) are replaced by Kalman filter based innovations. It is clear that the only risk factors that continue to be significant are the HML and marginally, based on the Fama and

MacBeth's (1973) cross-sectional regression, the SMB. Accordingly, it seems that the significance of the innovations to the second estimated factors is not robust to the innovation estimation technique. The hypothesis that the estimated risk premium of the traded risk factor is equal to its average return is accepted for the SMB while it is rejected for the market and HML, both at 5% significance level. Under the GMM, it is accepted for the market and SMB, and it is rejected for the HML at 10% significance level.

Panels (C and D) of Table (2.10) show the VAR based innovations to the second estimated factor is significant along with the HML and SMB. This finding is robust to the model's estimation method. This motivates replacing the VAR based innovations to the second estimated factor in Panels (C and D) of Table (2.10) with the Kalman filter based innovations to the second estimated factor to examine if this estimated factor is robust to the innovation estimation technique, although it is found to be insignificant in Table (2.11). Panel (A) and Panel (B) of Table (2.12) present the results from the Fama and MacBeth's (973) cross sectional regressions and Jagannathan and Wang's (2002) GMM method on the beta representation, respectively. The innovations to the second estimated factor is significant with a negative risk premium under the GMM method and the hypothesis that the estimated risk premium of the traded factor is equal to its corresponding average is accepted for the SMB, but it is rejected for the market and HML, at 10% and 1% significance level, respectively.

This chapter concludes that the innovations to the first and the sixth common factors are potential significant risk factors in the UK stock market and these results are robust to the innovations estimation technique and the model estimation method.

However, the results show that in the existence of the HML and SMB, it seems that the innovations in the second estimated factor is a potential significant risk factor in the cross section of UK Fama and French's (1993) 25 portfolios, nevertheless, it does not account for the information in the HML and SMB as they continue to be significant. Therefore Hypothesis (4B) is rejected. This is in contrast with the findings of Liew and Vassalou (2000) and Kelly (2003) who report the SMB and HML are linked to GDP growth.

2.5.5 The Macro Common Factors; Do they contain different news to stock prices?

The question now is whether the estimated common factors that are found priced in the cross section of the UK stock return in the previous sub-section carry information for stock returns that is not captured by Petkova's (2006) four selected state variables. In other words, this section examines if there are other variables that are valuable for stock's returns that are missing from Petkova's (2006) set of variables[19]. The aim of this chapter is to search for the potential macroeconomic factors that explain the changes in stock prices, which is the challenge that is posited by Campbell (2000) and Cochrane (2006). So in this context, Petkova's (2006) selected variables are just few potential risk factors. Mönch (2004) augments Campbell's (1996) model with estimated factors which he calls diffusion indexes and reports the estimated macro factors add additional risk information beyond those of the model of Campbell (1996). Mönch (2006) augments the conditioning variables set with factors estimated from a large set of variables. Furthermore, Ludvigson

[19] Watson (2001) points out that, in reality more variables need to be used than the limited number that can be handled by the VAR. Laganà and Mountford (2005) point out they follow Bernanke et al. (2005) in augmenting the VAR model with factors estimated from a large set of macro variables to study the monetary policy.

and Ng (2007) point out that their study examines whether the estimated factors do carry information that is not captured by the other widespread used predictive variables for predicting the conditional mean and volatility of stock returns. They point out for this purpose they augment the conditional set of variables to predict the conditional mean and volatility of stock returns with factors estimated from a large set of variables. This is section of the chapter follows Ludvigson and Ng's (2007) and Mönch's (2004, 2006) procedure in augmenting the potential risk factors with factors estimated from a large set of macro variables. More specifically it augments Petkova's (2006) model that includes excess market return, innovations in dividend yield and term spread, HML and SMB with the innovations to the second factor estimated from a large set of macro variables. Note that the other two variables in Petkova's (2006) model which are the innovations in the default spread and one month T-bill are not included as they are found previously in this chapter are insignificant in the UK market. Table (2.13) presents the results. Panels (A) and (B) show the estimates with VAR innovations using Fama and MacBeth's (1973) method and GMM on beta representation following Jagannathan and Wang (2002), respectively. Panels (C) and (D) show the corresponding results when Kalman filter-based innovations replace VAR innovations.

The results show that the innovations to dividend yield, HML and SMB continue to be significant regardless of the innovation estimation technique or the model estimation method. The innovations in term spread is significant under the GMM method regardless of the way the innovations are estimated and the innovations to the second macro estimated factor is significant when the innovations are estimated using the Kalman filter technique and the model is estimated using the GMM method as Panel (D) shows.

Indeed Panel (D) shows that all the factors are significantly priced, even more, the hypothesis that the factor estimated risk premium equals to its corresponding average return is accepted for the market, HML and SMB. Based on Fama and MacBeth's (1973) methodology, the hypothesis of zero jointly pricing error is rejected but under the GMM estimation the model specification is accepted as before.

In summary, the results from Table (2.13) suggest that the innovations in the term spread and the innovations in the second estimated macro factors share some information about stock prices, evidenced by the fact that in some of the estimations one of them loses power when both exist in the model. To shed more light on this, this chapter follows Stock and Watson (2002a) to examine what the estimated factors do represent.

2.5.6 What is the Priced Estimated Macro Factor?

Stock and Watson (2002a) point out that in order to characterize the estimated factors, and because of the identification problem, they estimate R^2 s from regressing each of the estimated factors on the individual macroeconomic variables that are used to estimate the factors. They interpret the factors by their loadings on the macroeconomic variables. This chapter applies Stock and Watson's (2002a) exercise to the second estimated factor by regressing this estimated factor on each of the 78 macroeconomic variables. It is found that the highest R^2 s are from regressing the second estimated factor on the employment rate (71%), term spread measures (53-58%) and unemployment rate (51%). Furthermore, the loadings of the second estimated factor on the employment and the term spread measures are positive while on the unemployment it is negative. This explains why, when innovations in the term spread and innovations in the second estimated factor exist together in the model, one of them or both lose power in some of the model estimations. However both of them are significantly priced when the Kalman filter –based innovations to the second estimated factor is used and the model is estimated by the GMM.

It could be concluded that the innovations in the estimated factors from a large dataset of macroeconomic variables bear important relationship to stock returns in the UK market. Even more the second estimated factor, which loads largely on employment and term spread, carry information that is not captured by the innovations to the state variables in Petkova's (2006) model which includes excess market return and innovations to dividend yield, term spread, default spread, short-term interest rates, HML and SMB, or by the Fama and French's (1993) HML and SMB. This new information seems to be related to shocks to the employment and unemployment. These findings are consistent with a number of studies. Mönch (2004) reports when he augments Campbell's (1996) model with the two estimated factors, the resulting model does a little better than his diffusion index model and much better than Campbell's (1996) model. Mönch (2006) reports that the estimated factors are important conditioning factors for stock returns and these estimated factors carry information beyond those contained in the widespread conditioning variables. He reports that one of the estimated factors is related to a number of variables including the term spread where the latter is consistent with the finding in this chapter. Mönch (2004, 2006) also uses the Fama and French's (1993) 25 portfolios.

Furthermore, Ludvigson and Ng (2007) point out that they find the estimated common factor that forecast stock market's conditional volatility is related to the employment and real output. Flannery and Protopapadakis (2002) report that they find employment is a potential risk factor that influences stock returns' conditional variance. Furthermore, Mönch (2004) report that he finds, for the US, the first priced estimated factor is related to unemployment, interest rate spreads and capacity utilization. Furthermore, Boyd, Hu and Jagannathan (2005) point out that they find a positive (negative) reaction by stock market prices to the increase in unemployment during expansion (recession) and as expansion times dominate the recession times, the general reaction is positive.

2.5.7 Visual Representation

Petkova (2006) depicts the fitted expected return against the actual average return for each of the 25 portfolios for her model which includes excess market return and innovations to dividend yield, term spread, default spread and one month T-Bill and for the Fama and French's (1993) three-factor model. She explains that this visual representation is informative about the relative performance of the different models. Petkova (2006) indicates that if the model fits the data then for all portfolios, both the fitted (from the model) and actual average returns should hit the 45 degree line. She explains that the model specification fitted value for each portfolio is calculated from estimating the model's parameters. This chapter follows her in performing this exercise for the Fama and French's (1993) three-factor model as shown in Panel (A) of Figure (2.2) and for the final model which includes all the priced risk factors that are found in this chapter to be priced in the UK market as shown in Panel (B) of Figure (2.2). This final model is Petkova's (2006) model that includes excess market return, innovations to dividend yield, term spread, HML and SMB [but without innovations to default spread and one month T-Bill as they are found not to be significant in the UK], augmented with the innovations to the second estimated factor (that relates to employment, unemployment and term spread). Note that the. Panel (C) of Figure (2.2) is for the same model in Panel (B) but Kalman Filter innovations replace VAR innovations.

Figure (2.2) shows that the points that represent the 25 portfolios are slightly closer to the 45-degree line in Panels (B and C) than in Panel (A).The calculated correlations between the fitted and actual returns for the portfolios are 0.92, 0.97 and 0.96 for Panels (A, B and C) respectively. This supports that the model in Panels (B and C) seem to provide a better description of the average returns on the Fama and French's (1993) 25 portfolio than the Fama and French's (1993) three-factor model. Petkova (2006) reports that her model with excess market return, innovations to dividend yield, term spread, default spread and one month T-Bill outperforms the Fama and French's (1993) three-factor model in producing closer points for the 25 portfolios to 45 degree-line especially for those portfolios that defy the Fama and French's (1993) three-factor model. In addition, Hodrick and Zhang (2001) report that the return on some of the 25 size and book-to-market portfolios is overstated by the Fama and French's (1993) three factor model and in particular, for the small growth one. Furthermore, Hodrick and Zhang (2001) point out that, what they call, Fama and French's (1993) five factor model that has extra two factors which are the term spread a nd default spread has slightly smaller pricing error compared with the three-factor model.

However as reported earlier the hypothesis of jointly zero pricing error is rejected for this model, although under the GMM estimation the model specification is accepted using Hansen's *J*-statistics. However, Lettau and Ludvigson (2001) emphasize that there is a small-size problem of the Wald statistic.

2.6 Conclusion

This chapter shows that Fama and French's (1993) three-factor model and Petkova's (2006) model of the ICAPM of Merton (1973) are successful in explaining the cross sectional returns of the UK 25 Fama and French's (1993) 25 size and book-to-market portfolios. It is found that the innovations in dividend yield and term spread are significantly priced risk factors, but the innovations in default spread and one-month T-Bill are not significantly priced. However, these state variables are not able to capture the pricing power of the HML and SMB, which continue to be significantly priced in the UK. The results are robust to the innovation estimation technique and the model estimation method.

This chapter augments Petkova's (2006) model with innovations to factors estimated from a large panel of 78 macroeconomic variables using the dynamic factor model and principal components analysis of Stock and Watson (2002a,b). To uncover the macroeconomic forces that explain stock returns as required by Campbell (2000) and Cochrane (2006), it is important not to confine the analysis to a small set of potential risk factors, but to a search in the wider set of the macroeconomy. This becomes important in light of the problem of omitted information (Ludvigson and Ng (2007)) and the findings of Mönch (2004). It is found that although two estimated factors are priced risk factors in the cross section of returns on stocks, one estimated factor (the second factor which relates to employment and term spread) is found to add information beyond those carried by the innovations to dividend yield, term spread, HML and SMB. In addition it is found that this second macro estimated factor is related to employment and term spread measures. This is consistent with Mönch (2004) who reports that augmenting Campbell's (1996) model with estimated factors provides better model than Campbell (1996) model. However, this chapter finds no link between the SMB and HML and the macroeconomic variables which contradicts the findings of Liew and Vassalou (2000) and Kelly (2003).

This chapter concludes that the potential best representation of the asset pricing model in the UK stock market is Petkova's (2006) model with excess market return, innovations to dividend yield, term spread, and HML and SMB [but without innovations to default spread and one month T-Bill as they are found not to be significant in the UK], augmented with the innovations to the second estimated factor relates to employment. This has important implications to those who are interested in estimating average returns on stocks that are traded in LSE. It warns them to not ignore the larger set of macroeconomic variables when they consider the potential determinants of stock prices. This chapter contributes by adding another attempt to the asset pricing literature that tries to address the challenges that are posited by Campbell (2000) and Cochrane (2006).

Table 2.1 Number of Stock in the Sample

Year	Number of firms per year	Year	Number of firms per year
1981	205	1994	972
1982	217	1995	1006
1983	224	1996	1002
1984	238	1997	1149
1985	315	1998	1242
1986	375	1999	1186
1987	408	2000	1101
1988	710	2001	1187
1989	947	2002	1211
1990	1023	2003	1134
1991	1059	2004	1077
1992	961	2005	1143
1993	959		

This table reports the number of UK stocks available for analysis in each year in the sample period of July-1981 to December-2005 after applying Fama and French's (1993) criteria regarding the availability of stock prices and book values. The data are from Datastream for non-financial stocks traded in London Stock Exchange excluding foreign stocks

Table 2.2 Average Returns on UK Fama and French's (1993) Factors

	Market	HML	SMB
Average (%)	0.07	0.59	-0.37
	(0.24)	(5.64)***	(-1.92)*

This table reports the monthly average excess returns on the market portfolio, the average returns on the SMB and HML portfolios. The t-statistics is reported in parentheses. The portfolios constructed following Fama and French (1993 and 1996). The study sample period is July-1981 to December-2005. ***significant at 1%, ** at 5% and * at 10%

Table 2.3 Fama and French's (1993) Three-Factor Model

	Panel A: Fama and MacBeth (1973)		*Panel B: GMM*	
	Parameters	$\mu = \delta$	Parameters	$\mu = \delta$
Intercept	-0.87 (-1.68) * [-0.70]			
Market	0.96 (1.63) * [1.37]	0.07 (1.51)	0.11 (0.40)	0.07 (0.15)
SMB	-0.47 (-2.02)** [-1.86*]	-0.37 (-0.46)	-0.47 (-2.48)**	-0.37 (-0.56)
HML	0.93 (5.14)*** [4.43 ***]	0.59 (1.88)*	0.69 (6.88)***	0.59 (0.99)
Adjusted R^2	82%			
χ^2	44.52 (0.00)			
Hansen J-statistic			28.80 (0.27)	

This table reports the parameters estimates of Fama and French (1993) three-factor model. Panel (A) reports the estimates from Fama–MacBeth (1973) cross-sectional regressions with betas estimated using one multiple regression over the full sample period. Panel (B) reports the estimates from GMM on beta representation following Jagannathan and Wang (2002). The study sample period is July-1981 to December-2005. The test assets are UK Fama and French's (1993) 25 portfolios and the risk factors are market excess return (Market) and returns on SMB and HML. For the parameters estimated using Fama and MacBeth's (1973) method, the Fama and MacBeth's (1973) t-statistics is reported in parentheses and Shanken's (1992) corrected t-statistics is reported in square brackets. μ is the average return on the traded risk factor i, δ is the estimated risk premium for traded factor i and reported in the previous column, and $\mu = \delta$ is the restriction that Jagannathan and Wang (2002) impose on the risk premium when the factor is traded under the beta method. χ^2 tests the hypothesis of jointly zero pricing error. *J- statistic* is Hansen (1982) *J*-statistic tests for model specification. R^2 is the adjusted cross sectional R^2.***significant at 1%, ** at 5% and * at 10%

Table 2.4 Petkova's (2006) Model of ICAPM : Five Risk Factors - VAR

	Panel A: Fama and MacBeth (1973)	*Panel B: GMM*
Intercept	-1.65 (-2.71)*** [-0.76]	
Market	1.32 (2.15)** [1.08]	-0.06 (-0.20)
FTDIV	-6.39 (-5.53)*** [-2.60]***	-5.67 (-3.15)***
TERM	-3.25 (-2.62)*** [-1.23]	-8.21 (-3.27)***
DEFAULT	-2.71 (-1.88)* [-0.87]	1.30 (0.55)
TBILL	-3.65 (-2.87)*** [-1.34]	-1.91 (-1.08)
Adjusted R^2	69%	
χ^2	36.77 (0.01)	
Hansen J-statistic		11.47 (0.65)

This table reports the parameters estimates of Petkova's (2006) model which includes the excess market returns (Market), innovations in dividend yield (FTDIV), term spread (TERM), default spread (DEFAULT), and one month T-Bill (TBILL), where the innovations are estimated from VAR model. Panel (A) reports the estimates from Fama and MacBeth's (1973) cross-sectional regressions with betas estimated using one multiple regression over the full sample period. Panel (B) reports the estimates from GMM on beta representation following Jagannathan and Wang (2002). The study sample period is July-1981 to December-2005. The test assets are UK Fama and French's (1993) 25 portfolios. For the parameters estimated using Fama and MacBeth's (1973) method, the Fama and MacBeth's (1973) t-statistics is reported in parentheses and Shanken's (1992) corrected t-statistics is reported in square brackets. χ^2 tests the hypothesis of jointly zero pricing error. *J- statistic* is Hansen (1982) *J*-statistic tests for model specification. R^2 is the adjusted cross sectional R^2. ***significant at 1%, ** at 5% and * at 10%

Table 2.5 Petkova's (2006) Model of ICAPM: Five Risk Factors – Kalman Filter

	Panel A: Fama and MacBeth (1973)	*Panel B: GMM*
Intercept	-0.59 (-1.03) [-0.25]	
Market	0.38 (0.64) [0.30]	-0.07 (-0.23)
FTDIV	-0.84 (-4.12)*** [-1.79] *	-0.48 (-1.97)**
TERM	-0.57 (-2.04)** [-0.87]	-2.35 (-3.22)***
DEFAULT	-0.25 -0.95 [-0.40]	0.15 (0.32)
TBILL	-0.02 -1.18 [-0.50]	0.07 (2.12)
Adjusted R^2	68%	
χ^2	5.13 (1.00)	
Hansen J-statistic		7.25 (0.92)

This table reports the parameters estimates of Petkova's (2006) model which includes the excess market returns (Market), innovations in dividend yield (FTDIV), term spread (TERM), default spread (DEFAULT), and one month T-Bill (TBILL), however the innovations are estimated based on Kalman-Filter technique. Panel (A) reports the estimates from Fama and MacBeth's (1973) cross-sectional regressions with betas estimated using one multiple regression over the full sample period. Panel (B) reports the estimates from GMM on beta representation following Jagannathan and Wang (2002). The study sample period is July-1981 to December-2005. The test assets are UK Fama and French's (1993) 25 portfolios. For the parameters estimated using Fama and MacBeth (1973) method, the Fama and MacBeth (1973) t-statistics is reported in parentheses and Shanken (1992) corrected t-statistics is reported in square brackets. χ^2 tests the hypothesis of jointly zero pricing error. *J- statistic* is Hansen (1982) *J*-statistic tests for model specification. R^2 is the adjusted cross sectional R^2. ***significant at 1%, ** at 5% and * at 10%

Table 2.6 Petkova's (2006) Model of ICAPM: Seven Risk Factors – VAR

	Panel A: Fama and MacBeth (1973)	*Panel B: GMM*
Intercept	-1.05 (-2.05)** [-0.67]	
Market	1.08 (1.85) * [1.26]	0.07 (0.24)
FTDIV	-3.57 (-3.21)*** [-2.08] **	-3.73 (-3.03)***
TERM	-2.27 (-2.20) ** [-1.43]	-4.69 (-2.94) ***
DEFAULT	-0.71 (-0.54) [-0.35]	0.02 (0.01)
TBILL	-1.92 (-1.58) [-1.02]	-2.53 (-1.69)*
HML	2.26 (3.19) *** [2.13]**	2.07 (2.33)**
SMB	-0.63 (-1.74) * [-1.33]	-0.95 (-2.11)**
Adjusted R^2	93%	
χ^2	40.74 (0.00)	
Hansen J-statistic		8.25 (0.97)

This table reports the parameters estimates of Petkova's (2006) model which includes the excess market returns (Market), innovations in dividend yield (FTDIV), term spread (TERM), default spread (DEFAULT), one month T-Bill (TBILL), HML and SMB where the innovations are estimated from VAR model. Panel (A) reports the estimates from Fama and MacBeth's (1973) cross-sectional regressions with betas estimated using one multiple regression over the full sample period. Panel (B) reports the estimates from GMM on beta representation following Jagannathan and Wang (2002). The study sample period is July-1981 to December-2005. The test assets are UK Fama and French's (1993) 25 portfolios. For the parameters estimated using Fama and MacBeth's (1973) method, the Fama and MacBeth's (1973) t-statistics is reported in parentheses and Shanken (1992) corrected t-statistics is reported in square brackets. χ^2 tests the hypothesis of jointly zero pricing error. *J- statistic* is Hansen (1982) *J*-statistic tests for model specification. R^2 is the adjusted cross sectional R^2. ***significant at 1%, ** at 5% and * at 10%

Table 2.7 Petkova's (2006) Model of ICAPM: Seven Risk Factors – Kalman Filter

	Panel A: Fama and MacBeth (1973)	*Panel B: GMM*
Intercept	-1.06 (-1.88) * [-0.72]	
Market	1.10 (1.74) * [1.25]	-0.05 (-0.16)
FTDIV	-0.40 (-2.39) ** [-1.67]*	-0.45 (-2.14) **
TERM	-0.63 (-2.27) ** [-1.55]	-1.43 (-2.52)**
DEFAULT	-0.28 (-1.03) [-0.71]	-0.08 (-0.20)
TBILL	0.02 (1.17) [0.80]	0.04 (1.68)*
HML	0.85 (4.64) *** [3.45] ***	0.42 (1.89)*
SMB	-0.62 (-2.57) ** [-2.13] **	-0.30 (-2.99) ***
Adjusted R^2	94%	
χ^2	38.69 (0.00)	
Hansen J-statistic		6.68 (0.99)

This table reports the parameters estimates of Petkova's (2006) model which includes the excess market returns (Market), innovations in dividend yield (FTDIV), term spread (TERM), default spread (DEFAULT), one month T-Bill (TBILL), HML and SMB but the innovations are estimated based on Kalman filter technique. Panel (A) reports the estimates from Fama and MacBeth's (1973) cross-sectional regressions with betas estimated using one multiple regression over the full sample period. Panel (B) reports the estimates from GMM on beta representation following Jagannathan and Wang (2002). The study sample period is July-1981 to December-2005. The test assets are UK Fama and French's (1993) 25 portfolios. For the parameters estimated using Fama and MacBeth's (1973) method, the Fama and MacBeth (1973) t-statistics is reported in parentheses and Shanken's (1992) corrected t-statistics is reported in square brackets. χ^2 tests the hypothesis of jointly zero pricing error. *J- statistic* is Hansen (1982) *J*-statistic tests for model specification. R^2 is the adjusted cross sectional R^2.***significant at 1%, ** at 5% and * at 10%

Table 2.8 Estimated Factors as Risk Factors - VAR

	Panel A: Fama and MacBeth (1973)	*Panel B: GMM*
Intercept	-0.53 (-0.89) [-0.23]	
Market	0.34 (0.56) [0.27]	-0.20 (-0.69)
DF1	7.50 (3.59) *** [1.58]	10.86 (2.52)**
DF2	1.75 (1.72) * [0.77]	0.14 (0.07)
DF3	-0.20 (-0.14) [-0.06]	3.35 (1.07)
DF4	-1.00 (-0.73) [-0.33]	2.72 (1.01)
DF5	3.81 (2.04) ** [0.90]	3.56 (1.15)
DF6	2.72 (2.35) ** [1.05]	4.17 (1.71)*
Adjusted R^2	29%	
χ^2	5.50 (1.00)	
Hansen J-statistic		12.67 (0.81)

This table reports the parameters estimates when innovations to six estimated factors (F1-F6) replace the innovations in the four state variables in Petkova's (2006) model that includes excess market returns and innovations to dividend yield, term spread, default spread and one month interest rate. The six factors are estimated from a large set of 78 macroeconomic variables using the dynamic factor model and principal components of Stock and Watson (2002a,b). The innovations are estimated from VAR model. Panel (A) reports the estimates from Fama and MacBeth's (1973) cross-sectional regressions with betas estimated using one multiple regression over the full sample period. Panel (B) reports the estimates from GMM on beta representation following Jagannathan and Wang (2002). The study sample period is July-1981 to December-2005. The test assets are UK Fama and French's (1993) 25 portfolios. For the parameters estimated using Fama and MacBeth's (1973) method, the Fama and MacBeth's (1973) t-statistics is reported in parentheses and Shanken (1992) corrected t-statistics is reported in square brackets. χ^2 tests the hypothesis of jointly zero pricing error. *J- statistic* is Hansen (1982) *J*-statistic tests for model specification. R^2 is the adjusted cross sectional R^2.***significant at 1%, ** at 5% and * at 10%

Table 2.9 Estimated Factors as Risk Factors – Kalman filter

	Panel A: Fama and MacBeth (1973)	*Panel B: GMM*
Intercept	0.45 (0.83) [0.21]	
Market	-0.44 (-0.74) [-0.38]	0.11 (0.36)
F1	0.10 (3.64)*** [1.69]*	0.21 (2.09)**
F2	0.02 (0.60) [0.28]	0.00 (0.02)
F3	-0.05 (-1.21) [-0.57]	-0.02 (-0.16)
F4	0.01 (0.16) [0.07]	0.29 (1.45)
F5	-0.01 (-0.12) [-0.06]	0.07 (0.49)
F6	0.17 (3.54)*** [1.66]*	0.26 (1.64)
Adjusted R^2	75%	
χ^2	4.45 (1.00)	
Hansen J-statistic		12.35 (0.83)

This table reports the parameters estimates when innovations to six estimated factors (F1-F6) replace the innovations in the four state variables in Petkova's (2006) model that includes excess market returns and innovations to dividend yield, term spread, default spread and one month interest rate. The six factors are estimated from a large set of 78 macroeconomic variables using the dynamic factor model and principal components of Stock and Watson (2002a,b). The innovations are estimated based on Kalman filter technique. Panel (A) reports the estimates from Fama and MacBeth's (1973) cross-sectional regressions with betas estimated using one multiple regression over the full sample period. Panel (B) reports the estimates from GMM on beta representation following Jagannathan and Wang (2002). The study sample period is July-1981 to December-2005. The test assets are UK Fama and French's (1993) 25 portfolios. For the parameters estimated using Fama and MacBeth's (1973) method, the Fama and MacBeth's (1973) t-statistics is reported in parentheses and Shanken (1992) corrected t-statistics is reported in square brackets. χ^2 tests the hypothesis of jointly zero pricing error. *J- statistic* is Hansen (1982) *J*-statistic tests for model specification. R^2 is the adjusted cross sectional R^2. ***significant at 1%, ** at 5% and * at 10%

Table 2. 10 Estimated Factors as Risk Factors and Fama and French's (1993) HML and SMB

	Panel A: Fama and MacBeth (1973)	*Panel B: GMM*	*Panel C: Fama and MacBeth (1973)*	*Panel D: GMM*
Intercept	-0.93 (-1.60) [-0.68]		-0.79 (-1.50) [-0.62]	
Market	0.95 (1.48) [1.13]	0.18 (0.65)	0.84 (1.40) [1.13]	0.20 (0.73)
F1	1.42 (0.87) [0.64]	1.16 (0.93)		
F2	-1.85 (-1.90)* [-1.42]	-2.57 (-2.89)***	-2.13 (-2.19)** [-1.73]*	-3.51 (-3.64)***
F5	0.42 (0.29) [0.21]	-0.02 (-0.01)		
F6	0.67 (0.61) [0.45]	1.58 (1.29)		
HML	1.00 (5.15)*** [4.06]***	1.02 (4.33)***	1.01 (5.33)*** [4.42]***	0.83 (4.07)***
SMB	-0.41 (-1.77)* [-1.56]	-0.39 (-1.65)*	-0.47 (-1.98)** [-1.79]*	-0.40 (-1.79)*
Adjusted R^2	92%		92%	
χ^2	33.45 (0.01)		29.72 (0.10)	
Hansen J-statistic		18.23 (0.44)		17.45 (0.68)

Panels (A and B) of this table report the parameters estimates when the innovations in the four estimated factors (F1, F2, F5 and F6) replace the innovations in the four state variables in Petkova's (2006) model that includes excess market returns and innovations to dividend yield, term spread, default spread, one month interest rate, HML and SMB. The factors are estimated from a large set of 78 macroeconomic variables using the dynamic factor model and principal components of Stock and Watson (2002a,b). More specifically these are four out of six factors used earlier. The innovations are estimated from VAR model while the HML and SMB are real returns. Panels (A) reports the estimates from Fama and MacBeth's (1973) cross-sectional regressions with betas estimated using one multiple regression over the full sample period. Panel (B) reports the estimates from the GMM on beta representation following Jagannathan and Wang (2002). Panels (C and D) estimate the same model in Panels (A and B) after excluding the estimated factors that are not significant. Panels (C) reports the estimates from Fama–MacBeth's (1973) cross-sectional regressions with betas estimated using one multiple regression over the full sample period. (D) report the estimates from GMM on beta representation following Jagannathan and Wang (2002). The study sample period is July-1981 to December-2005. The test assets are UK Fama and French's (1993) 25 portfolios. For the parameters estimated using Fama and MacBeth's (1973) method, the Fama and MacBeth's (1973) t-statistics is reported in parentheses and Shanken's (1992) corrected t-statistics is reported in square brackets. χ^2 tests the hypothesis of jointly zero pricing error. *J- statistic* is Hansen

(1982) *J*-statistic tests for model specification. R^2 is the adjusted cross sectional R^2 ***significant at 1%, ** at 5% and * at 10%

Table 2.11 Estimated Factors as Risk Factors and Fama and French's (1993) HML and SMB–Kalman filter

	Panel A: Fama and MacBeth (1973)	*Panel B: GMM*
Intercept	-1.24 (-2.27)** [-0.83]	
Market	1.28 (2.07)** [1.47]	0.11 (0.40)
F1	0.05 (1.70)* [1.15]	0.04 (1.61)
F2	-0.01 (-0.49) [-0.34]	-0.02 (-0.64)
F5	0.07 (1.42) [0.96]	0.04 (0.86)
F6	0.00 (0.03) [0.02]	0.01 (0.18)
HML	0.98 (4.98)*** [3.64]***	0.99 (4.42)***
SMB	-0.44 (-1.87)* [-1.57]	-0.29 (-1.23)
Adjusted R^2	92%	
χ^2	55.53 (0.00)	
Hansen J-statistic		40.78 (0.00)

Panels (A and B) of this table report the parameters estimates when the innovations in the four estimated factors (F1, F2, F5 and F6) replace the innovations in the four state variables in Petkova's (2006) model that includes excess market returns and innovations to dividend yield, term spread, default spread, one month interest rate, HML and SMB. The factors are estimated from a large set of 78 macroeconomic variables using the dynamic factor model and principal componets analysis of Stock and Watson (2002a,b). More specifically these are four out of six factors used earlier. The innovations are estimated based on Kalman filter technique, while the HML and SMB are real returns. Panels (A) reports the estimates from Fama and MacBeth's (1973) cross-sectional regressions with betas estimated using one multiple regression over the full sample period. Panel (B) reports the estimates from GMM on beta representation following Jagannathan and Wang (2002). The study sample period is July-1981 to December-2005. The test assets are UK Fama and French's (1993) 25 portfolios. For the parameters estimated using Fama and MacBeth's (1973) method, the Fama and MacBeth (1973) t-statistics is reported in parentheses and Shanken's (1992) corrected t-statistics is reported in between brackets. χ^2 tests the hypothesis of jointly zero pricing error. *J- statistic* is Hansen (1982) *J*-statistic tests for model specification. R^2 is the adjusted cross sectional R^2 ***significant at 1%, ** at 5% and * at 10%

Table 2.12 Estimated Factors as Risk Factors and HML and SMB–Kalman filter

	Panel A: Fama and MacBeth (1973)	*Panel B: GMM*
Intercept	-1.14 (-2.06)** [-0.84]	0.29 (1.07)
Market	1.20 (1.93)* [1.49]	-0.15 (-2.88)***
F2	-0.03 (-1.26) [-0.95]	
HML	1.09 (5.64)*** [4.48]***	0.92 (3.54)***
SMB	-0.53 (-2.24)** [-1.97]*	-0.44 (-1.84)*
Adjusted R^2	88%	
χ^2	54.95 (0.00	
Hansen J-statistic		21.49 (0.429)

This table reports the parameters estimates when the innovations in the second estimated factor (F2) replaces the innovations in the four state variables in Petkova's (2006) model that includes excess market returns and innovations to dividend yield, term spread, default spread, one month interest rate, HML and SMB. The second factor estimated from a large set of 78 macroeconomic variables using the dynamic factor model and principal components of Stock and Watson (2002a,b). More specifically this is the second factor out of the six factors used earlier. The innovations are estimated based on Kalman filter technique while the HML and SMB are real returns. This Table is the equivalent to Panels (C and D) in Table (2.10) with the Kalman filter innovations replace VAR innovations. Panels (A) reports the estimates from Fama and MacBeth's (1973) cross-sectional regressions with betas estimated using one multiple regression over the full sample period. Panel (B) reports the estimates from GMM on beta representation following Jagannathan and Wang (2002). The study sample period is July-1981 to December-2005. The test assets are UK Fama and French's (1993) 25 portfolios. For the parameters estimated using Fama and MacBeth's (1973) method, the Fama and MacBeth (1973) t-statistics is reported in parentheses and Shanken (1992) corrected t-statistics is reported in square. χ^2 tests the hypothesis of jointly zero pricing error. *J- statistic* is Hansen (1982) *J*-statistic tests for model specification. R^2 is the adjusted cross sectional R^2 ***significant at 1%, ** at 5% and * at 10%

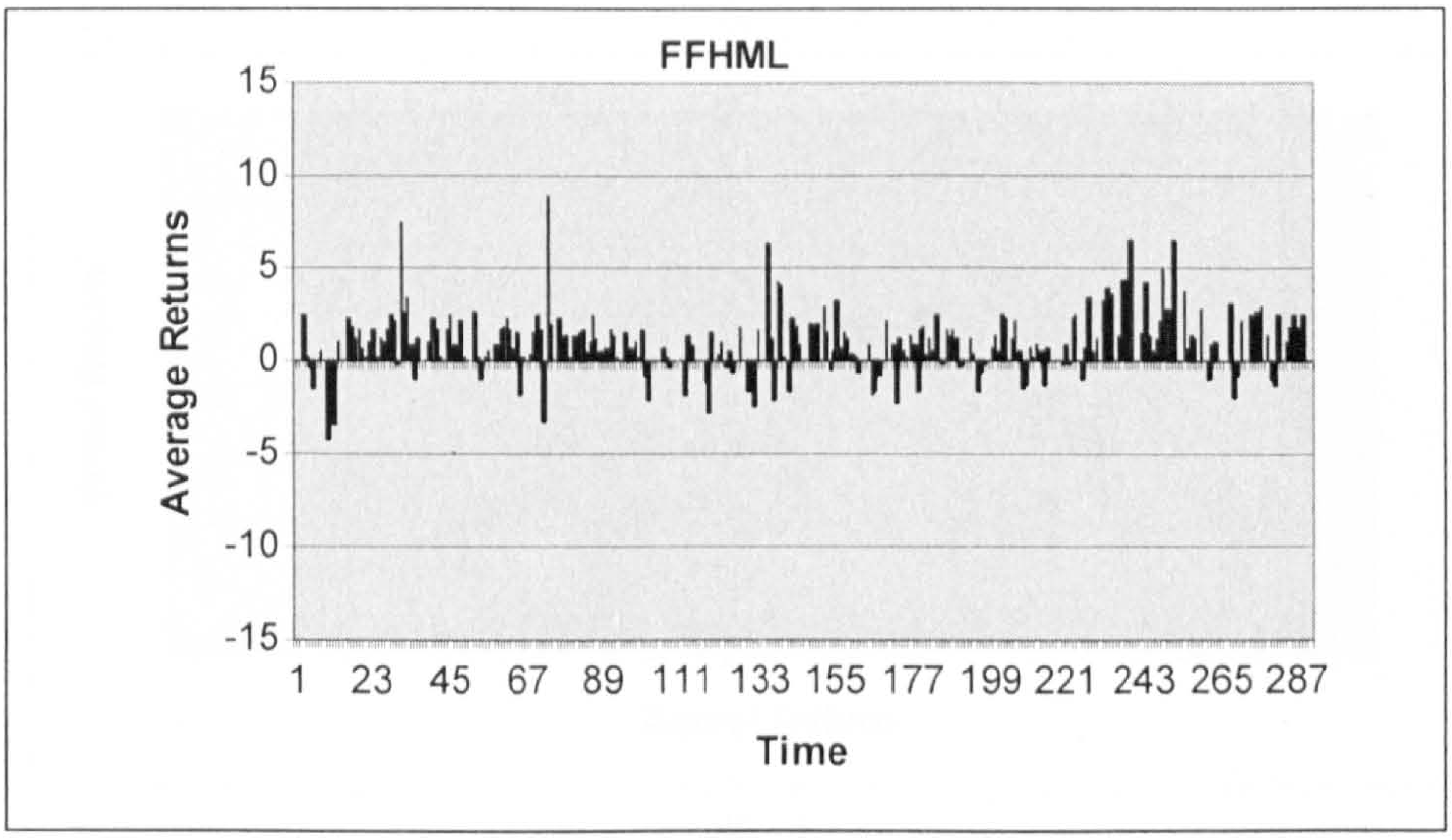
Table 2.13 Estimated Factors as Risk Factors as Augmenting Factors

	Panel A: Fama and MacBeth (1973)	*Panel B: GMM*	*Panel C: Fama and MacBeth (1973)*	*Panel D: GMM*
Intercept	-0.82 (-1.54) [-0.61]		-1.09 (-1.97)** [-0.78]	
Market	0.86 (1.42) [1.10]	0.00 (0.01)	1.11 (1.79)* [1.35]	0.08 (0.27)
FTADY	-2.25 (-2.27)** [-1.70]*	-4.02 (-2.94)***	-0.40 (-2.80)*** [-2.09]**	-0.46 (-2.56)**
TERM	-1.98 (-1.83)* [-1.37]	-5.35 (-2.95)***	-0.38 (-1.42) [-1.03]	-1.76 (-2.34)**
DF2	-1.48 (-1.44) [-1.08]	-0.10 (-0.08)	-0.03 (-1.14) [-0.83]	-0.08 (-1.68)*
HML	0.82 (4.07)*** [3.20]***	0.70 (2.86)***	0.92 (4.82)*** [3.74]***	0.72 (2.47)**
SMB	-0.59 (-2.46)** [-2.14]**	-0.72 (-2.95)***	-0.59 (-2.45)** [-2.11]**	-0.77 (-2.89)***
Adjusted R^2	94%		92%	
χ^2	30.72 (0.04)		47.67 (0.00)	
Hansen J-statistic		7.86 (0.99)		8.66 (0.98)

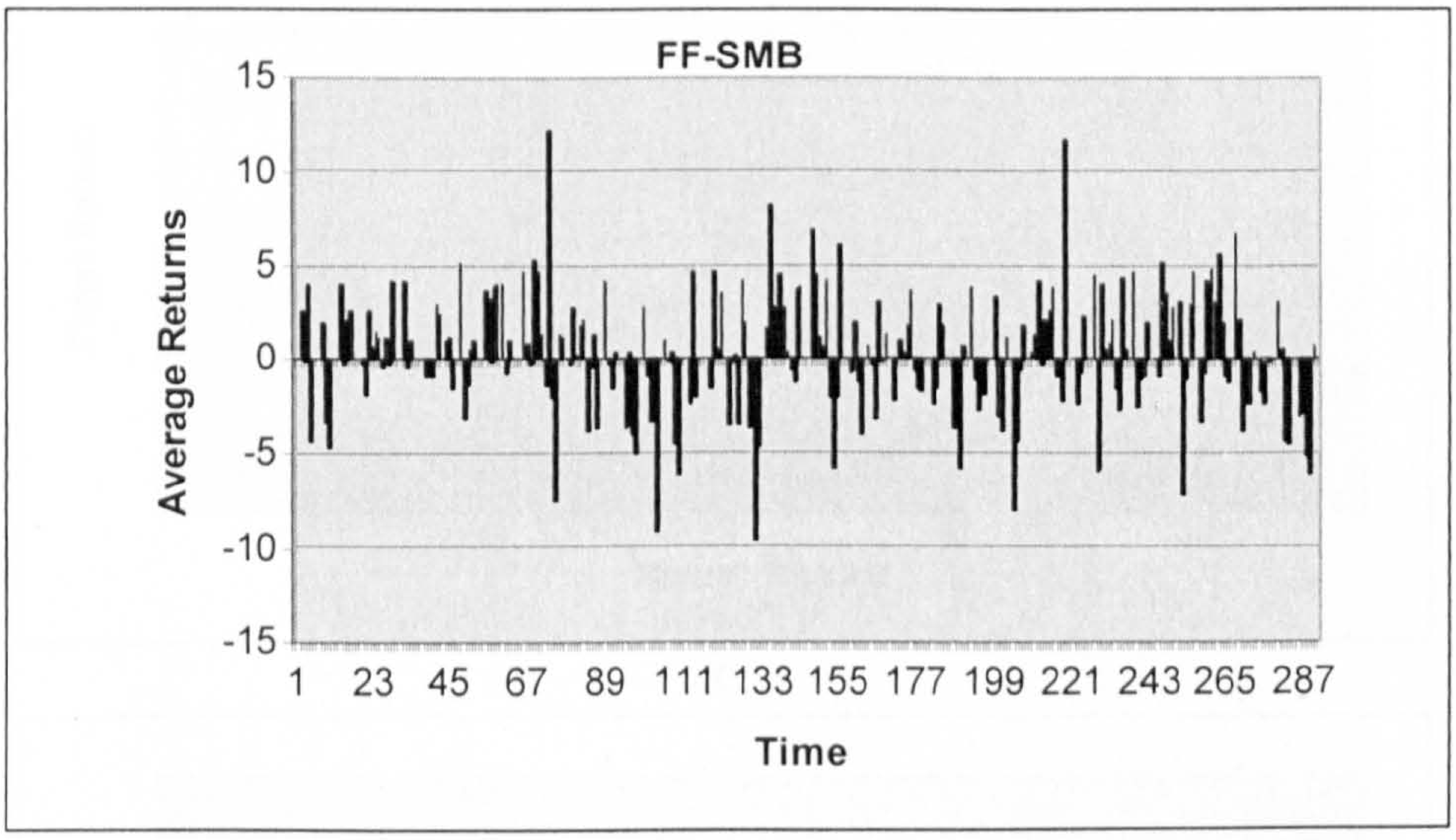
This table reports the parameters estimates of Petkova's (2006) model that includes excess market return, innovations to dividend yield and term spread, HML and SMB (without the innovations in the default spread and one month T-bill) augmented with the innovations to the second estimated factor (F2) that is found to be related to employment and term spread. The second factor is estimated from a large set of 78 macroeconomic variables using the dynamic factor model and the principal components of Stock and Watson (2002a,b). More specifically this is the second factor out of the six factors used earlier. Panels (A) and (C) report the estimates from Fama and MacBeth's (1973) cross-sectional regressions with betas estimated using one multiple regression over the full sample period. Panel (A) shows the results when the factors' innovations are estimated from VAR model and Panel (C) shows the results when the factors' innovations are estimated based on Kalman filter technique. Panels (B) and (D) report the estimates from the GMM on beta representation following Jagannathan and Wang (2002). Panel (B) shows the results where the factors' innovations are estimated from VAR model and Panel (D) shows the results when factors' innovations are estimated based on Kalman filter technique. The study sample period is July-1981 to December-2005. The test assets are UK Fama and French's (1993) 25 portfolios. For the parameters estimated using Fama and MacBeth's (1973) method, the Fama and MacBeth's (1973) t-statistics is reported in parentheses and Shanken's (1992) corrected t-statistics is reported in square brackets. χ^2 tests the hypothesis of jointly zero pricing error. *J- statistic* is Hansen (1982) *J*-statistic tests for model specification. R^2 is the adjusted cross sectional R^2 ***significant at 1%, ** at 5% and * at 10%

Figure 2.1 Average Returns on HML and SMB

(A): Monthly HML's Return



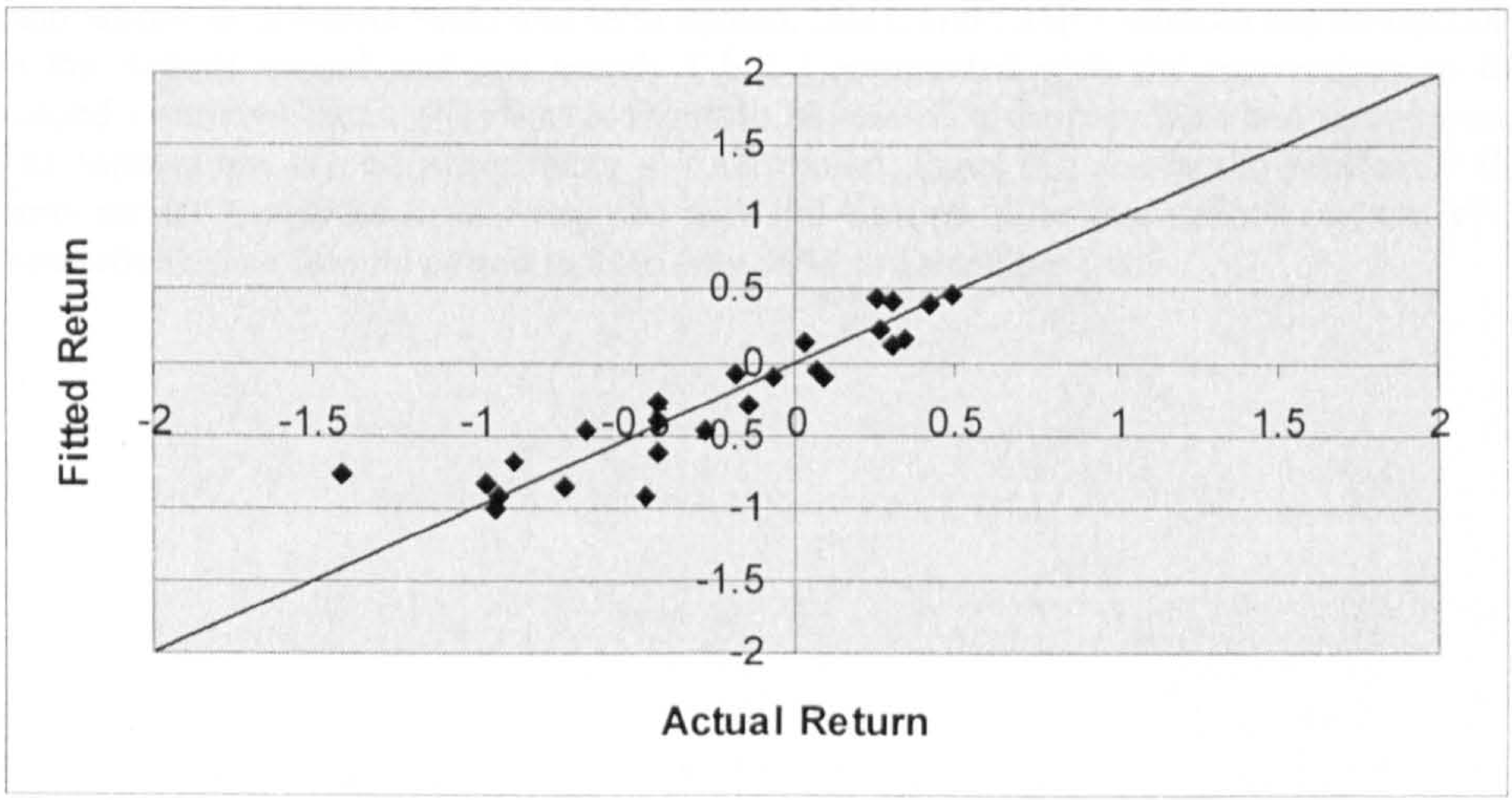
(B): Monthly SMB's Return



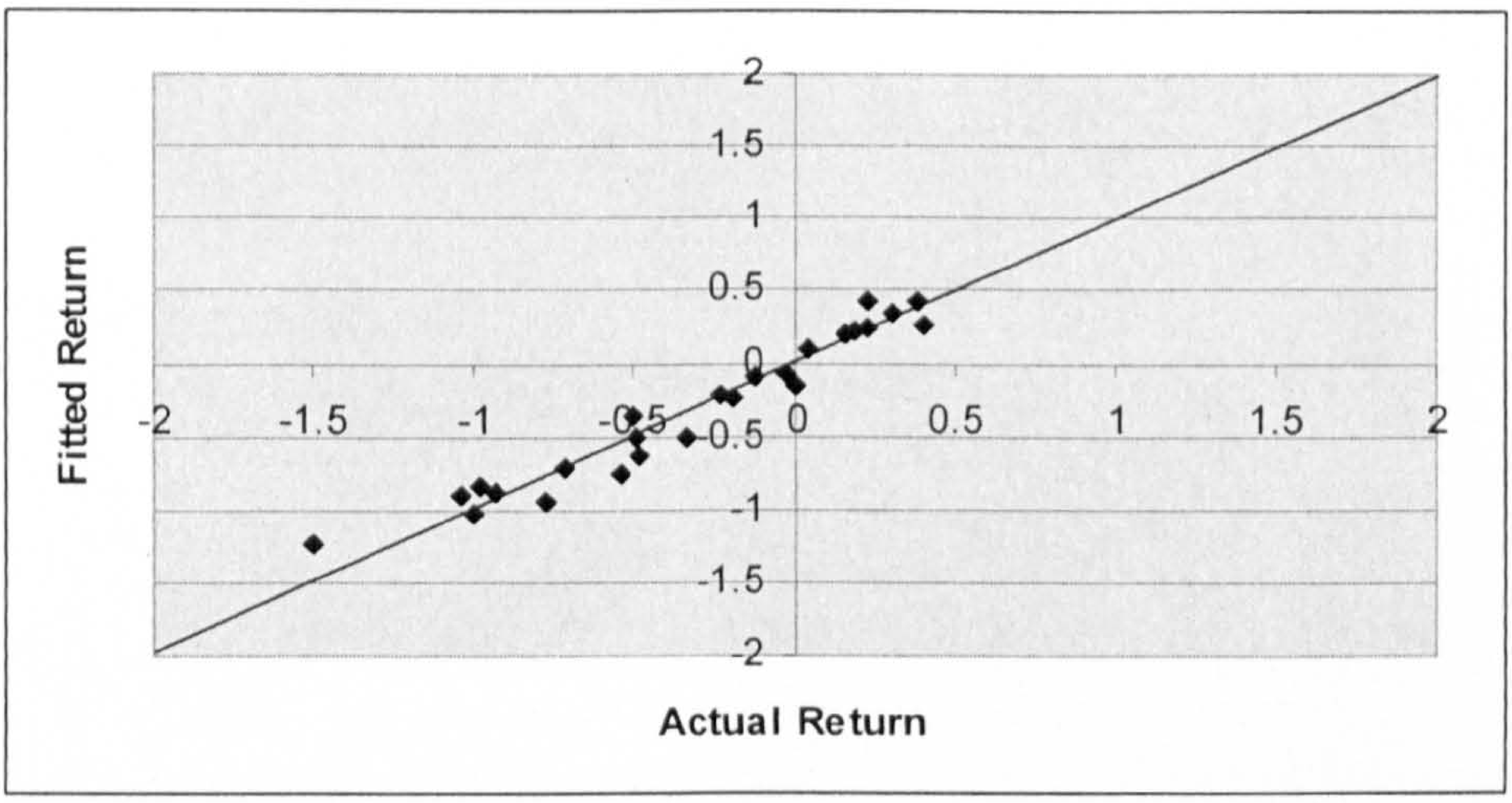
This Figure depicts the monthly average return on the Fama and French's (1993) HML (Panel A) and SMB (Panel B) over time.

Figure 2.2 Fitted Versus Actual Returns on the UK Fama and French (1993) 25 Portfolios

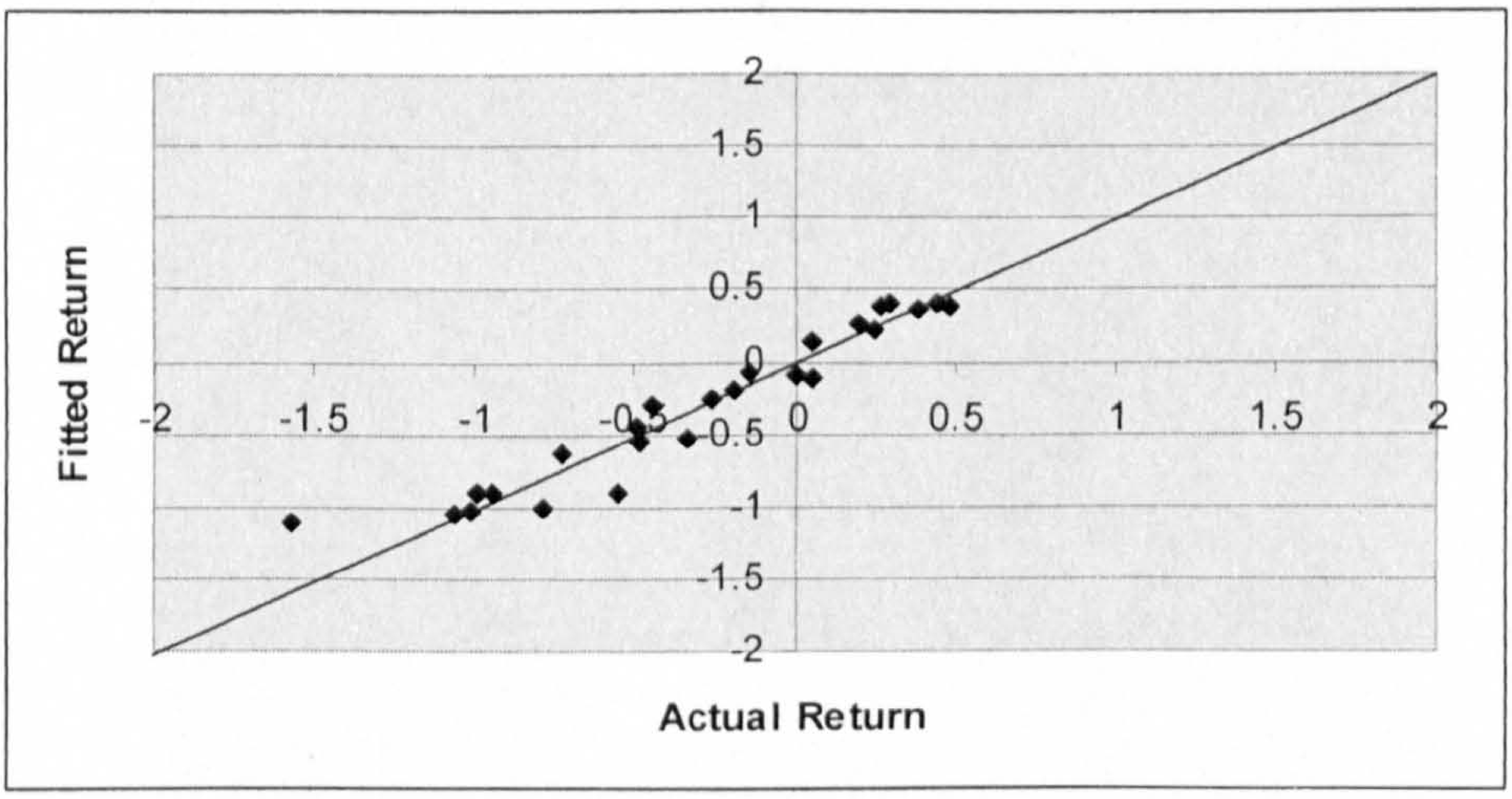
A



B



C



This figure depicts, for each of the UK Fama and French's (1993) 25 size and book-to-market portfolios, the fitted return on the y-axis against the actual return on the x-axis. Panel (A) shows the results for Fama and French (1993) three-factor model. Panel (B) shows the results for Petkova's (2006) model that includes excess market return, innovations to dividend yield and term spread, HML and SMB (without the innovations in the default spread and one month T-bill) augmented with the innovations to the second estimated factor (F2) that is found to be related to employment and term spread. The innovations are estimated from a VAR model. Panel (C) shows the results for the same model specification in Panel (B) with the Kalamn filter innovations replace VAR innovations. The sample period is from July 1981 to December 2005.

Appendix (A)

This Appendix shows the UK 78 monthly macroeconomic variables used in the chapter. The sample period is July- 1981 to December – 2005. All variables are collected from the Datastream. These variables are (1) those used by Laganà and Mountford[20] (2005) covering their macroeconomic categories. However, as this chapter does not manage to retrieve the entire 105 variable used by them for its balanced dataset over the period July – 1981 to December 2005, additional few variables are obtained similar to those used by (2) Artis, Banerjee and Marcellino[21] (2005) (UK) and (3) additional few variables are obtained similar to those of Kapetanios, Labhard, and Price[22] (200 6) (UK); and (4) variables of UK default spread similar to Ludvigson and Ng (2007) (US) are also included in the dataset.

Note that every study of these three studies has constructed a dataset of macroeconomic variables to cover the UK economy. However, this chapter focused on those variables that are used by Laganà and Mountford (2005) and then also used variables from the other two studies to increase the number of variables that can be collected from Datastream. Also note that some variables will be shared by more than one study.

Employment
UK LFS: ECONOMIC INACTIVITY RATE, ALL, AGED 16 & OVER SADJ
UK LFS: ECONOMIC ACTIVITY RATE, ALL, AGED 16-59/64 SADJ
UKLFS: EMPLOYMENT RATE, ALL, AGED 16-59/64 SADJ
UK LFS: IN EMPLOYMENT, ALL, AGED 16-59/64 VOLA
UK UNEMPLOYMENT VOLA
UK LFS: UNEMPLOYMENT RATE, ALL, AGED 16 & OVER SADJ
UKTOTAL CLAIMANT COUNT VOLN
Government finance
UKBOP: EXPORTS - MANUFACTURES CURN
UK EXPORTS VOLUME INDEX VOLN
UK IMPORTS VOLUME INDEX VOLN
UK TERMS OF TRADE NADJ
Output
UK INDUSTRIAL CONFIDENCE INDICATOR - UK SADJ
UK INDUSTRIAL PRODUCTION INDEX VOLA
UK INDUSTRIAL PRODUCTION INDEX - MANUFACTURING VOLA
UK INDUSTRIAL PRODUCTION - MANUFACTURING VOLA
UK PRODUCTION OF TOTAL MANUFACTURED INVESTMENT GOODS VOLA
UK PRODUCTION OF TOTAL MANUFACTURED INTERMEDIATE GOODS VOLA

[20] Laganà and Mountford (2005) use the following categories "employment; government finance; output; housing starts and vehicles; consumer and retail confidence; prices; money and loans; interest rates; composite leading indicator; and stock prices and exchange rates". See their Appendix (Laganà and Mountford (2005, p.94-97))

[21] Artis, Banerjee and Marcellino (2005) use the following categories "Real output and income, Employment and hours, Retail, manufacturing and trade sales, Housing,, Stock prices, Exchange rates, interest rates, Money aggregates, Price indices, Wages and Miscellaneous". See their Appendix (Artis, Banerjee and Marcellino (2005, p. 295-297))

[22] Kapetanios, Labhard, and Price (2006) use the following categories "Real output and income, Employment and hours, Trades, Consumption, Real inventories and inventories sales, Stock prices, Exchange rates, interest rates, Monetary and quantity credit aggregates, Price indices and surveys", see their Appendix (Kapetanios, Labhard, and Price (2006, p.34-38))

UK INDUSTRIAL PRODUCTION: ELECTRICITY, GAS & WATER SUPPLY VOLA[1]
UK INDUSTRY SURVEY: EXPORT ORDER BOOK POSITION - UKSADJ
UK INDUSTRY SURVEY: ORDER BOOK POSITION - UK SADJ
UK INDUSTRY SURVEY: PROD. EXPECTATION FOR MTH. AHEAD - UK SADJ
UK INDUSTRY SURVEY: PRODUCTION TRENDS IN RECENT MTH. - UK SADJ
UK INDUSTRY SURVEY: STOCKS OF FINISHED GOODS - UK SADJ
UK INDUSTRY SURVEY: SELLING PRC. EXPECT. MTH. AHEAD- UK SADJ
Housing starts and vehicles
UK NEW ORDERS FOR TOTAL CONSTRUCTION VOLA
Consumer and retail confidence
UK RETAIL SALES: ALL RETAILERS – ALL BUSINESS VOLA
UK CONSUMER CONFIDENCE INDICATOR - UK SADJ
UK BOP: BALANCE - TRADE IN GOODS CURA[1]
UK BOP: BALANCE - MANUFACTURES CURN[1]
Prices
UK RPI NADJ
UK RPI: ALL ITEMS EXC. MTG. INT. PMTS. (%YOY) CURN
UK RPI:PERCENTAGE CHANGE OVER 12 MONTHS - ALL ITEMS NADJ
UK RPI: ALL ITEMS EXCLUDING HOUSING (%YOY)
UK AEI: WHOLE ECONOMY INCL. BONUS NADJ
UK CPI NADJ
UK CPI - HOUSING NADJ[2]
UK CPI - FOOD NADJ[2]
UK MARKET PRICE INDEX - UK BRENT NADJ[2]
Money and loans
UK OFI : BLDG. SOCIETIES MORTGAGES COMMITMENT FOR ADVANCES CURA
UK BUILDING SOCIETIES MTG. COMMITMENT FOR ADVANCES CURN
UK M0 WIDE MONETARY BASE (END PERIOD): LEVEL CURA
UK NOTES AND COIN - 1 MONTH CHANGE SADJ
UK NOTES AND COIN - 6 MONTH ANNUALISED CHANGE NADJ
UK BOE: BANKING DEPARTMENT: RESERVES & OTHER A/C.S OUTSTANDING[1]
Interest rates
UK MONEY MARKET RATE(FEDERAL FUNDS)
UK GOVT BOND YIELD - MEDIUM TERM
UK GOVT BOND YIELD - LONGTERM
UK YIELD 10-YEAR CENTRAL GOVERNMENT SECURITIES NADJ
UK LENDING RATE (PRIME RATE)
UKLONDON INTERBANK RATE - 3 MONTH (EP)
UK3 - MONTH MONEY MARKET (MEAN) NADJ
UK 3 MONTHS TREASURY BILLS YIELD (EP)
UK 3 MONTHS TREASURY BILLS YIELD (EP)
UKSTERLING ONE YEAR INTERBANK RATE NADJ
UKSTERLING ONE WEEK INTERBANK RATE NADJ
UKSTERLING ONE MONTH INTERBANK RATE NADJ
UK ABBEY NATIONAL - MORTGAGE RATE[2]
SPREAD20[1]
SPREAD10[1]
SPREAD5[1]
DEFAULT20[3]
DEFAULT10[3]
Composite leading indicator
UK COMPOSITE LEADING INDICATOR (AMPLITUDE ADJUSTED)NADJ
UK COMPOSITE LEADING INDICATOR (RATIO TO TREND) NADJ
UK COMPOSITE LEADING INDICATOR (TREND RESTORED)

UK COMPOSITE LEADING INDICATOR: 3MTH PRIME BANK BILLS NADJ
UK COMPOSITE LEADING INDICATOR: 6-MONTHS RATE CHANGE AT ANNUAL R
UK COMPOSITE LEADING INDICATOR: 3MTH PRIME BANK BILLS NADJ
UK COMPOSITE LEADING INDICATOR: FTSE-A NON FIN SHARE PRICE INDEX
UK COMPOSITE LEADING INDICATOR: NEW CAR REGISTRATIONS VOLA
UK COMPOSITE LEADING INDICATOR: PRODN. - FUTURE TENDENCY SADJ
UK COMPOSITE LEADING INDICATOR: PRODN. - FUTURE TENDENCY SADJ
Exchange rates
UK US DOLLARS TO £ (EP) VOLN
UK YEN TO £1 (PURCHASING POWER PARITY LEVEL: 1975 BASED)
UK EURO TO NATIONAL CURRENCY UNIT (AVG)
UK REAL EFFECTIVE EXCHANGE RATES VOLN[2]
Wage[2]
UK WEEKLY EARNINGS - WHOLE ECONOMY NADJ[2]
UK UNIT LABOUR COSTS, RELATIVE NORMALIZED SADJ[2]

[1] those used by Kapetanios, Labhard and Price (2006), although they didn't use spread for 20 but this chapter uses it.

[2] those used by Artis Banerejee and Marcellino (2005)

[3] those used by Ludvigson and Ng (2007) for USA.

The rest of the variables are used by Laganà and Mountford (2005), although few of them are also downloaded from Datastream guided by Laganà and Mountford (2005) dataset, however, they have slight differences in their names compared to the names of these variables in Laganà and Mountford's (2005) dataset.

Chapter 3 Idiosyncratic Risk and Time-Varying Betas

3.1 Introduction

> "More generally, one gets no compensation or risk adjustment for holding idiosyncratic risk. Only systematic risk generates a risk correction" (Cochrane, 2001, p.18).

The findings from the previous chapter that systematic risk factors are priced factors in the cross section of UK stock returns are consistent with the statement of Cochrane (2001, Ch(1)) that systematic risk should be priced and compensated for. However, no examination of idiosyncratic risk was undertaken in the previous chapter which leaves the first part of Cochrane's (2001, Ch(1)) statement unexamined in the current thesis. The need to investigate idiosyncratic risk is important. Theoretically, Merton (1987) validates the potential importance of stock's specific variance (idiosyncratic volatility). He questions the practicality of the assumption of perfect market and develops a model based on incomplete information. He derives the cross-sectional stock returns as a positive function of the stock's specific variance, along with other variables.

However, Ang, Hodrick, Xing and Zhang (2006) report that they find that idiosyncratic risk is related negatively to stock returns which they describe as a puzzling finding. They point out that this opposes Merton (1987) and previous findings of a positive or an insignificant relationship. Furthermore, Ang, Hodrick, Xing and Zhang (2008[23]) report that in 23 countries (including the UK), they find similar idiosyncratic volatility effect where lagged idiosyncratic volatility is related negatively to future stock returns. Diavatopoulos et al., (2007) point out that the short sales constraint and limits to arbitrage could be behind the

[23] A ng, Hodrick, Xing and Zhang's (2008) is forthcoming in *Journal of Financial Economics*, based on correspondence with professor Hodrick

perplexing findings of Ang, Hodrick, Xing and Zhang (2006). Diavatopoulos et al., (2007) indicate that the latter study may have combined constrained and unconstrained stocks which may result in idiosyncratic risk being negatively priced. They report that idiosyncratic risk has a positive relationship with future returns on stocks when the former is measured by implied idiosyncratic volatility. Furthermore, Huang, Liu, Rhee and Zhang (2006) report that the findings of Ang, Hodrick, Xing and Zhang's (2006) and Ang, Hodrick, Xing and Zhang's (later version as 2008) of negative idiosyncratic risk effect on stock returns is explained by the short term reversals in returns of high idiosyncratic risk winner stocks and disappear once this phenomenon and size are accounted for.

On the other hand, Spiegel and Wang (2005) report that idiosyncratic risk is positively related to stock returns based on monthly returns and they point out that they have no answer to the negative relationship uncovered by Ang, Hodrick, Xing and Zhang's (later published as Ang, Hodrick, Xing and Zhang (2006)) using daily returns. Furthermore, Malkiel and Xu (2006) report that idiosyncratic volatility is able to explain positively the cross section of return on stocks. Furthermore, Fu (2007) argues that idiosyncratic risk varies over time and Ang, Hodrick, Xing and Zhang's (2006) finding is not pertinent for the expected stock returns relationship with idiosyncratic volatility. He points out that when he models the expected idiosyncratic risk using EGARCH model he finds the relationship between this conditional measure of idiosyncratic risk and stock returns is positive.

A study that attempts to reconcile the evidence regarding idiosyncratic risk is Bali and Cakici (2008). Bali and Cakici (2008) refer to above cited studies and state that the empirical evidence provided by these and other studies as to how idiosyncratic risk is related to the cross sectional expected returns on stocks is conflicting. They indicate that this is because of the differences in the methodologies employed by the studies. Furthermore, they report that Ang, Hodrick, Xing and Zhang's (2006) results are caused by illiquid and small stocks, and once these are excluded, the negative effect of idiosyncratic risk on the cross section of stock returns loses its significance. Bali and Cakici (2008) conclude by stating that idiosyncratic risk role in explaining cross sectional expected returns on stocks is not robust.

An important issue related to idiosyncratic risk is discussed by Chen and Keown (1981). Chen and Keown (1981) point out that when market beta is time varying, then the residual risk is contaminated by an amount that is equal to the time-varying part of the beta times the market excess returns. They point out that this will cause the estimated residual variance from the ordinary least square method not to be pure when the beta is time-varying. Furthermore, they indicate that when they capture the time variation in beta, they find that the residual risk has no relationship with the market beta. Malkiel and Xu (2006) point out that Miller and Scholes (1972) argue that the errors in measuring betas could be among the reasons behind the significant idiosyncratic risk. Therefore, combining this with Bali and Cakici's (2008) findings and Chen and Keown's (1981) argument and findings, the evidence of the ability of idiosyncratic risk to drive stock returns could arise from the failure to capture the time variation in the measures of risk (i.e. betas) when modeling stock returns. In other words, idiosyncratic risk is not robust in the cross-section of stock returns as concluded by Bali and Cakici (2008) and in those studies that find otherwise, idiosyncratic risk actually captures the time-variation of betas rather than being significant on its own as Chen and

Keown (1981) state the residual risk will be not be pure in this case. In fact, Malkiel and Xu (2006) point out that the residuals from any asset pricing model could be proxy for omitted factors and for this reason the residuals are interpreted as a measure of idiosyncratic risk relative to that particular model from which they are calculated.

Inspired by this, this chapter attempts to contribute to the literature of idiosyncratic risk in the cross section of stock returns by attempting to provide further evidence toward reaching a more conclusive conclusion regarding the effect of idiosyncratic risk in the cross sectional returns on stocks which is essential in light of the current findings. Toward this end this chapter examines if measuring idiosyncratic risk from an asset pricing model that accounts for the time-variation in the measures of risk, support the findings of Bali and Cakici (2008) and others who find that idiosyncratic risk is not significant. Fletcher (2007) employs conditional asset pricing models among other models to study idiosyncratic risk in the UK market. However, an important point in order here, Ghysels (1998) state that the time-varying beta should be modeled correctly otherwise it will be outperformed by the constant beta. Avramov and Chordia (2006) develop a methodology for explicitly modeling time varying beta in asset pricing models. They point out that their methodology of modeling beta explicitly provides a significant improvement for the asset pricing models including the Fama and French's (1993) three-factor model.

Therefore, this chapter starts first by examining idiosyncratic risk in the cross sectional stock returns in the UK market by applying Ang, Hodrick, Xing and Zhang's (2006, 2008) and Spiegel and Wang's (2005) studies on the UK stock market. Then it applies Avramov and Chordia's (2006) conditional model and methodology to model the time-varying betas to examine if this captures idiosyncratic risk i.e. it reapplies Ang, Hodrick, Xing and Zhang's (2006) and Spiegel and Wang's (2005) studies but with explicit modeling of time varying beta following Avramov and Chordia (2006). It is important to make clear that Fletcher (2007) studies idiosyncratic risk in the UK and uses conditional CAPM and conditional consumption CAPM among other models. He points out that he models the stochastic discount factor (SDF) model's coefficients of these models as function of both constant and lagged dividend yield. In addition, Ang, Hodrick, Xing and Zhang (2006) and Spiegel and Wang (2005), among other studies in idiosyncratic risk, allow for time variation in betas. In fact, Ang, Hodrick, Xing and Zhang (2006) point out that the potentially time-varying beta is the motivation behind their use of daily return over a month. In addition, Ang, Hodrick, Xing and Zhang (2006) indicate that all risk factors and the conditioning variables on which the time-varying beta is conditional need be known in order for the conditional models to be estimated accurately. Furthermore, Ghysels (1998) state that the crucial issue is the correct modeling of the time-varying beta and Avramov and Chordia (2006) point out that their explicit modeling of time-variation in beta using firm level characteristics is what distinguishes their study from the previous studies.

The rest of the chapter is organized as follows: Section 3.2 reviews the relevant literature. Section 3.3 states the hypotheses to be studied, Section 3.4 presents the methodology employed and the data used. Section 3.5 presents the results and the discussion of the empirical findings and finally Section 3.6 presents a findings summary table and section 3.7 concludes.

3.2 Literature Review

3.2.1 Idiosyncratic Volatility and Stocks Returns

Merton (1987) develops a models based on incomplete information. He points out this is motivated by the fact that investors' portfolios are made of a small number of securities relative to what is really available. Furthermore, Malkiel and Xu (2006) point out that idiosyncratic risk is not priced in the CAPM, however when holding the market portfolio is not a realistic investment option for investors, then idiosyncratic risk can be rationally priced. They report that idiosyncratic volatility is positively related to the cross-section of stock returns and this relationship is robust to controlling for other explanatory variables such as size and book-to-marker value. In addition, Lehmann (1990) indicates that the findings that residual risk is insignificant contradict with the findings of the mean-variance inefficiency of market portfolio. He points out that as the latter is partially attributable to omitted risk factors, then coefficients on these factors should be included in the residual risk.

Goyal and Santa-Clara (2003) point out that they study the relationship between return on the stock market and average stock variance. They report that average stock risk which is mainly idiosyncratic is positively related to market return in the predictive time-series regression while the market variance is not si gnificant. They point out further that this finding is in line with investor heterogeneity-time-varying risk premia models and background risk-time-varying risk premia models. They point out as there is countercyclicality in average risk, it could be argued that average stock risk captures the fluctuations in business cycle. Then they report that average risk effect is robust to predictive macroeconomic variables. In contrast, Bali et al (2005) report that they find that Goyal and Santa-Clara's (2003) findings lack robustness and are caused by small stocks and liquidity premium. Bali, et al (2005) also point out that once average stock variance is calculated on a value weighted basis rather than on an equal weighted basis as in Goyal and Santa-Clara (2003), the predictive ability of average risk to expected market return does not survive.

Guo and Savickas (2006) argue that aggregate idiosyncratic volatility is essential for pricing stock premium because, among other reasons, it measures an ICAPM's risk factor's conditional variance. They point out that aggregate idiosyncratic risk could be a candidate for a pervasive macro factor. They report that value-weighted idiosyncratic and stock market risks are jointly significantly related to future market returns with a negative and a positive relationship, respectively. They point out that the omitted factors could lie behind why the previous studies do not find such positive association. Furthermore, Guo and Savickas (2006) point out that Goyal and Santa-Clara's (2003) finding is due to the correlation between their measure of idiosyncratic risk and market volatility. Finally, they report that idiosyncratic risk is significant in other international markets including the UK (with negative sign).

Guo and Savickas (2008) report that they find generally market return is predicted jointly by idiosyncratic (negatively) and market (positively) risks in the G7 countries. In addition they point out that they uncover for the UK, among other countries, a positive association between the value premium and idiosyncratic risk. In addition they report that idiosyncratic volatility explains returns on stocks cross sectionally similar to the book-to-market factor and also it proxies investment opportunities shifts and the value premium volatility in Fama and French's (1993) model. Furthermore they point out that the negative relationship between the aggregated book-to-market value and average idiosyncratic volatility could be behind the latter negative relationship with future market returns.

Furthermore, Angelidis and Tessaromatis (2008a) indicate that there is confusing findings related to the performance of idiosyncratic risk in predicting market returns. They report that they find a negative relationship between value-weighted idiosyncratic risk only in the UK and Germany (out of 10 European countries) and future market returns. Furthermore, they report that the SMB (including for UK) and HML premiums are forecasted (positively) by equally weighted idiosyncratic volatility and value premium is also related to value weighted idiosyncratic volatility. Angelidis and Tessaromatis (2008b) study the UK. They point out that they use (1) all stocks based, (2) large capitalization stocks based and (3) small capitalization stocks based idiosyncratic risks. They report that they found the third measure (i.e. based on small stocks) of idiosyncratic risk forecasts robustly future SMB.

Ang, Hodrick, Xing and Zhang (2006) report that there is a cross sectionally negatively priced innovations to market volatility. They argue that this is in agreement with the ICAPM. On the other hand, Ang, Hodrick, Xing and Zhang (2006) also point out that they find that idiosyncratic volatility, estimated from Fama and French's (1993) three-factor model, is significantly and negatively related to average returns. They point out that this contradicts others like Merton's (1987) theory as well as the positive or insignificant relationship found by earlier studies. Ang, Hodrick, Xing and Zhang (2006) point out that their finding of this negative relationship is a puzzle and is not captured by aggregate volatility risk factor.

Furthermore, they point out that the reason that their findings are different from other authors is due to not using firm's level idiosyncratic risk as measure of risk or for forming portfolios by those studies.

Ang, Hodrick, Xing and Zhang (2008) point out that this negative influence of lagged idiosyncratic risk on stock returns is global. They report that they find this negative relationship is significant in the G7 and in the rest of the 23 developed counties that they study. They state that there may be risk factors responsible for this phenomenon. Furthermore, they point out that this, what they call, idiosyncratic volatility effect, is robust in the US to many economic explanations.

On the other hand, Spiegel and Wang (2005) point out that they studied the interaction of idiosyncratic risk with liquidity in capturing the cross sectional return on stocks. They report that stock return is related positively to idiosyncratic risk while negatively to liquidity. Furthermore, they point out that they find when the two variables present together in the relationship with stock returns, idiosyncratic risk maintains its explanatory power of stock returns while only one measure of liquidity (dollar volume) remains significant. They point out that they find idiosyncratic risk based on EGARCH is superior to idiosyncratic risk based on OLS method.

In addition, Fu (2007) points out that Ang, Hodrick, Xing and Zhang's (2006) findings are result of return reversal that occur to high idiosyncratic risk stocks. Fu (2007) points out that the latter study's findings do not apply to the expected relationship because idiosyncratic volatility varies over time. Fu (2007) points out that the EGARCH model accounts for this time-varying feature. He reports that the conditional idiosyncratic risk from EGARCH model has a positive relationship with expected stock returns. In addition Fu (2007) points out that Brockman and Schutte (2007) support this positive contemporaneous relationship using international data and using his method of estimating idiosyncratic volatility using EGARCH model.

Conversely, Liang and Wei (2006) indicate that they calculate idiosyncratic volatility based on monthly returns and find, generally in 23 developed countries, idiosyncratic risk is negatively related to stock expected returns. They point out that these findings confirm that this puzzle is robust and state that idiosyncratic risk could be seen as capturing some sort of undesirable risk. In addition, Liang and Wei (2006) point out that they find that the relationship is positive using country market portfolios and point out that this is in agreement with Merton's (1987) global version model. Furthermore, they point out that innovation to local market volatility has a robust negative price of risk in the UK in addition to Spain, and the negative relationship applies to innovations to global market volatility as well.

Boehme, Danielsen, Kumar and Sorescu (2005) point out that this mixed evidence of idiosyncratic risk results from ignoring the short sales constraints when conducting the analysis. They point out that Merton's (1987) model of positive idiosyncratic risk influence on the cross sectional returns on stocks, assumes frictionless market. Furthermore, Boehme, Danielsen, Kumar and Sorescu (2005) point out that Miller (1977) predicts dispersion of opinion is negatively related to stock returns given that there is binding constraint on short sale. They report that idiosyncratic risk has a cross sectional positive relationship with stock returns with no constraints. They point out that this agrees with Merton (1987). Furthermore, Boehme, Danielsen, Kumar and Sorescu (2005) point out that in agreement with Miller (1977) constrained stocks' idiosyncratic risk relates negatively to stock return.

Furthermore, Diavatopoulos, Doran and Peterson (2007) indicate that they measure idiosyncratic risk as implied idiosyncratic volatility and study its relationship with future stock returns and find a cross sectional positive relationship. Furthermore they point out that implied idiosyncratic risk outperforms the AR (2) as well as the EGARCH based idiosyncratic volatility. They point out that the positive idiosyncratic risk – return relationship is more apparent in small and high book-to- market stocks and could be related to these two effects. Furthermore they report that short sale constraint is negatively associated with future returns on stocks

On the other hand, Huang, Liu, Rhee and Zhang (2006) point out that the finding of Ang, Hodrick, Xing and Zhang (2006) and Ang, Hodrick, Xing and Zhang (later version as 2008) of the negative idiosyncratic risk effect on future returns is a result of short-term return reversal. They state that this is because of the reversal of the returns on the large winner highest idiosyncratic risk stocks. They report that once the latter reversal effect and size are controlled for, the negative significant relationship disappears. In addition they point out that they find the relationship of expected stock returns with expected idiosyncratic risk is not robust whether they forecast the latter using, among other methods, EGRACH (1, 1), GARCH, ARIMA, or past month idiosyncratic volatility.

French, Schwert and Stambaugh (1987) report that they find the unexpected market volatility has a negative relationship with the unexpected excess market returns that results from the positive relationship between the expected components of two measures. They point out that they calculate monthly market volatility from one month of daily returns and decompose it into two parts of expected and unexpected via ARIMA. Furthermore they point out that they calculate volatility using GARCH from daily and monthly returns. In addition, French, Schwert and Stambaugh (1987) indicate that studying expected volatility relationship with expected excess return should also include time-varying risk's measure.

Furthermore, Chua, Goh and Zhang (2007) point out that the inconclusive and confusing evidence concerning the importance of idiosyncratic risk could be due to the practice of other authors of employing realized rather than expected returns on stock with expected idiosyncratic risk when the realized returns are not good measures of their expected values. They point out for this reason they split idiosyncratic volatility to its two components expected part and unexpected part and use AR (2) for the decomposition. They point out that the positive expected relationship is uncovered once unexpected returns are controlled for. They report that they find that unexpected (expected) idiosyncratic volatility has a contemporaneously robust positive relationship with its return counterpart; i.e. unexpected (expected) stock returns. In addition they point out that the unexpected relationship is consistent with Merton's (1974) option effect.

Bali and Cakici (2008) report that they find idiosyncratic risk is not robustly related to expected returns on stocks. They point out that they find a number of key players namely, the frequency of the data, the stock sorting breakpoints and the portfolios returns weighting method as well as stock's size, degree of liquidity and price decide whether idiosyncratic risk has any significant cross sectional relationship with stock expected returns. They report that they find idiosyncratic risk influence on returns is not significant using monthly returns while for daily returns it is significant just in the case of using value weighted returns on portfolios (with CRSP breakpoints). Furthermore, they point out that once the smallest, most illiquid and lowest price stocks are excluded, Ang, Hodrick, Xing and Zhang's (2006) finding of the negative relationship disappears as it is driven by these types of stocks. In addition, they point out that monthly-return-based idiosyncratic volatility is better measure of expected idiosyncratic volatility than daily-return-based estimates.

Fletcher (2007) studies the UK idiosyncratic volatility. He states that he studies to what extent idiosyncratic risk is correctly priced by several asset pricing models, including among others, Fama and French's (1993) three-factor model, what he calls Petkova's (2006) application of Campbell's (1996) model, conditional CAPM and conditional consumption CAPM. Fletcher (2007) reports that he finds that idiosyncratic risk is important and consistent with Ang, Hodrick, Xing and Zhang (2006) and Ang, Hodrick, Xing and Zhang (later version as Ang, Hodrick, Xing and Zhang (2008)) among others. Furthermore, Fletcher (2007) points out that for idiosyncratic risk to be correctly priced is not an easy task for some pricing models and whether to price this latter risk or systematic risk correctly is a matter of tradeoff for these models. Furthermore, Au, Doukas and Onayev (2007) report that they find in the UK market for stocks that have high idiosyncratic risk, short-interest is negatively related to returns. They point out that this is in line with Ang, Hodrick, Xing and Zhang (2006)

3.2.2 Time-Varying Betas

Chen and Keown (1981) point out that when beta is time-varying the estimation of unsystematic risk by the OLS will be biased and heteroskedastic because the unaccounted for beta's variability will show up in residuals risk. They point out that they study residual risk relationship with market beta after accounting for time variation in the betas and find no significant relationship between the two measures of risk. They state that this insignificant relationship is unlike what was found previously.

In addition, Ang and Chen (2007) point out that the OLS delivers heteroskedastic residuals which are not independent of the risk factor when the risk measures are time-varying and the correct conditional beta's variance will be underestimated when the betas are calculated by rolling OLS. They point out that no anomalies in sock returns should be considered significant in the conditional CAPM's context until time varying betas are modeled.

In addition, Ghysels (1998) indicate that because market beta are found empirically to be time varying, there have been calls in the literature to replace the unconditional asset pricing models by their conditional counterparts. He points out that it is crucial to model beta risk correctly in order for models with time-varying beta to deliver better results than unconditional models (with constant betas), otherwise the reverse will occur.

Avramov and Chordia (2006) argue that the correct beta dynamics is impossible to identify. They point out that, nevertheless, they model time varying factor beta using individual firm's characteristics and the business-cycle variables where the former includes size and book-to-market. They point out that as a result of this modeling of time varying beta, the conditional version of the asset pricing models improve substantially over their unconditional counterparts. They report that they find the book-to-market and size characteristics remain cross sectionally significant for stock returns under the unconditional Fama and French's (1993) three-factor model while Fama and French's (1993) model with time-varying beta cause these effects to lose their explanatory power. Furthermore, they report that they find the momentum effect disappears when the model's alpha is modeled to be time-varying.

In fact, also a number of idiosyncratic risk studies point to the potential that idiosyncratic risk carries other effects, Ang, Hodrick, Xing and Zhang (2008) point out that Ang, Hodrick, Xing and Zhang (2006) explained that Fama and French's (1993) three-factor model will not correctly price the portfolios that result from sorting the stocks according to their idiosyncratic risk, given that there are missing factors in this pricing model and hence the its residuals reflect their these missing risk factors' effect. Furthermore, Diavatopoulos et al., (2007) state that there is a potential association between idiosyncratic risk positive effect on stock returns and stock's size and stock's book-to-market effects. They state that idiosyncratic risk could be interpreted as a risk factor that should part of the pricing models.

In addition, Fletcher (2007) studies UK idiosyncratic risk using among other models, conditional consumption CAPM and conditional CAPM. He points out that he models the SDF model's coefficients of these models as functions of two arguments which are constant and lagged dividend yield. Despite this he states that he leaves examining fully whether the conditional factor models (including the Fama and French's (1993) model) capability to price idiosyncratic risk is superior to their unconditional counterparts for the future.

Antoniou et al (2007) study the momentum and point out that they apply Avramov and Chrodia's (2006) conditional factor models to three countries including UK. They report that they find the time varying alphas are behind the momentum profits. They indicate that this is in agreement with Avramov and Chordia's (2006) findings. Antoniou et al (2007) indicate that their findings show that momentum profits might be captured by variables related business cycle, but not by stock return's idiosyncratic component.

In light of these findings of time-varying betas – although Fletcher (2007) uses conditional pricing models in studying UK idiosyncratic risk – this chapter examines whether capturing time-variation in betas by following Avramov and Chordia's (2006) study would cause idiosyncratic risk effect to die out.

3.3 Hypotheses Development

This chapter examines idiosyncratic risk in the cross sectional returns of stocks in United Kingdom and then it studies whether allowing for time variation in beta explicitly following Avramov and Chordia's (2006) conditional pricing model and methodology, has an effect on the relationship between idiosyncratic risk and stock returns. In other words it examines if time variation in risk measures cause the idiosyncratic risk effect to die out.

3.3.1. Idiosyncratic Risk in UK

For time-series studies; Guo and Savickas (2006) report a significant negative relationship between the UK future returns on stock market and idiosyncratic risk. Guo and Savickas (2008) confirm this negative relationship, in addition they report the value premium in the UK is positively predicted by idiosyncratic risk. Angelidis and Tessaromatis[24] (2008a) also report a negative and positive effect of idiosyncratic risk on future returns on the market and SMB portfolio, respectively. Angelidis and Tessaromatis (2008b) report that it is idiosyncratic risk calculated using UK small size stocks which predicts future SMB.

For cross sectional tests; Ang, Hodrick, Xing and Zhang (2008) report, using daily frequency, that a negative predictive cross sectional idiosyncratic risk effect on stock returns exists in the UK; i.e. higher idiosyncratic risk stocks are associated with lower future returns. They mention that the smallest size (5%) stocks are left out of the sample. Liang and Wei

[24] Angelidis and Tessaromatis (2008a) report a negative average return for SMB and positive average return for HML in UK over the period starting January 1988 and ending August 2005.

(2006) report using monthly frequency for idiosyncratic risk for stock level a negative insignificant idiosyncratic risk predictive effect for the UK. They also report that the market volatility shocks carry a significant price of risk in the UK with negative sign. Fletcher (2007) uses several asset pricing models including conditional pricing models and he points out that he finds assigning to idiosyncratic risk its correct price, is difficult for some of these models and Au, Doukas and Onayev (2007) relate idiosyncratic risk to short selling in the UK and both the last two papers indicate that their findings are in agreement with that of Ang, Hodrick, Xing and Zhang (2006).

It appears from the above cited studies that the cross sectional relationship between idiosyncratic risk and stock returns in the UK market is not totally conclusive, although there is evidence of a negative relationship. However, it seems it is stronger using daily frequency for returns as in Ang, Hodrick, Xing and Zhang (2008) than using monthly frequency as in Liang and Wei (2006). Spiegel and Wang (2005) point out that different return frequencies result in different findings. Also Bali and Cakici (2008) report that monthly and daily frequencies result in different findings with the latter frequency shows significant idiosyncratic risk effect while the former show insignificant effect. Given this, the first objective of this chapter is to study idiosyncratic risk in the UK cross sectional stock returns to examine the robustness of the relationship between idiosyncratic risk and returns to different frequencies and different measures of idiosyncratic risk. This objective is in line with Bali and Cakici (2008) who point out that they examine the effect of the variant methodologies on the relationship.

Given the above, the first two hypotheses of the chapter are stated as follows;

Hypothesis (1) idiosyncratic risk is priced by the cross-sectional variation of expected stock returns in the UK market.

Hypothesis (2) if the first hypothesis holds, then the relationship between idiosyncratic risk and stock returns is robust to data frequency and methods used to calculate idiosyncratic risk.

These hypothesises will be tested on the UK market in this chapter by applying the studies of Ang, Hodrick, Xing and Zhang (2006, 2008) who focus on daily frequency returns and OLS and find negative relationship (including for UK), and Spiegel and Wang (2005) who use monthly frequency returns and EGARCH and OLS and find positive relationship. This is also motivated by Bali and Cakici (2008) who study variation in idiosyncratic risk studies' approaches and reject the idea that idiosyncratic risk has a robust effect on the cross sectional return in the US.

3.3.2 Time-Varying Beta and Idiosyncratic Risk

Different potential explanations have been suggested for why idiosyncratic risk is a significant cross sectional explanatory variable for the returns on stocks. For the negative relationship documented by Ang, Hodrick, Xing and Zhang (2006, 2008), for example, Huang, Liu, Rhee and Zhang (2006) suggest that the return reversals is responsible for this negative idiosyncratic risk effect while Liang and Wei (2006) argue it is consistent with short-selling analysis of Miller (1977)[25]. On the other hand, for the positive relationship, Diavatopoulos, Doran and Peterson (2007) suggest value and size effects are related to idiosyncratic risk effect in stock returns while Chua, Goh and Zhang (2007) point out that Merton's (1974) analysis of equity as a type of option is consistent with the positive sign of unexpected idiosyncratic risk effect.

French, Schwert and Stambaugh (1987) point out that alternative time varying risk measures, among other things, should be included in studying the relationship between market's expected excess return and volatility. They point out that they find in unreported results ambiguous findings when they examined these issues and point out that this could be attributed to problems with the used risk measures among other things. In addition, Fletcher (2007) points out that he is planning to examine whether the conditional factor models are able to assign the correct price to idiosyncratic risk superiorly to their unconditional versions in future work, although he examined conditional CAPM and conditional consumption CAPM in studying idiosyncratic risk in the UK.

Furthermore, Ang and Chen (2007) point out that they show the time-varying beta in the OLS should be estimated directly in order to know the inconsistency between the unconditional and the correct conditional alphas. They point out further that this inconsistency could not be solved neither by employing short subperiods to estimate the risk measures (betas) nor by using data with high frequency. In addition, Chen and Keown (1981) point out that when not accounting for time-varying beta, the OLS produce residual risk that

[25] Liang and Wei (2006) don't have Miller (1977) in their references, although they cite Miller (1977) in their paper as their above quoted argument show.

contains part of this time variation in the beta. Ang and Chen (2007) point to this issue as well. Furthermore, Malkiel and Xu (2006) point out that Miller and Scholes (1972) indicate that the errors in measure of betas could be cne of the reasons for the significant idiosyncratic risk effect.

Motivated by the above cited studies, this chapter contributes to the literature of idiosyncratic risk by examining whether the time-varying beta conditional model and methodology of Avramov and Chordia (2006) can capture idiosyncratic risk effect. Therefore, the third hypothesis of this chapter is stated as following

Hypothesis (3) if the first hypothesis holds, then modeling the time-variation in betas may capture the idiosyncratic risk effect on the stock returns, in other words, idiosyncratic risk is not priced per se.

Previous idiosyncratic risk studies also allow for time variation in betas in the return equation. Some use daily OLS with month- window for estimating idiosyncratic risk, such as Ang, Hodrick, Xing and Zhang (2006, 2008) among the others. Others use EGARCH and monthly OLS, such as Spiegel and Wang (2005) who calculate idiosyncratic risk for each period using a window of past 60 months (for OLS) and all past data (for EGARCH) and hence allow for time variation in betas in the return equations. However, Ghysels (1998) points out that time-varying beta should be correctly specified and failing to achieve this so probably may result in a time-varying beta model with substantially higher pricing errors than the pricing errors that are produced by a pricing model with constant beta

3.4 Data and Methodology

3.4.1. Data

Datastream is the source of data. This chapter employs daily and monthly returns on all stock that are still traded on London Stock Exchange as well dead stocks which were traded at some point in time between 1st, July, 1981 to 31st, December, 2005. Therefore it starts with the 3706 non-financial stocks (see Data section ((2.4.1.1. Stock Returns in Chapter (2)) but ends up with a sample of 2020 as the further refinements are made as follows.

For the daily returns on stocks to be included in the sample, it should have market capitalization and book-to-market value. Ang, Hodrick, Xing and Zhang (2006) point out that they need the number of daily returns for the stock in the month to exceed 17 observations. Fu (2007) demands the stock have at least 15 observations of returns associated with trading volume that is not zero in the month. He points out that this is to alleviate the infrequent trading problem. Following them this chapter requires for the stock to be included in the analysis it should have in excess of 17 daily returns as Ang, Hodrick, Xing and Zhang (2006) but it requires these observations to be all non-zero returns which is in line with Fu's (2007) criteria for infrequent trading problem. 2020 stocks met these criteria and will be the dataset for this chapter and all the analyses will use them including for monthly returns described below. Despite of the fact of applying these criteria, this does not totally eliminate the potential problem that the database could contain highly illiquid and very small shares that are not frequently traded which may severely affect the results and therefore the findings should be read in light of this limitation.

For monthly returns, Avramov and Chordia (2006) point out that they require the stock to have (1) return for current month and for the previous 36 months (2) market capitalization and (3) the previous December book-to-market value. This chapter follows Avramov and Chordia's (2006) requirement for stock to be included in the monthly analysis of idiosyncratic risk. In addition to be used for the EGARCH analysis, Spiegel and Wang (2005) point out that the stock should have 60 months of returns. This chapter therefore follows this Spiegel and Wang's (2005) criteria for EGARCH analysis.

The Monthly UK Fama and French (1993) HML and SMB and market portfolio are obtained as in chapter (2) [see Chapter (2) section 2.*4.1.1 Stock returns*, for more details]. For daily frequency similarly, Professor Krishna Paudyal provided the chapter with the UK Fama and French's (1993) HML and SMB from July 1981 to December 2003 which are constructed by following the methods explained in Fama and French (1993, 1996). For the last two years of the sample period which are 2004 and 2005, the UK HML and SMB are constructed following closely Fama and French (1993), which is the same method used by Professor Paudyal to construct the factors for the period 1981-2003. Furthermore, similarly market portfolio is constructed for the whole sample period following closely Fama and French (1993). For all the details see Chapter (2) section *2.4.1.1. Stock returns*, which details the Fama and French's (1993) methods of constructing these factors.

3.4.2 Methodology

3.4.2.1 Idiosyncratic Risk Measures

a) *OLS with Daily Returns*

Ang, Hodrick, Xing and Zhang (2006,2008) explain that they measure stock's idiosyncratic risk for every month based on the residuals from Fama and French's (1993) three factor model estimated over the preceding month as follows, Ang, Hodrick, Xing and Zhang (2006, p.283, Equation (8))

$$r_t^i = \alpha^i + \beta_{MKT}^i MKT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \varepsilon_t^i \quad (1)$$

Equation (1) above is in Ang, Hodrick, Xing and Zhang's (2006) notations. They define the notations in the above equation as follows; the dependent variable (r_t^i) is the stock's return in excess of risk-free rate. They explain that they estimate the equation above with month of daily returns. They define stock's idiosyncratic risk to be the square root (standard deviation) of the variance of ε_t^i. This chapter follows Ang, Hodrick, Xing and Zhang (2006, 2008) in computing idiosyncratic risk for daily frequency.

Ang, Hodrick, Xing and Zhang (2008) use the above equation at different levels (country, region and world levels) and annualize idiosyncratic risk. However this chapter follows Huang et al (2006) in converting idiosyncratic risk into monthly basis. Huang et al (2006) point out that they follow Ang, Hodrick, Xing and Zhang (2006) in calculating idiosyncratic risk. Then Huang et al (2006) point out that they follow French et al., (1987) and calculate stock's monthly idiosyncratic risk by multiplying its daily idiosyncratic risk by the square root of that month's total trading days.

b) *OLS with Monthly Returns*

Spiegel and Wang (2005) point out that they calculate stock's monthly idiosyncratic risk for each month, using monthly returns over the preceding 60 months, as the square root of the Fama and French (1993) three-factor model's residuals, where they estimate the model by the OLS method over this preceding 60 months. More technically, Spiegel and Wang (2005, p.9,) define idiosyncratic risk as

$$(T-k)^{-1}\sum_{t=1}^{T}\hat{\varepsilon}_{i,t}^{2}$$

The above equation is in Spiegel and Wang (2005) notations. They define the above notations as $\hat{\varepsilon}_{i,t}^{2}$ is the Fama and French's (1993) model residuals, T and k are the number of non-missing time series observations (at least 24 observations) used in the regression and the number of regression coefficients, respectively. This chapter follows them in calculating monthly OLS measure of idiosyncratic risk, however for the denominator it uses T for simplicity.

c) *Exponential Generalized Autoregressive Conditional Heteroskedasticiy - EGARCH*

Spiegel and Wang (2005) also use the EGARCH model to calculate conditional idiosyncratic risk. They point out that EGARCH accounts for time-variation in idiosyncratic risk. Spiegel and Wang (2005, p. 10, Equation (3)) write EGARCH Model as

$$R_t^i - R_{ft} = \alpha_i + \beta_{i,MKT}(R_{MKT,t} - R_{ft}) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \varepsilon_{i,t}\ ,\ \varepsilon_{i,t} = \sqrt{h_{i,t}} \times v_t$$

$$\ln h_{i,t} = \varpi_i + \sum_{m=1}^{p} \delta_{i,m} \ln h_{i,t-m} + \sum_{m=1}^{p} \eta_{i,n}\left(|v_{t-n}| - E|v_{t-n}| + \psi_i v_{t-n}\right) \qquad (2)$$

Equation (2) above is in Spiegel and Wang's (2005) notation. [Note that it is clear that m in $\sum_{m=1}^{p}$ in the second term is a mistake and it should be n.] Spiegel and Wang (2005) define the notations in the above equations as; $h_{i,t}$, ϖ_i, $\delta_{i,m}$, $\eta_{i,n}$, ,ψ_i and v_t as residuals' conditional variance, $\ln h_{i,t}$'s unconditional mean, the next three terms are parameters to be estimated and the final term is an i.i.d (0,1) term, respectively. They indicate that they estimate the above EGARCH model every month for every stock using all previous returns to that month and 60 monthly returns are required for the stock to be in the sample. Furthermore they point out that they employ as a measure for conditional idiosyncratic risk for month *t*, the conditional idiosyncratic volatility's estimate for month *t-1*. Ang, Hodrick, Xing and Zhang (2008) point out in their footnote number (11) that they, in unreported findings, use EGARCH (1, 1) with daily data to calculate the subsequent day's conditional volatility. Also Fu (2007) employs EGARCH and Huang, et al (2006) use EGARCH (1,1). Furthermore, Bali and Cakici (2008) also use EGARCH (1,1).

Therefore, following Spiegel and Wang (2005) this chapter estimates EGARCH (1,1) to calculate conditional idiosyncratic risk . To keep consistency, note that all the terms in the conditional mean equation in Equation (2) have the same meanings as their counterpart terms in Equation (1) above.

3.4.2.2 The Cross-Sectional Regression

The majority of idiosyncratic risk studies employ both the cross sectional regression of Fama and MacBeth (1973) and portfolio formation strategies (Ang Hodrick Xing and Zhang, (2006) to study the effect of idisoycnrtaic risk in the cross section of stock returns.

Ang, Hodrick, Xing and Zhang's (2008) use Fama and MacBeth's (1973) cross sectional regression to study the significance of idiosyncratic risk in explaining stock returns. They point out that every month (t) they run a cross sectional regression where the left hand side of the equation is the monthly excess returns on the stocks and the right hand side includes constant, the contemporaneous betas (of market, HML and SMB factors estimated over month (t) with daily returns (i.e, Fama and French's (1993) three factor model)), lagged idiosyncratic risk (*t-1*) and a number of firm's characteristics as controlling variables, including the logarithm of size (market capitalization) measured at the month's beginning (i.e, at t-1), six month lagged book-to-market and prior six month returns (momentum). They point out that they calculate *t* statistics based on four lags Newey-West (1987) to correct for serial correlation and calculate the adjusted R^2 as average of the adjusted R^2 resulting from the cross sectional regressions.

This chapter follows Ang, Hodrick, Xing and Zhang's (2008) application of Fama and MacBeth's (1973) cross sectional regression and calculation of the relevant statistics. However, it uses for past returns, measures similar to those in Spiegel and Wang (2005). Spiegel and Wang (2005) point out that they use natural logarithms of past returns cumulated over the previous (1) second and third months, (2) fourth to sixth (included) months and (3) seven to twelve (included) months, however this chapter does not take natural logarithm. In addition, for simplicity and consistency, this chapter replaces the six month lagged book-to-market with the month's beginning log book-to-market value measured at time t-1, where log is also used to keep consistency with Avramov and Chordia (2006) definition [see section 3.4.2.4: The Time-Varying Beta Model of Avramov and Chordia (2006)]

As mentioned earlier this chapter also employs another two measures of idiosyncratic risk following Spiegel and Wang (2005) which are idiosyncratic risk based on OLS with the previous 60 months data and EGARCH idiosyncratic risk based on all previous data. Spiegel and Wang (2005) point out that they run Fama and MacBeth's (1973) cross sectional regression using the approach of Brennan, Chordia and Subrahmanyam (1998). Spiegel and Wang (2005) point out that under Brennan, Chordia and Subrahmanyam's (1998) approach the risk adjusted-returns is calculated in the first stage as the difference between the realized excess returns and fitted returns where the latter is calculated using the estimated parameters, and then the risk adjusted return is used as the dependent variable in the second stage cross sectional regression and is regressed every month on a number of characteristics including amonth others idiosyncratic risk, natual log of size, three measures of past returns. The latter measures of past returns are mentioned and detailed earlier in the section. Spiegel and Wang (2005) point out that they estimate the Fama and French's (1993) factor betas (estimated parameters) (i.e. Fama and French's (1993) model) in the first step using the previous 60 months. Spiegel and Wang (2005) point out that Brennan, Chordia and Subrahmanyam (1998) indicate that this approach overcomes the problem of the errors in variable.

This chapter follows Spiegel and Wang (2005) in using Brennan, Chordia and Subrahmanyam's (1998) risk adjusted returns as the dependent variable in the second step of Fama and MacBeth's (1973) cross sectional regression for studying the cross sectional relationship between returns and the forecasted idiosyncratic risk (EGARCH and OLS with monthly data) as Spiegel and Wang (2005) do. To keep consistency with Fama and MacBeth's (1973) cross sectional regression used by Ang, Hodrick, Xing and Zhang (2008) and applied in this chapter for their measure of idiosyncratic risk as described earlier in this section, the size and book-to-market value used in the second step regression as independent variables have the same definitions as described above.

3.4.2.3 Portfolio Formation

Portfolio formation is used by most of studies including Ang, Hodrick, Xing and Zhang (2006), Bali and Cakici (2008), Fu (2007), and Spiegel and Wang (2005) among others.

Spiegel and Wang (2005) point out that for each month, they sort stocks on their OLS based idiosyncratic risk (from Fama and French's (1993) model) estimated from the past 60 months data or EGARCH idiosyncratic risk (where the conditional mean equation is Fama and French's (1993) three-factor model as mentioned in section (3.4.2.1 (C) above) estimated from all previously available data, into ten deciles portfolios and calculate the value weighted average returns on each of these portfolios over one month. Furthermore, they perform another sorting to control for other characteristics such as size. They explain this in detail that in each month, they first sort the stock on their size into five portfolios using their current size (market capitalization) and in the second step, within each of these five portfolios, another ten deciles portfolios are formed by sorting stocks according to their idiosyncratic risk forecasted for the current month. They indicate that the value weighted returns are calculated for each of these 50 portfolios and the idiosyncratic risk portfolios are averaged across the size quintile portfolios.

Furthermore, Spiegel and Wang (2005) calculate, for all sorting whether single or double, the following statistics (1) Fama and French's (1993) alpha for each portfolio, (2) the difference in returns between the average monthly returns on the highest idiosyncratic risk portfolio and the average monthly returns on the lowest idiosyncratic risk portfolio as well as (3) the difference in Fama and French's (1993) alpha of the highest idiosyncratic risk portfolio and Fama and French's (1993) alpha of the lowest idiosyncratic risk portfolio for the single sorting and within each first step- characteristic portfolio in the double sorting as well as (4) difference in alphas for highest and lowest idiosyncratic risk portfolios that control for the characteristic. Spiegel and Wang (2005) also calculate t-statistics based on Newey West (1987) for all of the above; i.e. differences in returns as well as for portfolios' alphas and differences in alphas.

This chapter follows Spiegel and Wang (2005) in forming portfolios for stocks based on monthly OLS idiosyncratic risk and EGARCH idiosyncratic risk which are calculated following their approach. It also follows Spiegel and Wang (2005) in forming portfolios that control for size effect and in addition applies their double sorting procedure for controlling for book-to-market effect. Furthermore, it follows Spiegel and Wang (2005) in calculating all the above statistics. However, this chapter calculates the Newey-West (1987) t-statistics only for Fama and French's (1993) alphas and difference in alphas of the idiosyncratic risk portfolios from single sort and for Fama and French's (1993) alphas and difference in alphas of the characteristics (size of book-to-market value) controlled idiosyncratic risk portfolios from double sort.

Ang, Hodrick, Xing and Zhang (2006) point out that they construct idiosyncratic portfolios by concentrating on what they call strategy of 1/0/1 which stands for formation/ waiting/ holding periods, respectively. They indicate that, for each month, they create five idiosyncratic risk portfolios by sorting the stocks on their measures of idiosyncratic risk calculated over the previous month, using daily returns and then calculate the value weighted average return on each portfolio over the subsequent month. Furthermore, they point out that they also use double sorting procedure to control for other known characteristics such as size and value effects. Ang, Hodrick, Xing and Zhang (2006) explain this in detail that for each characteristic under consideration, they sort the stocks in each month on that characteristic into five quintile portfolios and then, within each of these portfolios, stocks are sorted using their lagged idiosyncratic risk into another five portfolios. They point out that portfolios with different levels of idiosyncratic risk but similar levels of that characteristic are then generated by averaging the second-sort portfolios (idiosyncratic risk quintiles) across the first-sort quintile portfolios (characteristic).

In addition, Ang, Hodrick, Xing and Zhang (2006, 2008) calculate, for both the single and double sorting, the following statistics (1) the spread between the monthly average return on the highest idiosyncratic risk portfolio and the monthly average return on the lowest idiosyncratic risk portfolio as well as (2) Fama and French's (1993) time series alpha for each quintile portfolio and (3) the difference in Fama and French's (1993) alphas for the highest and lowest idiosyncratic risk portfolios for the single sorting and within each first-step characteristic portfolio in the double sorting in addition to (4) the difference in Fama and French's (1993) alphas for highest and lowest idiosyncratic risk portfolios that control for the characteristic. They point out that all *t* statistics are calculated based on Newey West (1987).

This chapter follows Ang, Hodrick, Xing and Zhang (2006, 2008) in forming idiosyncratic risk portfolios with and without controlling for size and book to market values, when, following them, idiosyncratic risk is calculated as lagged idiosyncratic risk using daily returns with OLS. In addition, it follows them in calculating all the above statistics and Newey-West (1987)based t-statistic where the latter is calculated only for alphas and difference in alpha for the single sort- idiosyncratic risk portfolios and alphas and difference in alphas for the characteristic controlled idiosyncratic risk portfolios from the double sort. However, this chapter uses ten deciles portfolios for idiosyncratic risk portfolios instead of five quintile portfolios to be consistent with its calculation for the OLS monthly and EGARCH idiosyncratic risk portfolios following Spiegel and Wang (2005) as described above. Also Ang, Hodrick, Xing and Zhang (2008) point out that they use deciles portfolios and report some results.

3.4.2.4 The Time-Varying Beta Model of Avramov and Chordia (2006)

To examine the main hypothesis of this chapter that is, if time-varying risk measures capture the significance of idiosyncratic risk, this chapter follows the conditional model and methodology of Avramov and Chordia (2006). They point out that they extend Brennan, Chordia and Subrahmanyam's (1998) approach that uses the risk adjusted returns.

Avramov and Chordia (2006) apply their methodology to a number of models including Fama and French's (1993) model and CAPM. They describe the time series regression of the stock's excess returns under the most general specification, and assuming CAPM as an example, as follows (Avramov and Chordia, 2006, p.1010, Equation (8))

$$r_{jt} = \alpha_j + \beta_{j1} r_{mt} + \beta_{j2} z_{t-1} r_{mt} + \beta_{j3} Size_{jt-1} r_{mt} + \beta_{j4} z_{t-1} Size_{jt-1} r_{mt} + \beta_{j5} BM_{jt-1} r_{mt}$$

$$+ \beta_{j6} z_{t-1} BM_{jt-1} r_{mt} + u_{jt} \qquad (3)$$

Equation (3) above is in Avramov and Chordia's (2006) notation. They define the notations in the equation above as follows; the left hand side dependent variable is the return on stock j in excess of the risk free rate at time t , r_{mt} , $Size_{jt-1}$, BM_{jt-1} and z_{t-1} are market excess return at time t, log of market capitalization (size), log of book-to-market value and macroeconomic variable (default spread) respectively and all the last three variables are at time t-1,. They point out that they also use alternatives to default spread but the results remain unchanged.

Then in the second step, they use the following cross sectional regression, (Avramov and Chordia, 2006, p.1009, Equation (4))

$$R^*_{jt} = c_{0t} + \sum_{m=1}^{M} c_{mt} Z_{mjt-1} + e_{jt} \quad (4)$$

Equation (4) above in Avramov and Chordia's (2006) notation, they define the notations in the above equation as follows; R^*_{jt} = constant (α_j) plus residuals (u_{jt}) from equation (3) ; i.e. the stock's j risk adjusted returns, and Z_{mjt-1}, c_{mt} and M are stock characteristics -which includes log market capitalization (size), log book-to-market value and three measures of lagged returns; returns cumulated over the previous (1) second to third months, (2) fourth to sixth months and (3) seventh to twelve months-, stock characteristics' coefficients and their number, respectively. They point out the Fama and MacBeth (1973) averages of the time- series coefficients (c_{mt}'s) should be significantly not different from zero if exact pricing holds.

Furthermore, Avramov and Chordia (2006) develop a conditional (time-varying beta) version of Fama and French's (1993) three-factor model by applying their time varying beta methodology to Fama and French's (1993) three-factor model in which they replace r_{mt} in Equation (3) above by a vector which includes market, SMB and HML factors. Therefore this chapter applies Avramov and Chordia's (2006) conditional version of Fama and French's (1993) three-factor model and methodology.

Avramov and Chordia (2006) point out that they run Equation (3) using the full sample, however, this chapter runs it every month over the prior monthly 60 observations for monthly OLS idiosyncratic risk and over all the previous observations for EGARCH idiosyncratic risk in order to calculate these monthly OLS and EGARCH measures of idiosyncratic risk to be consistent with the ways these measures are calculated following Spiegel and Wang (2005) as described in the subsection 3.4.2.1 above. Hence these resulting measures of idiosyncratic risk (OLS monthly and EGARCH) are calculated following Spiegel and Wang (2005) but using Avramov and Chordia's (2006) conditional Fama and French's (1993) three-factor model as the asset pricing model instead of the Fama and French's (1993) three factor model used by Spiegel and Wang (2005). Spiegel and Wang (2005) use the Fama and French's (1993) three factor model for the monthly OLS and as the conditional mean equation for the EGARCH. Also this chapter adds these measures of idiosyncratic risk into the group of firm's characteristics in Eq. (4) each time which becomes similar to Siegel and Wang (2005) application of the cross sectional regression for studying idiosyncratic risk. Furthermore this chapter follows Spiegel and Wang (2005) in forming idiosyncratic risk portfolios (single and doube sort) based on these measures of idiosyncratic risk which are, as mentioned above, also calculated following Spiegel and Wang (2005) but using Avramov and Chordia (2006) conditional Fama and French (1993) three-factor model.

3.5 Results

3.5.1 Idiosyncratic Risk and Stock Returns

This subsection tests the first two hypotheses of this chapter which examines whether idiosyncratic risk explains the UK cross sectional stock returns and whether this relationship is robust, in both cross sectional regression and portfolio formations analyses.

3.5.1.1 OLS Daily - Idiosyncratic risk / Cross Sectional Regression

Table (3.1) presents the coefficients of Fama and MacBeth's (1973) cross sectional regression of monthly excess return on the stocks on (a) Fama and French's (1993) factors betas, (b) idiosyncratic risks measured as in Ang, Hodrick, Xing and Zhang (2006, 2008) using past month's daily excess returns, (c) and a number of firms characteristics which are size, book-to-market value and three measures of lagged returns.

The regression that includes only Fama and French's (1993) factors betas and idiosyncratic risk, shows that idiosyncratic risk is negative and significant in the cross section of stock returns. Even after controlling for the other effects, the second regression shows that idiosyncratic risk's negative effect remains robust although the coefficient of idiosyncratic risk and the associated t-statistics become smaller. These findings are consistent with Ang, Hodrick, Xing and Zhang's (2008) findings for UK and US. Furthermore and also similar to Ang, Hodrick, Xing and Zhang's (2008), none of the Fama and French's (1993) three risk measures is significant in both specifications and the second regression's specification shows that size, book-to-market and past returns are all significant. Ang, Hodrick, Xing and Zhang (2008) point out that the finding that stock's non risk characteristics are significant while the risk measures are not is in line with Daniel and Titman (1997).

3.5.1.2 OLS Daily - Idiosyncratic risk / Portfolios

Table (3.2) shows the results of sorting stocks based on their past month idiosyncratic risk, measured as in Ang, Hodrick, Xing and Zhang (2006, 2008) using daily frequency, into ten equal portfolios. The first row shows the Fama and French (1993) three-factor model's alphas for each of thèse ten portfolios. It shows that there is no clear association between idiosyncratic risk and Fama and French's (1993) alphas. Furthermore, the first row shows that the difference between the alpha of the highest idiosyncratic risk portfolio and the alpha of the lowest idiosyncratic portfolio is negative but insignificant, and although the sign is negative this is inconsistent with the findings of Fama and MacBeth's (1973) cross sectional regression in Table (3.1) above which shows that idiosyncratic risk is significant in explaining the cross sectional returns. The last cell in the first row shows that the difference in the average excess return on the highest idiosyncratic risk portfolio and the average excess return on the lowest idiosyncratic portfolio is negative. Au, Doukas and Onayev (2007) point out that their study's findings for idiosyncratic risk in UK and its relation with short selling are in line with Ang, Hodrick, Xing and Zhang (2006).

The second row in Table (3.2) shows the average size while the third row shows the average book-to-market value for each of the ten portfolios. Both measures; average size and average book-to-market value are calculated as in Ang, Hodrick, Xing and Zhang (2006). Ang, Hodrick, Xing and Zhang (2006) point out that they calculate the average size and the average book-to-market value for the portfolio as the average of the stocks' logarithms of size that are in that portfolio and the average of the stocks' book-to-market values of the stocks in that portfolio, respectively. Note that however this chapter uses log book-to-market value. It is apparent from the second row that there is a decreasing trend in the average size from the second lowest to the highest idiosyncratic risk portfolio, this is also consistent with Ang, Hodrick, Xing and Zhang (2006) for the US, although note that they use five instead of ten portfolios as mentioned above in the relevant section of the methodology of this chapter. For the average book-to-market value there is no clear pattern.

Table (3.3) presents the results of the double sorting procedure to control for size and book-to-market value effects. Panel (A) presents the Fama and French' (1993) alphas for the 50 portfolios that result from sorting the stocks on their market capitalization and then on their idiosyncratic risk. The last column shows the difference between the alpha of the highest idiosyncratic risk portfolio and the alpha of the lowest idiosyncratic risk portfolio within each size portfolio. In addition the last row presents the Fama and French's (1993) alphas for the portfolios that have different idiosyncratic risk but similar size; i.e. control for size.

It is clear after controlling for the size effect that, the difference in Fama and French's (1993) alphas between the highest and lowest idiosyncratic risk portfolios is negative and significant. By examining the alphas of each of the ten size-controlled idiosyncratic risk portfolios, it emerges that this significant difference results from the positive significant return on the lowest idiosyncratic risk portfolio rather than from the low negative return on the highest idiosyncratic risk portfolio where the Fama and French's (1993) alpha of the latter is negative but insignificant while the Fama and French's (1993) alpha of the former is positive and significant. This is different from Ang, Hodrick, Xing and Zhang (2006) pattern, as Huang et al., (2006) point out that the negative relationship in the Ang, Hodrick, Xing and Zhang (2006) is mainly due to the very low return on the portfolio with highest idiosyncratic risk. Similarly, Fu (2007) points out that the stocks with high idiosyncratic risk in Ang, Hodrick, Xing and Zhang (2006) have exceptionally low subsequent returns.

In addition, Panel (A) shows that within size portfolios, the high-low alphas are significant only for the smallest two portfolios but insignificant for the biggest three portfolios. In fact Bali and Cakici (2008) point out that they find that the negative effect of idiosyncratic risk of Ang, Hodrick, Xing and Zhang (2006) presents amongst stocks with small size, low liquidity, and cheap prices. Accordingly the finding in Panel (A) of Table (3.3) for the UK could be seen as consistent with Bali and Cakici (2008). In addition, Diavatopoulos et al., (2007) point out that they find idiosyncratic risk effect is positive and significant within the smallest of the five size portfolio and also within the highest two of the five boot-to-market portfolios. Diavatopoulos et al., (2007) point out that they find that idiosyncratic risk positive effect may be associated with size and book-to-market value. Ang Hodrick Xing and Zhang (2008) point out that their results show that large stocks show greater idiosyncratic risk effect than small stocks, using value weighted Fama and MacBeth's (1973) regression in 23 countries (including UK).

Furthermore, Angelidis and Tessaromatis (2008b) point out that they find that the UK idiosyncratic risk estimated from small size stocks is a robust significant forecasting variable of future SMB but not other elements of market return. They state that whether this idiosyncratic risk is a risk factor or not remain to be investigated.

Panel (B) shows the results of the double sorting where book-to-market value replaces size (market capitalization) in the first-step sort in Panel (A). The last row shows that the difference in Fama and French's (1993) alpha between the highest idiosyncratic risk portfolio that controls for value effect, and Fama and French's (1993) alpha for its lowest counterpart, is negative but statistically insignificant. In addition the H-L Fama and French's (1993) alphas, as shown in the last column, are insignificant within each of the book-to-market value portfolios.

In summary, Fama and MacBeth's (1973) cross sectional regression shows that idiosyncratic risk calculated following Ang, Hodrick, Xing and Zhang (2006, 2008) using daily returns, is related robustly negatively and significantly to the cross sectional returns on UK stocks, while the portfolio formation's findings are not robust and therefore not consistent with the cross sectional regression findings.

3.5.1.3 OLS Monthly Idiosyncratic Risk / Cross Sectional Regression

This subsection presents the results of an examination of the effect of idiosyncratic risk in the cross sectional returns on the UK stock, where idiosyncratic risk is calculated as in Spiegel and Wang (2005) using OLS with the past 60 months of returns. Bali and Cakici (2008) point out that they find the frequency of returns that is employed to calculate idiosyncratic risk is an important determining factor. Furthermore, Spiegel and Wang (2005) point out that Ang, Hodrick, Xing and Zhang's (later published as Ang, Hodrick, Xing and Zhang (2006)) idiosyncratic risk that is based on daily returns generates different findings from idiosyncratic risk estimated from monthly frequency. In fact the results below are consistent with these studies that daily–based and monthly–based idiosyncratic risks provide different results.

Table (3.4) presents the Fama and MacBeth's (1973) cross sectional regression with risk adjusted returns used in the second step as the dependent variable following Spiegel and Wang (2005) who use Brennan, Chordia and Subrahmanyam's (1998) approach. Reg.1 shows that when idiosyncratic risk exists alone in the second step cross sectional regression, it is insignificant and has a negative sign. However when the other control variables are included in the regression as Reg.2 shows, idiosyncratic risk becomes positively and marginally significantly (at 10%) related to stock returns.

3.5.1.4 OLS Monthly Idiosyncratic Risk / Portfolios

Table (3.5) presents the Fama and French' (1993) alphas of the 10 portfolios formed by sorting the stocks on idiosyncratic risk estimated using the prior 60 monthly returns following Spiegel and Wang (2005). The H-L alpha for the difference between Fama and French's (1993) alpha of the highest idiosyncratic risk portfolio and the Fama and French's (1993) alpha of the lowest idiosyncratic risk portfolio is negative but insignificant. This finding is consistent with the Reg.1 in Table (3.4) above. Also it is consistent with Spiegel and Wang (2005). Spiegel and Wang (2005) point out that they find idiosyncratic risk, calculated based on OLS with the prior 60 monthly returns, has no clear relationship with US stock returns. Furthermore, Liang and Wei (2006) study 23 countries and point out that they calculate idiosyncratic risk volatility via Fama and French's (1993) three-factor model estimated using the previous 36 of monthly returns. They report for the UK a negative and insignificant Fama and French's (1993) alpha. Another observation in Table (3.5) is that the highest idiosyncratic risk portfolio has lower average book-to-market value than the lowest idiosyncratic risk portfolio. Guo and Savickas (2008) point out that they find the value premium is positively associated with idiosyncratic risk in some of the G7 including for the UK. Furthermore, they point out that they find aggregate book-to-market ratio is negatively associated with idiosyncratic risk for US.

Table (3.6) presents the double sorting procedure that controls for size and book-to-market value each a time in Panel (A) and Panel (B) respectively. The last row in Panel (A) shows Fama and French's (1993) alphas for idiosyncratic risk portfolios that control for size. It is clear that for these portfolios, the difference between Fama and French (1993) alpha of the highest idiosyncratic risk portfolio and Fama and French's (1993) alpha of the lowest idiosyncratic risk portfolio is negative and significant. The sign here is in contrast to the positive sign of the relationship between idiosyncratic risk and stock returns in Reg.2 in Table (3.4). Panel (A) of Table (3.6) also shows the H-L Fama and French (1993) alpha is significant only for the smallest and middle size portfolios this is somewhat similar to Panel (A) of Table (3.3) (See section 3.5.1.2 OLS Daily - Idiosyncratic risk).

On the other hand the insignificant difference in Fama and French's (1993) alphas in the single sorting in Table (3.5) as well as the negative and significant difference in Fama and French's (1993) alphas for idiosyncratic risk portfolios that control for size in Panel (A) in Table (3.6) are consistent with their counterparts in Table (3.2) and Panel (A) of Table (3.3) for idiosyncratic risk that is measured based on past month daily returns as in Ang, Hodrick, Xing and Zhang (2006, 2008). However there is a difference, for monthly frequency in Panel (A) of Table (3.6) the negative difference in the alphas appears to be due to the low returns on the highest idiosyncratic risk portfolio that control for size which has a negative and significant Fama and French's (1993) alpha while the lowest idiosyncratic risk portfolio that control for size has positive but insignificant Fama and French (1993) alpha, the opposite occurs for the daily frequency as mentioned above.

Panel (B) of Table (3.6) presents the results of the double sorting when book-to-market value replaces size in Panel (A), in the first step sort. The last row shows the Fama and French (1993) alpha for the book-to-market controlled idiosyncratic risk portfolios. It shows that the difference between the Fama and French's (1993) alpha of the highest idiosyncratic risk portfolio and Fama and French's (1993) alpha of the lowest idiosyncratic risk portfolio is negative but insignificant. Again this is inconsistent with Reg.2 in Table (3.4) but consistent with Panel (B) of Table (3.3) which shows the same double sorting procedure for idiosyncratic risk estimated as in Ang, Hodrick, Xing and Zhang (2006, 2008).

Panel (B) of Table (3.6) also shows that idiosyncratic risk effect is positive and significant within the highest book-to-market portfolios. This particular observation is consistent with Diavatopoulos et al., (2007). Diavatopoulos et al., (2007) point out that they find the positive idiosyncratic risk could be associated with high value and small stocks. On the other hand idiosyncratic risk effect is negative and significant within the lowest book-to-market portfolio. Although Panel (B) shows that overall there is no significant relationship between idiosyncratic risk and the cross sectional returns on UK stocks.

In summary, the cross sectional regression analysis shows a positive relationship between idiosyncratic risk, calculated using OLS with monthly frequency following Spiegel and Wang (2005), and stocks returns. However, this relationship is not robust to portfolio formation analysis. In addition there is a strong association between idiosyncratic risk and small and value stocks. Generally speaking, the findings so far suggest the portfolio formation does not provide robust results for idiosyncratic risk effect in the UK whether idiosyncratic risk is calculated using daily or monthly data.

3.5.1.5 EGARCH / Cross Sectional Regression

Fu (2007) uses EGARCH and points out that in the light of the time-variation in idiosyncratic volatility, the EGARCH model produces a better estimate of idiosyncratic risk than a lagged idiosyncratic measure of risk. Therefore, Table (3.7) presents the results, following Spiegel and Wang (2005) who use Brennan et al (1998) approach of Fama and MacBeth's (1973) cross sectional regression that uses risk adjusted returns as dependent variables. Also following Spiegel and Wang (2005), the forecasted idiosyncratic risk is calculated from EGARCH model using all previous data.

Reg.1 shows the that forecasted EGARCH (1,1) idiosyncratic risk is negatively related to the cross sectional regression of the UK returns. However, Reg.2 shows the EGARCH idiosyncratic risk effect is not robust for controlling for the size, value and momentum variables, as it loses its explanatory power and become positive. This finding is consistent with Huang et al., (2006) who report that they find insignificant relationship between the cross section of returns and forecasted EGARCH (1,1) idiosyncratic risk in the US. However, it is inconsistent with Spiegel and Wang (2005) and Fu (2007) who report significant positive relationship for the US, based on both cross sectional regression and portfolio formation analyses. Fu (2007) makes it clear that he chooses the EGARCH idiosyncratic risk series from a number of EGARCH with different lags of variance and shocks.

3.5.1.6 EGARCH / Portfolios

Table (3.8) presents the results of sorting stocks into 10 portfolios on their EGARCH idiosyncratic risk as in Spiegel and Wang (2005). It shows the difference between Fama and French's (1993) alpha of the highest idiosyncratic risk portfolio and Fama and French's (1993) alpha of the lowest idiosyncratic risk portfolio is negative and significant. This is consistent with Reg.1 findings in Table (3.7). Furthermore, it is apparent that the negative effect of idiosyncratic risk comes from the low returns on the highest idiosyncratic risk portfolio which has a negative and significant alpha while the lowest idiosyncratic risk portfolio has a positive but insignificant alpha. However, it is important to note that moving from the lowest to the highest idiosyncratic risk portfolios, shows no relationship between Fama and French's (1993) alpha and idiosyncratic risk. Taking into consideration that, as motioned earlier, the database employed in the thesis has not been filtered for the very small and illiquid shares, this may suggest that the highest idiosyncratic risk stocks may be unrepresentative as that they are, possibly very small and illiquid shares.

Table (3.9) shows the results of the double sorting where stocks are first sorted on their size (Panel A) or book-to-market (Panel B) and then on EGARCH based idiosyncratic risk. The last row in Panel (A) shows Fama and French's (1993) alpha for the 10 idiosyncratic portfolios after controlling for size. The difference between Fama and French's (1993) alpha of the highest idiosyncratic risk portfolio that controls for size and the Fama and French's (1993) alpha of its lowest counterpart is negative and significant; i.e. controlling for size does not cause idiosyncratic risk to lose its effect on the cross section of returns. The last row shows that once the size is controlled for, there is a better relationship between idiosyncratic risk and Fama and French's (1993) alpha (apart from the lowest and third lowest idiosyncratic risk portfolios) compared with Table (3.8). The last column shows the difference between the Fama and French (1993) alpha of the highest idiosyncratic portfolio and the Fama and French's (1993) alpha of the lowest idiosyncratic risk portfolio within each size portfolio. This column shows that in the UK, idiosyncratic risk effect exists within the smallest and middle size portfolios which is consistent with the patterns reported earlier for the other measures of idiosyncratic risk and reported in other studies (See section 3.5.1.2 above).

Panel (B) of Table (3.9) shows the results of the double sorting procedure where book-to-market value replaces the size as a criterion in the first step of sorting. The last row shows that, similar to Table (3.8), there is no clear relationship between Fama and French's (1993) alpha and idiosyncratic risk portfolios by moving from the lowest to the highest idiosyncratic risk portfolios. Furthermore, it shows the difference between Fama and French's (1993) alpha of the highest idiosyncratic risk portfolio and Fama and French's (1993) alpha of the lowest idiosyncratic risk portfolio is negative but insignificant. This is consistent with the findings of Reg.2 in Table (3.7) and it seems that book-to-market value captures the effect of EGARCH idiosyncratic risk. Guo and Savickas (2008) report that they find for a number of countries including UK that average idiosyncratic volatility positively predicts value premium. Furthermore they point out that average idiosyncratic volatility has a negative relationship with aggregate book-to-market ratio in the US. Panel (B) also shows that idiosyncratic risk effect is negative and significant within the lowest two book-to-market portfolios.

In summary EGARCH idiosyncratic risk has a significant and negative relationship with the UK cross section of returns, when only comparing the alphas of the highest and lowest idiosyncratic risk portfolios. However, this negative relationship is not robust to controlling for size and book-to-market effect. Furthermore, it seems that idiosyncratic risk effect exists mainly in the smallest to middle size stocks and within lowest book-to-market stocks.

3.5.2 Time Varying Beta and Idiosyncratic Risk

This subsection tests that third hypothesis of this chapter which examines if time-varying beta can capture idiosyncratic risk effect.

The findings of the chapter so far regarding the effect of idiosyncratic risk in the cross sectional of returns UK stocks are confusing. Ang, Hodrick, Xing and Zhang (2006) point out that the Fama and French (1993) model's residuals may carry the effect of aggregate volatility factor conditional on the latter factor is a priced risk factor and hence Fama and French's (1993) model misses this factor out. However, they report that aggregate volatility factor can not totally explain the effect of idiosyncratic risk that they document. On the other hand, as mentioned earlier, Chen and Keown (1981) point out that the time-variation effect of factors' betas will contaminate the residuals of the constant beta model when the latter is estimated by the OLS. This chapter examines whether the time-varying beta that is modeled explicitly following Avramov and Chordia (2006) will resolve these conflicting findings. Therefore this chapter applies the conditional Fama and French's (1993) three-factor model of Avramov and Chordia (2006) and their methodology.

The chapter's findings above show that idiosyncratic risk based on OLS with monthly returns becomes positively significant when size, book-to-market and past returns are included in the regression while when idiosyncratic risk exists alone in the regression it is insignificant. Contrary to this, EGARCH based idiosyncratic is negatively significant but when size, book-to-market and past returns are included in the regression, it loses its explanatory power. Avramov and Chordia (2006) point out that Fama and French (1992) point out that the information that is contained in market prices and affect stock's returns is captured by the value and size variables. Furthermore, Avramov and Chordia (2006) point out that also Ball (1978) states that the variation in the expected returns is captured by market ratios.

This section applies Avramov and Chordia's (2006) conditional Fama and French's (1993) three-factor models and methodology. In this conditional model, Avramov and Chordia (2006) model the factor beta as function of the following variables; size, book-to-market value and default spread in the time-series regression step of the Fama and MacBeth's (1973) regression. Then Avramov and Chordia (2006) regress, in the second step cross sectional regression, the risk adjusted return on firm's characteristics which includes size, book-to-market and past returns. In this chapter, for each month, the time –series regression is regressed over the past 60 months and the standard deviation of the residuals is used as measure of idiosyncratic risk which is then added to the other firm's characteristics in the second step cross sectional regression. This measure of idiosyncratic risk is that of Spiegel and Wang (2005) except that here betas in the time series regression are explicitly time-varying modeled following Avramov and Chordia's (2006) as described above and in the methodology section. Table (3.10) shows the results

Table (3.10) shows idiosyncratic risk has a positive sign and is not significant in explaining the risk-adjusted returns, whether it exists alone in the regression or with other explanatory variables. In comparison Table (3.4) shows that when the betas are not modeled explicitly but estimated over a window of 60 months as in Spiegel and Wang (2005), this similar measure of idiosyncratic risk is positively significant when it exists in the cross sectional regression along with the other explanatory variables.

Furthermore, Panel (A) in Table (3.12) shows the results of the ten portfolios formed by idiosyncratic risk. It shows that when time-varying betas are accounted for, idiosyncratic risk effect is not significant whether in the single sorting or double sorting. Whereas Table (3.6), where betas are constant over the 60 month estimation period, shows the difference between Fama and French's (1993) alpha of the highest idiosyncratic risk and Fama and French's (1993) alpha of the lowest idiosyncratic risk, is negatively significant for idiosyncratic risk portfolios that control for size.

Table (3.11) shows the results of applying Avramov and Chordia's (2006) conditional Fama and French's (1993) three-factor model methodology as in Table (3.10) but where the OLS monthly idiosyncratic risk in Table (3.10) is replaced by EGARCH (1,1) idiosyncratic risk calculated also following Spiegel and Wang (2005) (i.e. the time-series step becomes EGARCH model). To calculate this EGARCH idiosyncratic risk, the conditional mean equation of Fama and French's (1993) three factor model is the conditional Fama and French's (1993) three-factor model of Avramov and Chordia (2006), where they model the factor beta as function of following variables; size, book-to-market and defaults spread. This resulting EGARCH measure of idiosyncratic risk is calculated following Spiegel and Wang (2005) except that betas are explicitly time-varying here.

It is clear from Reg.1 and Reg.2 that EGARCH (1,1) idiosyncratic risk, although it has a positive coefficient it is insignificant whether it is the only variable in the second step cross sectional regression or when the size, book-to-market and momentum effects are controlled for. In comparison Table (3.7) shows EGARCH (1,1) idiosyncratic risk is negatively significant when it exists alone, although it loses power when other explanatory firm's characteristics are controlled for.

Panel (B) of Table (3.12) shows the results of sorting stocks on EGARCH (1,1) idiosyncratic risk into deciles portfolio where betas in the conditional mean equation are time varying. It confirms the findings in Table (3.11). Its shows the difference between Fama and French's (1993) alpha of the highest idiosyncratic risk portfolio and the Fama and French's (1993) alpha of the lowest idiosyncratic risk portfolio is insignificant whether in the single sort or after controlling for size and book-to-market each a time. In contrast Table (3.8) and Table (3.9) show a negative and significant idiosyncratic risk in the single sort and when controlling for size.

In summary, the results show that idiosyncratic risk is not priced in the cross sectional returns of the UK stocks. Even though they show that it has some power in explaining stock returns, these findings are not robust and more importantly when the time-variation in factors betas are taken into account, idiosyncratic risk has conclusively lost its explanatory power. This chapter does not examine the time variation in beta effect on idiosyncratic risk calculated as in Ang, Hodrick, Xing and Zhang (2006, 2008), using daily returns, as this includes obstacles such as requiring daily frequency for the book value and this will be constant within the month. However, having found that the portfolio formation's results for OLS daily idiosyncratic risk is not robust, this potentially supports the idea that accounting for time-variation in beta could have the effect of causing idiosyncratic risk to lose its explanatory power completely. Bali and Cakici (2008) report that they find that idiosyncratic risk of Ang, Hodrick, Xing and Zhang (2006) based on daily returns disappears when small stocks along with stocks with low liquidity and low price are omitted for US stocks. Furthermore, Bali and Cakici (2008) point out that size is negatively correlated with idiosyncratic risk when one type of breakpoint is used. Tables (3.2) of this chapter, also shows that there is a negative relation between average portfolios size and idiosyncratic risk.

This chapter's conclusion of idiosyncratic risk is not significant in the cross section of returns, supports Bali and Cakici's (2008) and Huang, Liu, Rhee and Zhang's (2006) conclusions that idiosyncratic risk is not priced.

3.6 Findings Summary

The results are mixed and these non-consistent findings are summarized in the summary table below

Summary Table						
Idiosyncratic risk Measure	**No control**		**Controlling for Size**		**Controlling for Book-to-Market**	
	Sign	**Significance**	**Sign**	**Significance**	**Sign**	**Significance**
Daily Frequency						
lagged OLS-daily / regression	Negative	Significant	Negative and Significant			
lagged OLS -daily / Portfolio	Negative	Insignificant	Negative	Significant	Negative	Insignificant
Monthly Frequency						
lagged OLS – monthly / regression	Negative	Insignificant	Positive and Significant			
lagged OLS – monthly / Portfolio	Negative	Insignificant	Negative	Significant	Negative	Insignificant
EGARCH (1,1) / regression	Negative	Significant	Positive and Insignificant			
EGARCH (1,1) / portfolios	Negative	Significant	Negative	Significant	Negative	Insignificant
Time-Varying Betas						
lagged OLS – monthly / regression	Positive	Insignificant	Positive and Insignificant			
lagged OLS – monthly / Portfolio	Negative	Insignificant	Positive	Insignificant	Positive	Insignificant
EGARCH (1,1) / regression	Positive	Insignificant	Positive and Insignificant			
EGARCH (1,1) / portfolios	Positive	Insignificant	Positive	Insignificant	Positive	Insignificant

3.7 Conclusion

This chapter attempts to study the relationship between idiosyncratic risk and the cross sectional returns on the UK stocks. It employs idiosyncratic risk measures that are based on daily frequency with OLS following Ang Hodrick Xing and Zhang (2006, 2008) and monthly frequency with OLS or EGARCH models following Spiegel and Wang (2005). Then it examines if time varying beta modeled following Avramov and Chordia (2006) does capture the effect of idiosyncratic risk.

This chapter sheds more light on the behavior of idiosyncratic risk in the UK cross section of returns and more importantly, it applies the time-varying beta model and methodology of Avramov and Chordia (2006) to examine whether accounting for time-variation in factor beta helps in reaching a more decisive evidence regarding the importance of idiosyncratic risk in stock returns.

3.7.1 OLS Daily Frequency

Ang, Hodrick, Xing and Zhang's (2006, 2008) measure of idiosyncratic risk, which is based on the daily returns with OLS, is found in this chapter to be negatively related to the cross sectional returns on stocks in the UK, when the relationship is estimated using the Fama and MacBeth's (1973) cross sectional regression. This is consistent with Ang, Hodrick, Xing and Zhang (2008) who find a similar negative relationship for the UK. However, portfolio formation results provide mixed and confusing findings. Ang, Hodrick, Xing and Zhang (2008) point out that the alphas of these portfolios' are investable returns. Nevertheless the results in this chapter suggest that the alphas of portfolios formed on this measure of idiosyncratic risk are not source of returns for investors in the UK.

The findings from the portfolio formation also suggest that there is a strong association between idiosyncratic risk effect, based on daily returns and stock's size. It has been shown that the difference between the Fama and French's (1993) alpha of the highest idiosyncratic risk portfolio and the Fama and French's (1993) alpha of the lowest idiosyncratic risk portfolio is negative within each of the five size portfolios but it is monotonically decreasing in absolute magnitude from the smallest to the largest size portfolio. Indeed as mentioned earlier Bali and Cakici (2008) and Diavatopoulos et al., (2007), point out that there is association between idiosyncratic risk and small stocks in the US. Also Angelidis and Tessaromatis (2008b) point out that they find idiosyncratic risk based on small size stocks has predictive power for SMB in the UK.

3.7.2 OLS Monthly Frequency

When idiosyncratic risk is calculated based on OLS and monthly returns following Spiegel and Wang (2005), this chapter finds a positive and significant relationship between idiosyncratic risk and the cross section of returns in the presence of size, book-to-market and momentum variables, when the relationship is estimated using Fama and MacBeth's (1973) cross sectional regression. However, the findings from portfolios formation are not consistent with the cross sectional regression findings. It has been shown that the relationship is negative but insignificant based on the single sorting, this in line with Liang and Wei (2006) who report a difference between the Fama and French's (1993) alpha of the highest idiosyncratic risk portfolio and Fama and French's (1993) alpha of the lowest idiosyncratic risk portfolio that is negative and insignificant for UK. On the other hand, this chapter shows that when size is controlled for, the difference becomes significant although negative.

3.7.3 EGARCH Monthly Frequency

When idiosyncratic risk is calculated based on the EGARCH model, following Spiegel and Wang (2005), this chapter finds a negative significant relationship between EGARCH (1,1) idiosyncratic risk and the cross section of stocks returns, when the relationship is estimated based on Fama and MacBeth's (1973) cross sectional regression. However this relationship disappears after controlling for size and book-to-market and momentum variables. The findings from the portfolio formation are consistent with the cross sectional regression findings and suggest it may be the book-to-market ratio that captures the effect of idiosyncratic risk. The overall findings of EGARCH idiosyncratic risk effect in this chapter are in contrast with both Spiegel and Wang (2005) and Fu (2007) who report a positive relationship for the US.

3.7.4 Time-Varying Betas and Idiosyncratic Risk

As discussed above the findings of whether idiosyncratic risk is priced in the UK are mixed, question the potential usefulness of idiosyncratic risk in explaining the cross section of returns.

Then, factor betas are modeled explicitly to be time-varying following Avramov and Chordia (2006). This is done by applying the time-varying beta Fama and French's (1993) three factor model of Avramov and Chordia (2006) and then the residuals from this time varying beta model are used to calculate the monthly OLS and EGARCH idiosyncratic risks following Spiegel and Wang's (2005). The results show that, after accounting for time-variation in beta, idiosyncratic risk is insignificant in the cross section of returns, based on both Fama and MacBeth's (1973) cross sectional regression and portfolio formation analysis.

3.7.5 Concluding Remark

Although idiosyncratic risk appears to have some potential explanatory power for the UK stock returns, such explanatory power completely disappears when time-variation in betas is accounted for. Therefore, it could be concluded that idiosyncratic risk is not priced in the UK market. The results suggest that the initial confusing findings may be explained by idiosyncratic risk having captured the effect of not correctly modeling time-varying risk measures. The finding that idiosyncratic risk is not significant supports Bali and Cakici's (2008) findings for the USA.

Although, this chapter does not examine the effect of time-varying beta on idiosyncratic risk effect, when the latter is calculated using daily return as in Ang Hodrick Xing and Zhang (2006, 2008), the findings in this chapter show the negative relationship between this measure of idiosyncratic risk and stock returns is significant using cross sectional regression but not portfolio formation. This questions the real usefulness of daily OLS idiosyncratic risk in stock returns.

Table 3.1 Cross-Sectional Regression with OLS Daily Idiosyncratic Risk

	Intercept	Market	HML	SMB	Idiosyncratic risk	Market capitalization (size)	Book-to-Market	Lagged cumulative return 2-3	Lagged cumulative return 4-6	Lagged cumulative return 7-12	Adj. R^2
Reg. I	0.76	-0.10	0.02	0.08	-0.07						0.15
	(3.1)	(-0.57)	(0.34)	(0.60)	(-3.03)						
	[3.15]***	[-0.55]	[0.34]	[0.56]	[-2.70]***						
Reg. 2	0.986	0.085	-0.005	0.012	-0.04	-0.314	1.044	0.025	0.026	0.018	0.20
	(1.71)	(0.49)	(-0.09)	(0.08)	(-2.06)	(-2.08)	(6.32)	(3.86)	(5.02)	(5.33)	
	[1.53]	[0.44]	[-0.09]	[0.07]	[-2.02]**	[-1.84]*	[5.27]***	[3.75]***	[4.97]***	[5.84]***	

This table presents the average coefficients from the monthly Fama and MacBeth's (1973) cross sectional regression using Fama and French's (1993) model as the asset pricing model. The sample period is from July 1981 to December 2005. In the second step regression, the independent variable which is the stock's excess return (t) is regressed on market beta (t), HML beta (t), SMB beta (t), past month idiosyncratic risk (t-1), one month lagged log of market capitalization, one month lagged log book-to-market value, three measures of past returns; returns cumulated over the previous (1) second to third months, (2) fourth to sixth (included) months and (3) seven to twelve (included) months. Idiosyncratic risk is measured as the standard deviation of the residuals from the first – step time series regression of Fama and French's (1993) model over the past month daily returns. T-statistics in parenthesis is Fama and MacBeth's (1973) statistics and t-statistics in square brackets are Newey-West (1987) statistics. Adj. R^2 is the average adjusted R^2. ***significant at 1%, ** at 5% and * at 10%

Table 3.2 OLS Daily Idiosyncratic Risk Portfolios

	Portfolios sorted on idiosyncratic risk											
	Lowest L	2	3	4	5	6	7	8	9	Highest H	Diff. (H-L) Alphas	Diff. (H-L) Returns
Alpha - FF (1993)	0.15 (0.68) [0.65]	0.45 (2.29)** [2.64]***	0.36 (1.95)* [2.17]**	0.14 (0.75) [0.87]	0.41 (2.05)** [1.97]**	0.15 (0.74) [0.75]	-0.17 (-0.71) [-0.79]	0.15 (0.53) [0.65]	0.01 (0.01) [0.01]	-0.39 (-0.72) [-0.77]	-0.54 (-0.82) [-0.85]	-1.69
Market Capitalization	2.99	3.09	3.05	3.02	2.98	2.89	2.82	2.68	2.47	2.04		
Book-to-Market	0.63	0.63	0.63	0.62	0.67	0.65	0.62	0.63	0.64	0.61		

This table presents the results of portfolio formation. Each month stocks are allocated into 10 deciles portfolios based on their idiosyncratic risk. Then the value weighted returns are calculated over one month. The sample period is from July 1981 to December 2005. Idiosyncratic risk is measured as the standard deviation of the residuals from the first – step time series regression of Fama and French's (1993) model over the past month daily returns. Alpha - FF (1993) is the Fama and French's (1993) alpha. Diff. (H-L) Alphas is the difference between Fama and French's (1993) alpha of the highest idiosyncratic risk portfolio and Fama and French's (1993) alpha of the lowest idiosyncratic risk portfolio. Diff. (H-L) Returns is the difference between the average monthly returns on the highest idiosyncratic risk portfolio and the average monthly returns on the lowest idiosyncratic risk portfolio. t-statistics are in parenthesis and the t-statistics in square brackets are Newey-West (1987) statistics. Market Capitalization is the average of the portfolio's constituents' log market capitalization and Book-to-Market is the average of the portfolio's constituents' log book-to-market value. ***significant at 1%, ** at 5% and * at 10%

Table 3.3 OLS Daily Idiosyncratic Risk Portfolios –Double Sorting

Panel (A): Portfolios sorted on idiosyncratic risk

Size Portfolios	Lowest L	2	3	4	5	6	7	8	9	Highest H	Diff. (H-L) Alphas
Smallest	1.01	1.41	0.87	0.55	0.59	-0.61	0.48	0.60	0.48	-1.53	-2.54
	(2.27)**	(3.74)***	(1.95)*	(1.32)	(1.13)	(-1.20)	(0.84)	(0.93)	(0.70)	(-1.73)*	(-2.56)**
2	0.27	1.04	1.04	0.77	0.26	0.47	0.38	0.51	0.16	-0.98	-1.25
	(0.80)	(3.58)***	(3.10)***	(2.08)**	(0.65)	(1.21)	(0.92)	(0.96)	(0.30)	(-1.44)	(-1.67)*
3	0.68	0.28	0.39	0.95	0.50	0.53	-0.55	0.32	0.46	0.03	-0.65
	(2.46)**	(0.92)	(1.08)	(3.14)***	(1.56)	(1.68)*	(-1.39)	(0.86)	(1.00)	(0.05)	(-0.95)
4	0.39	0.67	0.74	0.22	0.36	0.60	0.51	0.12	-0.39	0.02	-0.37
	(1.38)	(2.70)***	(2.82)***	(0.80)	(1.39)	(2.05)**	(1.57)	(0.35)	(-1.07)	(0.04)	(-0.58)
Largest	0.20	0.42	0.20	0.09	0.24	-0.08	0.54	-0.65	0.13	-0.02	-0.23
	(0.94)	(1.98)**	(0.93)	(0.43)	(1.05)	(-0.35)	(2.26)**	(-2.44)**	(0.46)	(-0.06)	(-0.48)
Idiosyncratic Portfolios controlled for size	0.51	0.76	0.65	0.52	0.39	0.18	0.27	0.18	0.17	-0.50	-1.01
	(2.91)***	(4.89)***	(3.67)***	(3.13)***	(2.04)**	(0.98)	(1.21)	(0.71)	(0.63)	(-1.29)	(-2.25)**
	[3.13]***	[4.78]***	[3.72]***	[2.88]***	[2.01]**	[0.86]	[1.36]	[0.63]	[0.62]	[-1.20]	[-2.14]**

Table (3.3) Continued

Panel (B): Portfolios sorted on idiosyncratic risk

Book-to-Market Portfolios	Lowest L	2	3	4	5	6	7	8	9	Highest H	Diff. (H-L) Alphas
Lowest	0.08	0.80	0.25	0.38	0.41	-0.57	-0.24	-0.74	-0.38	-0.61	-0.70
	(0.29)	(2.51)**	(0.75)	(1.12)	(0.99)	(-1.34)	(-0.49)	(-1.46)	(-0.59)	(-0.73)	(-0.77)
2	0.31	0.37	0.27	0.39	0.04	0.04	0.25	-0.61	0.03	-0.82	-1.13
	(1.11)	(1.25)	(0.86)	(1.23)	(0.11)	(0.11)	(0.56)	(-1.27)	(0.06)	(-1.22)	(-1.57)
3	0.59	0.83	0.37	0.36	-0.35	-0.09	-0.38	0.66	0.13	-0.17	-0.77
	(2.04)**	(3.19)***	(1.21)	(1.36)	(-1.09)	(-0.28)	(-1.13)	(1.70)*	(0.29)	(-0.27)	(-1.02)
4	0.24	0.47	0.46	0.02	0.86	0.81	0.53	0.68	0.23	1.05	0.81
	(0.81)	(1.84)*	(1.55)	(0.07)	(2.85)***	(2.84)***	(1.57)	(1.89)*	(0.56)	(1.70)*	(1.15)
Highest	0.80	0.61	1.21	0.98	1.05	1.19	1.08	0.71	0.74	-0.01	-0.81
	(2.68)***	(2.05)**	(3.83)***	(3.11)***	(3.39)***	(3.54)***	(2.65)***	(1.70)*	(1.68)*	(-0.01)	(-1.01)
Idiosyncratic Portfolios controlled for book-to-market value	0.40	0.61	0.51	0.42	0.40	0.28	0.25	0.14	0.15	-0.11	-0.52
	(2.44)**	(3.96)***	(3.11)***	(2.79)***	(2.23)**	(1.36)	(1.15)	(0.59)	(0.49)	(-0.29)	(-1.13)
	[1.82]*	[4.07]***	[3.44]***	[2.91]***	[2.56]**	[1.36]	[1.19]	[0.50]	[0.44]	[-0.23]	[-0.79]

This table presents the results of portfolio formation. Each month stocks are allocated into five portfolios based on their market capitalization (Panel A) or book-to-market value (Panel B) and then within each size or book-to-market portfolio, stocks are allocated into 10 deciles portfolios based on their idiosyncratic risk. Then the value weighted returns are calculated over one month. The sample period is from July 1981 to December 2005. Idiosyncratic risk is measured as the standard deviation of the residuals from the first – step time series regression of Fama and French's (1993) model over the past month daily returns. The Table presents the Fama and French's (1993) alphas for each of the resulting 50 portfolios. Diff. (H-L) Alphas is the difference between Fama and French's (1993) alpha of the highest idiosyncratic risk portfolio and Fama and French's (1993) alpha of the lowest idiosyncratic risk portfolio. Idiosyncratic Portfolios controlled for size, and Idiosyncratic Portfolios controlled for book-to-market value present the portfolios results from averaging idiosyncratic risk portfolios across size and book-to-market value respectively. t-statistics are in parenthesis and the t-statistics in square brackets are Newey-West (1987) statistics. ***significant at 1%, ** at 5% and * at 10%

Table 3.4 Cross-Sectional Regression with OLS Monthly Idiosyncratic Risk

	Intercept	Idiosyncratic risk	Market capitalization (size)	Book-to-Market	Lagged cumulative return *2-3*	Lagged cumulative return *4-6*	Lagged cumulative return *7-12*	*Adj.* R^2
Reg.1	0.239	-0.016						0.01
	(1.21)	(-0.85)						
	[1.03]	[-0.69]						
Reg.2	0.328	0.034	-0.063	2.024	0.009	0.019	0.013	0.03
	(1.39)	(2.01)**	(-0.98)	(15.12)***	(2.00)**	(6.07)***	(6.31)***	
	[1.06]	[1.63]	[-0.70]	[11.31]***	[1.81]*	[5.51]***	[5.47]***	

This table presents the average coefficients from the monthly Fama and MacBeth's (1973) cross sectional regression using Fama and French's (1993) model as the asset pricing model. The sample period is from July 1981 to December 2005. In the second step regression, the independent variable which is the stock's risk adjusted returns is regressed on idiosyncratic risk, one month lagged log of market capitalization, one month lagged log book-to-market value, three measures of past returns; returns cumulated over the previous (1) second to third months, (2) fourth to sixth (included) months and (3) seven to twelve (included) months. Idiosyncratic risk is measured as the standard deviation of the residuals from the first – step time series regression of Fama and French's (1993) model over the past 60 monthly returns. T-statistics in parenthesis is Fama and MacBeth's (1973) statistics and t-statistics in square brackets are Newey-West (1987) statistics. Adj. R^2 is the average adjusted R^2. ***significant at 1%, ** at 5% and * at 10%

Table 3.5 OLS Monthly Idiosyncratic Risk Portfolios

	Portfolios sorted on idiosyncratic risk											
	Lowest L	2	3	4	5	6	7	8	9	Highest H	Diff. (H-L) Alphas	Diff. (H-L) Returns
Alpha - FF (1993)	-0.04 (-0.30) [-0.35]	-0.01 (-0.07) [-0.08]	0.18 (1.03) [1.15]	-0.03 (-0.18) [-0.18]	0.48 (2.31)** [1.89]*	0.13 (0.46) [0.52]	-0.33 (-1.13) [-1.28]	-0.07 (-0.22) [-0.21]	-0.12 (-0.28) [-0.25]	-0.17 (-0.36) [-0.29]	-0.13 (-0.24) [-0.20]	-1.5
Market Capitalization	2.36	2.33	2.18	2.00	1.86	1.70	1.59	0.77	1.35	1.18		
Book-to-Market	1.36	0.93	0.93	0.74	0.76	0.77	1.47	0.79	0.71	0.75		

This table presents the results of portfolio formation. Each month stocks are allocated into 10 deciles portfolios based on their idiosyncratic risk. Then the value weighted returns are calculated over one month. The sample period is from July 1981 to December 2005. Idiosyncratic risk is measured as the standard deviation of the residuals from the first – step time series regression of Fama and French's (1993) model over the past 60 monthly returns. Alpha - FF (1993) is the Fama and French's (1993) alpha. Diff. (H-L) Alphas is the difference between Fama and French's (1993) alpha of the highest idiosyncratic risk portfolio and Fama and French's (1993) alpha of the lowest idiosyncratic risk portfolio. Diff. (H-L) Returns is the difference between the average monthly returns on the highest idiosyncratic risk portfolio and the average monthly returns on the lowest idiosyncratic risk portfolio. t-statistics is in parenthesis and the t-statistics in square brackets are Newey-West (1987) statistics. Market Capitalization is the average of the portfolio's constituents' log market capitalization and Book-to-Market is the average of the portfolio's constituents' log book-to-market value. ***significant at 1%, ** at 5% and * at 10%

Table 3.6 OLS Monthly Idiosyncratic Risk Portfolios – Double Sorting

Panel (A): Portfolios sorted on idiosyncratic risk

Size Portfolios	Lowest L	2	3	4	5	6	7	8	9	Highest H	Diff. (H-L) Alphas
Smallest	0.05	0.30	0.35	0.14	0.26	0.15	0.04	-0.57	-0.68	-1.39	-1.45
	(0.30)	(1.31)	(1.44)	(0.55)	(0.87)	(0.53)	(0.15)	(-1.42)	(-1.75)*	(-3.02)***	(-2.94)***
2	-0.14	0.15	0.30	-0.14	0.00	-0.15	-0.72	-0.17	0.17	-0.84	-0.69
	(-0.88)	(0.85)	(1.60)	(-0.73)	(0.01)	(-0.70)	(-2.76)***	(-0.62)	(0.58)	(-2.04)**	(-1.48)
3	0.47	0.33	-0.12	0.12	0.12	0.39	0.09	0.27	-0.47	-0.89	-1.36
	(2.90)***	(1.93)*	(-0.62)	(0.57)	(0.59)	(1.87)*	(0.38)	(1.11)	(-1.38)	(-2.41)**	(-3.22)***
4	0.43	0.42	0.50	0.30	0.24	0.14	0.45	0.21	0.02	0.07	-0.36
	(2.64)***	(2.20)**	(2.57)**	(1.53)	(1.20)	(0.69)	(2.05)**	(0.93)	(0.05)	(0.18)	(-0.88)
Largest	0.01	0.17	0.26	0.31	0.30	0.04	0.06	0.17	-0.02	-0.18	-0.18
	(0.05)	(1.15)	(1.80)*	(1.88)*	(1.76)*	(0.24)	(0.34)	(0.87)	(-0.09)	(-0.42)	(-0.36)
Idiosyncratic Portfolios controlled for size	0.16	0.27	0.26	0.15	0.19	0.11	-0.01	-0.02	-0.20	-0.65	-0.80
	(1.59)	(2.31)**	(2.13)**	(1.23)	(1.46)	(0.96)	(-0.11)	(-0.12)	(-0.98)	(-2.42)**	(-2.57)**
	[1.21]	[2.28]**	[1.68]*	[1.11]	[1.26]	[0.89]	[-0.11]	[-0.11]	[-0.71]	[-1.77]*	[-1.74]*

Table (3.6) Continued

Panel (B): Portfolios sorted on idiosyncratic risk

Book-to-Market Portfolios	Lowest L	2	3	4	5	6	7	8	9	Highest H	Diff. (H-L) Alphas
Lowest	-0.07	0.05	0.12	-0.03	-0.27	-0.69	-0.64	-0.61	-0.57	-1.50	-1.43
	(-0.49)	(0.27)	(0.63)	(-0.15)	(-1.07)	(-2.36)**	(-2.00)**	(-1.61)	(-1.37)	(-3.28)***	(-2.94)***
2	0.21	0.20	0.21	0.10	0.14	0.13	0.37	-0.32	-0.64	-0.30	-0.51
	(1.63)	(1.33)	(1.26)	(0.55)	(0.79)	(0.65)	(1.70)*	(-1.17)	(-2.21)**	(-0.82)	(-1.24)
3	0.26	0.26	0.31	-0.02	0.05	0.09	0.54	0.38	0.03	0.40	0.14
	(1.76)*	(1.51)	(1.63)	(-0.12)	(0.25)	(0.40)	(2.39)**	(1.63)	(0.12)	(1.08)	(0.32)
4	0.35	0.46	0.45	0.46	0.24	0.15	0.08	0.36	0.32	0.94	0.59
	(2.01)**	(2.42)**	(2.22)**	(2.05)**	(1.01)	(0.66)	(0.40)	(1.37)	(1.05)	(2.76)***	(1.46)
Highest	0.57	0.63	0.88	0.44	0.39	0.69	0.99	1.21	0.87	1.41	0.83
	(3.40)***	(3.16)***	(4.57)***	(2.03)**	(1.81)*	(2.65)***	(3.47)***	(4.08)***	(2.47)**	(3.55)***	(1.88)*
Idiosyncratic Portfolios controlled for book-to-market value	0.26	0.32	0.39	0.19	0.11	0.07	0.27	0.20	0.00	0.19	-0.07
	(2.66)***	(2.68)***	(3.57)***	(1.34)	(0.94)	(0.52)	(1.92)*	(1.27)	(0.01)	(0.76)	(-0.25)
	[2.05]**	[2.32]**	[2.79]***	[1.12]	[0.78]	[0.49]	[1.77]*	[1.08]	[0.01]	[0.53]	[-0.16]

This table presents the results of portfolio formation. Each month stocks are allocated into five portfolios based on their market capitalization (Panel A) or book-to-market value (Panel B) and then within each size or book-to-market portfolio, stocks are allocated into 10 deciles portfolios based on their idiosyncratic risk. Then the value weighted returns are calculated over one month. The sample period is from July 1981 to December 2005. Idiosyncratic risk is measured as the standard deviation of the residuals from the first – step time series regression of Fama and French's (1993) model over the past 60 monthly returns. The Table presents the Fama and French's (1993) alphas for each of the resulting 50 portfolios. Diff. (H-L) Alphas is the difference between Fama and French's (1993) alpha of the highest idiosyncratic risk portfolio and Fama and French's (1993) alpha of the lowest idiosyncratic risk portfolio. Idiosyncratic Portfolios controlled for size, and Idiosyncratic Portfolios controlled for book-to-market value present the portfolios results from averaging idiosyncratic risk portfolios across size and book-to-market value respectively. t-statistics is in parenthesis and the t-statistics in square brackets are Newey-West (1987) statistics. ***significant at 1%, ** at 5% and * at 10%

Table 3.7 Cross-Sectional Regression with EGARCH (1, 1) Idiosyncratic Risk

	Intercept	Idiosyncratic risk	Market capitalization (size)	Book-to-Market	Lagged cumulative return *2-3*	Lagged cumulative return *4-6*	Lagged cumulative return *7-12*	*Adj.* R^2
Reg.1	0.341 (2.73) [2.31]**	-0.023 (-2.22) [-2.08]**						0.01
Reg.2	0.755 (3.75) [3.70]***	0.002 (0.22) [0.23]	-0.125 (-1.76) [-1.47]	1.824 (11.99) [9.26]***	0.007 (1.50) [1.44]	0.019 (5.57) [4.83]***	0.013 (6.06) [5.86]***	0.03

This table presents the average coefficients from the monthly Fama and MacBeth's (1973) cross sectional regression using Fama and French's (1993) model as the asset pricing model. The sample period is from July 1981 to December 2005. In the second step regression, the independent variable which is the stock's risk adjusted returns is regressed on idiosyncratic risk, one month lagged log of market capitalization, one month lagged log book-to-market value, three measures of past returns; returns cumulated over the previous (1) second to third months, (2) fourth to sixth (included) months and (3) seven to twelve (included) months. Idiosyncratic risk is based on EGARCH (1, 1) which is estimated using all prior monthly returns. T-statistics in parenthesis is Fama and MacBeth's (1973) statistics t-statistics in square brackets is Newey-West (1987) statistics. Adj. R^2 is the average adjusted R^2.
***significant at 1%, ** at 5% and * at 10%

Table 3.8 EGARCH (1, 1) Idiosyncratic Risk Portfolios

	Portfolios sorted on idiosyncratic risk										
	Lowest L	2	3	4	5	6	7	8	9	Highest H	Diff. (H-L) Alphas	Diff. (H-L) Returns
Alpha - FF (1993)	0.04 (0.25) [0.27]	-0.05 (-0.34) [-0.37]	0.29 (1.79)* [1.38]	0.05 (0.22) [0.25]	-0.12 (-0.57) [-0.58]	-0.03 (-0.15) [-0.13]	0.43 (1.57) [1.62]	0.05 (0.15) [0.12]	-0.35 (-1.04) [-1.09]	-1.12 (-2.46)** [-2.70]***	-1.15 (-2.22)** [-2.42]**	-2.14
Market Capitalization	2.29	2.42	2.32	2.21	2.10	1.98	1.88	1.74	1.60	1.43		
Book-to-Market	0.73	0.70	1.89	0.99	0.78	0.77	0.77	0.77	0.78	0.87		

This table presents the results of portfolio formation. Each month stocks are allocated into 10 deciles portfolios based on their idiosyncratic risk. Then the value weighted returns are calculated over one month. The sample period is from July 1981 to December 2005. Idiosyncratic risk is based on EGARCH (1, 1) which is estimated using all prior monthly returns with Fama and French's (1993) model is the mean equation. Alpha - FF (1993) is the Fama and French's (1993) alpha. Diff. (H-L) Alphas is the difference between Fama and French's (1993) alpha of the highest idiosyncratic risk portfolio and Fama and French's (1993) alpha of the lowest idiosyncratic risk portfolio. Diff. (H-L) Returns is the difference between the average monthly returns on the highest idiosyncratic risk portfolio and the average monthly returns on the lowest idiosyncratic risk portfolio. t-statistics is in parenthesis and the t-statistics in square brackets are Newey-West (1987) statistics. Market Capitalization is the average of the portfolio's constituents' log market capitalization and Book-to-Market is the average of the portfolio's constituents' log book-to-market value. ***significant at 1%, ** at 5% and * at 10%

Table 3.9 EGARCH (1, 1) Idiosyncratic Risk Portfolios – Double Sorting

Panel (A): Portfolios sorted on idiosyncratic risk

Size Portfolios	Lowest L	2	3	4	5	6	7	8	9	Highest H	Diff. (H-L) Alphas
Smallest	0.36	0.30	0.12	0.31	-0.10	0.12	-0.37	-0.06	-0.76	-0.55	-0.91
	(1.36)	(1.35)	(0.46)	(1.16)	(-0.36)	(0.36)	(-0.98)	(-0.17)	(-1.96)*	(-1.08)	(-1.63)
											[-1.63]
2	-0.27	0.25	0.47	0.24	-0.09	-0.15	-0.09	-0.51	-0.47	-0.89	-0.62
	(-1.21)	(1.12)	(2.11)**	(0.99)	(-0.34)	(-0.59)	(-0.31)	(-1.84)*	(-1.48)	(-2.22)**	(-1.35)
3	0.48	0.58	0.38	0.42	0.53	0.33	0.14	0.10	0.07	-0.55	-1.03
	(2.09)**	(2.70)**	(1.84)*	(2.08)**	(2.48)**	(1.37)	(0.54)	(0.35)	(0.24)	(-1.49)	(-2.46)**
4	0.12	0.35	0.35	0.37	0.62	0.18	0.16	0.06	-0.07	-0.26	-0.38
	(0.55)	(1.59)	(1.49)	(1.79)*	(2.93)***	(0.75)	(0.67)	(0.22)	(-0.26)	(-0.71)	(-0.93)
Largest	0.33	0.12	0.05	0.13	0.35	0.20	0.17	0.35	-0.16	-0.20	-0.53
	(1.90)*	(0.75)	(0.31)	(0.84)	(1.80)*	(0.98)	(0.86)	(1.61)	(-0.65)	(-0.56)	(-1.27)
Idiosyncratic Portfolios controlled for size	0.20	0.32	0.28	0.29	0.26	0.13	0.00	-0.01	-0.28	-0.49	-0.69
	(1.62)	(2.52)**	(2.15)**	(2.39)**	(1.99)**	(0.97)	(0.01)	(-0.08)	(-1.61)	(-2.03)**	(-2.45)**
	[1.55]	[2.13]**	[1.82]*	[2.06]**	[1.81]*	[0.86]	[0.01]	[-0.06]	[-1.46]	[-1.79]*	[-2.06]**

Table (3.9) Continued

Panel (B): Portfolios sorted on idiosyncratic risk

Book-to-Market Portfolios	Lowest L	2	3	4	5	6	7	8	9	Highest H	Diff. (H-L) Alphas
Lowest	0.02	0.05	0.03	0.15	-0.38	-0.01	-0.04	-0.41	-1.29	-1.46	-1.48
	(0.09)	(0.27)	(0.17)	(0.68)	(-1.78)*	(-0.02)	(-0.12)	(-1.16)	(-3.20)***	(-3.11)***	(-2.89)***
2	0.54	-0.01	0.05	0.33	0.62	-0.07	0.08	0.14	-0.54	-0.84	-1.38
	(3.04)***	(-0.08)	(0.26)	(1.71)*	(3.19)***	(-0.29)	(0.33)	(0.62)	(-1.92)*	(-2.50)**	(-3.74)***
3	0.00	0.08	0.54	0.47	0.21	0.45	0.32	0.13	0.36	0.21	0.22
	(-0.02)	(0.38)	(2.76)***	(2.32)**	(0.98)	(1.81)*	(1.21)	(0.54)	(1.07)	(0.60)	(0.54)
4	0.12	0.20	0.50	0.79	0.29	0.52	0.08	-0.20	0.64	0.17	0.05
	(0.49)	(0.92)	(2.18)**	(3.58)***	(1.38)	(2.29)**	(0.34)	(-0.71)	(2.16)**	(0.44)	(0.12)
Highest	0.43	0.87	0.88	0.46	0.63	0.79	0.55	0.76	0.75	1.10	0.68
	(2.08)**	(4.34)***	(3.71)***	(1.95)*	(2.59)**	(2.75)***	(2.16)**	(2.21)**	(1.95)*	(2.48)**	(1.46)
Idiosyncratic Portfolios controlled for book-to-market value	0.22	0.24	0.40	0.44	0.27	0.34	0.20	0.08	-0.02	-0.16	-0.38
	(1.77)*	(1.91)*	(3.10)***	(3.14)***	(2.10)**	(2.30)**	(1.42)	(0.56)	(-0.09)	(-0.76)	(-1.55)
	[1.35]	[1.49]	[2.47]**	[2.58]**	[1.74]*	[1.94]*	[1.22]	[0.50]	[-0.07]	[-0.67]	[-1.25]

This table presents the results of portfolio formation. Each month stocks are allocated into five portfolios based on their market capitalization (Panel A) or book-to-market value (Panel B) and then within each size or book-to-market portfolio, stocks are allocated into 10 deciles portfolios based on their idiosyncratic risk. Then the value weighted returns are calculated over one month. The sample period is from July 1981 to December 2005. Idiosyncratic risk is based on EGARCH (1, 1) which is estimated using all prior monthly returns with Fama and French's (1993) model is the mean equation. The Table presents the Fama and French's (1993) alphas for each of the resulting 50 portfolios. Diff. (H-L) Alphas is the difference between Fama and French's (1993) alpha of the highest idiosyncratic risk portfolio and Fama and French's (1993) alpha of the lowest idiosyncratic risk portfolio. Idiosyncratic Portfolios controlled for size, and Idiosyncratic Portfolios controlled for book-to-market value present the portfolios results from averaging idiosyncratic risk portfolios across size and book-to-market value respectively. t-statistics is in parenthesis and the t-statistics in square brackets are Newey-West (1987) statistics. ***significant at 1%, ** at 5% and * at 10%

Table 3.10 Avramov and Chordia's (2006) Time Varying Beta Fama and French's (1993) Model with OLS Monthly Idiosyncratic Risk

	Intercept	Idiosyncratic volatility	Market capitalization (size)	Book-to-Market	Lagged cumulative return *2-3*	Lagged cumulative return *4-6*	Lagged cumulative return *7-12*	*Adj. R2*
Reg.1	-0.563	0.080						0.001
	(-0.97)	(1.36)						
	[-0.99]	[1.55]						
Reg.2	-0.359	0.096	0.483	3.915	-0.005	0.014	-0.004	0.05
	(-0.41)	(1.42)	(1.29)	(2.09)	(-0.11)	(0.94)	(-0.28)	
	[-0.47]	[1.59]	[1.24]	[2.03]**	[-0.12]	[0.86]	[-0.28]	

This table presents the average coefficients from the monthly Fama and MacBeth's (1973) cross sectional regression using Fama and French's (1993) model as the asset pricing model. The sample period is from July 1981 to December 2005. In the first-step regression the model is Equation (3) with r_{mt} is replaced by a vector of market, SMB and HML. The independent variable in the second step regression is the stock's risk adjusted return. Idiosyncratic risk is measured as the standard deviation of the residuals from the above time-series model estimated using past 60 monthly returns as before. T-statistics in parenthesis is Fama and MacBeth's (1973) statistics and t-statistics in square brackets is Newey-West (1987) statistics. Adj. R^2 is the average adjusted R^2. ***significant at 1%, ** at 5% and * at 10%

Table 3.11 Avramov and Chordia's (2006) Time Varying Beta Fama and French's (1993) Model with EGARCH (1, 1) Idiosyncratic Risk

	Intercept	Idiosyncratic volatility	Market capitalization (size)	Book-to-Market	Lagged cumulative return *2-3*	Lagged cumulative return *4-6*	Lagged cumulative return *7-12*	*Adj. R2*
Reg.1	-0.075	0.027						0.0004
	(-0.12)	(0.47)						
	[-0.14]	[0.48]						
Reg.2	-0.200	0.044	0.213	1.434	0.013	0.001	0.024	0.05
	(-0.24)	(0.78)	(0.73)	(0.78)	(0.62)	(0.04)	(1.51)	
	[-0.27]	[0.81]	[0.68]	[0.73	[0.57]	[0.04]	[1.53]	

This table presents the average coefficients from the monthly Fama and MacBeth's (1973) cross sectional regression using Fama and French's (1993) model as the asset pricing model. The sample period is from July 1981 to December 2005. In the first-step EGARCH (1, 1) is estimated with the mean equation being Equation (3) with r_{mt} is replaced by a vector of market, SMB and HML. The independent variable in the second step regression is the stock's risk adjusted return. Idiosyncratic risk is based on EGARCH (1, 1) estimated in the first step using all prior monthly returns as before. T-statistics in parenthesis is Fama and MacBeth's (1973) statistics and t-statistics in square brackets is Newey-West (1987) statistics. Adj. R^2 is the average adjusted R^2. ***significant at 1%, ** at 5% and * at 10%

Table 3.12 Avramov and Chordia's (2006) Time Varying Beta Fama and French's (1993) Model with Idiosyncratic Risk Portfolios

	Portfolios sorted on idiosyncratic risk										
	Lowest L	2	3	4	5	6	7	8	9	Highest H	Diff. (H-L) Alphas
Panel (A): Portfolios sorted on Idiosyncratic Risk based on OLS with monthly returns											
Single sorting	0.26	0.02	-0.54	0.49	0.30	0.27	0.22	0.38	0.00	0.24	-0.03
	(1.45)	(0.11)	(-2.38)**	(2.25)**	(1.29)	(1.09)	(0.92)	(1.49)	(0.01)	(0.74)	(-0.07)
	[1.50]	[0.11]	[-2.01]**	[2.64]***	[1.34]	[1.36]	[1.04]	[1.39]	[0.01]	[0.78]	[-0.09]
Controlling for size	0.19	0.07	0.07	-0.11	-0.12	0.30	0.25	0.08	0.42	0.23	0.04
	(1.24)	(0.44)	(0.43)	(-0.76)	(-0.82)	(1.97)**	(1.77)*	(0.47)	(2.64)***	(1.33)	(0.20)
	[1.35]	[0.46]	[0.48]	[-0.67]	[-0.73]	[1.89]*	[1.38]	[0.42]	[2.21]**	[1.04]	[0.17]
Controlling for boo-to-market	0.25	0.24	0.08	0.49	0.43	0.37	0.34	0.28	0.44	0.27	0.02
	(1.32)	(1.32)	(0.40)	(2.89)***	(1.91)*	(1.95)*	(1.66)*	(1.28)	(2.17)**	(1.21)	(0.08)
	[1.38]	[1.13]	[0.30]	[2.58]**	[1.86]*	[2.35]**	[1.82]*	[1.27]	[2.58]**	[1.68]*	[0.10]
Panel (B): Portfolios sorted on Idiosyncratic Risk based on EGARCH with monthly returns											
Single sorting	0.09	0.23	0.50	0.16	-0.43	-0.13	-0.63	0.20	0.75	0.21	0.12
	(0.39)	(0.99)	(2.05)**	(0.66)	(-1.62)	(-0.54)	(-2.73)***	(0.76)	(2.87)***	(0.78)	(0.32)
	[0.43]	[1.10]	[2.23]**	[0.82]	[-1.16]	[-0.50]	[-2.80]***	[0.95]	[2.59]**	[0.82]	[0.39]
Controlling for size	0.08	-0.10	0.16	0.07	0.09	0.18	-0.12	-0.34	0.13	0.22	0.14
	(0.60)	(-0.70)	(1.25)	(0.52)	(0.60)	(1.33)	(-0.88)	(-2.42)**	(0.95)	(1.57)	(0.70)
	[0.56]	[-0.73]	[1.29]	[0.57]	[0.65]	[1.41]	[-0.80]	[-2.77]***	[0.89]	[1.57]	[0.67]
Controlling for book-to-market	0.43	0.10	0.33	0.23	0.31	0.23	0.06	0.33	0.44	0.53	0.10
	(2.03)**	(0.53)	(1.81)*	(1.32)	(1.63)	(1.23)	(0.31)	(1.83)*	(2.27)**	(2.50)**	(0.36)
	[1.86]*	[0.40]	[1.66]*	[1.11]	[1.20]	[1.18]	[0.30]	[2.02]**	[2.76]***	[2.90]***	[0.45]

This table presents the results of portfolio formation. The sample period is from July 1981 to December 2005. Single sorting presents monthly allocation of stocks into 10 deciles portfolios based on their idiosyncratic risk. Then the value weighted returns are calculated over one month. Controlling for size and Controlling for book-to-market present the portfolios that results from averaging idiosyncratic risk portfolios across size and book-to-market value respectively, where stocks are first allocated into five portfolios based on their market capitalization or book-to-market value and then within each size or book-to-market portfolio, stocks are allocated into 10 deciles portfolios based on their idiosyncratic risk, then the value weighted returns are calculated over one month. The Table presents the Fama and French's (1993) alphas for the single and double sorting portfolios. In Panel (A) idiosyncratic risk is measured as in Table (3.10) and in Panel (B) idiosyncratic risk is measured as in Table (3.11). Diff. (H-L) Alphas is the difference between Fama and French's (1993) alpha of the highest idiosyncratic risk portfolio and Fama and French's (1993) alpha of the lowest idiosyncratic risk portfolio. t-statistics is in parenthesis and the t-statistics in square brackets are Newey-West (1987) statistics. ***significant at 1%, ** at 5% and * at 10%

Chapter 4 Downside Risk and Business Cycle

4.1 Introduction

> "The attraction of the CAPM is that it offers powerful and intuitively pleasing predictions about how to measure risk and the relation between expected return and risk. Unfortunately, the empirical record of the model is poor-poor enough to invalidate the way it is used in applications. The CAPM's empirical problems may reflect theoretical failings, the result of many simplifying assumptions. But they may also be caused by difficulties in implementing valid tests of the model." (Fama and French (2004, first page (p.25))).

Sharpe (1964) states that, in developing his capital asset pricing model, investors are assumed to be risk-averse and the investor's utility function is based on the expected return and its standard deviation. Levy and Markowitz (1979) point out that several researchers stressed that either the normality assumption or the quadratic utility function assumption should hold in order for the mean-variance rule to deliver the right solution. Furthermore, Sarnat (1974) indicates that the problems of the quadratic utility function that are discussed by others are the increasing absolute risk aversion and ultimate satiation. He points out but the mean-variance criterion is still valid as long as returns are normally distributed.

On the other hand, Post and Vliet (2006) point out that stock returns are not normal but kurtoic and positively skewed and Pedersen and Hwang (2007) report that normality assumption is rejected for high frequency returns in the UK. Post and Vliet (2006) point out that in light of the evidence that is not in favour of the variance, a criterion that considers the higher and lower moments of the distribution of returns should substitute the mean-variance rule. In fact, Markowitz (1959) points out that the semi-variance, which focuses on losses, is better than the variance, but when the returns distributions are normal both have similar results. Bawa and Lindenberg (1977) develop a mean-lower partial moment capital asset pricing model that uses the mean-lower partial moment beta as a measure of risk.

More recently, Ang, Chen and Xing (2006) propose a model which assumes investors with a disappointment utility function. They reported that they find around 6% annual cross-sectional downside risk premium in the US stock market. They point out that the reason that previous studies fail to find strong support for downside risk is that these studies did not examine all individual stocks. Furthermore Ang, Chen and Xing (2006) point out that their methodology has a statistical power advantage to capture time variation in beta. Despite of all of this, Post and Vliet (2005) criticize Ang, Chen and Xing's (later published as Ang Chen and Xing (2006[26])) methodology. More specifically, Post and Vliet (2005) point out that the latter study does not perform a conditional downside risk's tests. Indeed, although Ang, Chen and Xing (2006) allow for beta to be time-varying but do not allow for time-variation in downside risk premium.

Fama and French (1989) reported that they find a negative relation between expected risk premium and economic (business cycle) conditions. They argue that this is

[26] Post and Vliet (2005) uses and cites Ang Chen Xing (2004), which is missed from the references' section of Post and Vliet (2005). On the other hand, Post and Vliet (2005) use Equation (5) of downside beta of Ang Chen and Xing (2004), the same equation is given in Ang Chen and Xing (2006). Therefore, I anticipate that Post and Vliet (2005) using the paper that is later published as Ang, Chen and Xing (2006),

in line with the consumption smoothing of the inter-temporal asset pricing models. Even more, Cochrane (2006) points out that when the marginal utility of investor's wealth is high in bad times of the economy, expected return is high. The time-varying risk premium is supported by Ferson, Kandel and Stambaugh (1987), and Lettau and Ludvigson (2001).

Post and Vliet (2005) overcome this problem. They point out that they perform conditional tests to take into account the time variation in risk and risk aversion and this allow for market risk premium of downside risk to be time-varying conditional on the economic conditions. They reported that they find downside beta in the US captures the cross-sectional variation in returns on stocks superiorly better than beta of the CAPM. Furthermore, they pointed out that they find this occurs in particular in bad times of the economy. However, Post and Vliet (2005) state that their findings of the superiority of downside risk over beta of the CAPM is not strong over Ang, Chen and Xing's (later published as Ang Chen and Xing (2006)) sample period. In addition, Post and Vliet (2005) point out that the two studies differ in the methodology and the data. This raises the issue of whether the priced downside risk premium that has been found by Ang Chen and Xing (2006) is applicable during all the stages of the business cycle, or during a particular economic state as Post and Vleit (2005) find that downside risk has almost perfect relationship with returns in bad times.

Therefore, downside risk-return relationship of Ang, Chen and Xing (2006) conditional on the economic conditions needs to be investigated. This chapter attempts to study this issue. It starts by first examining the relationship between downside risk and returns on stocks by applying Ang, Chen and Xing's (2006) study on the UK market. Then it follows Post and Vliet's (2005) downside risk conditional test approach which includes splitting the full sample period into two periods. In the next step it reapplies Ang Chen and Xing's (2006) study over the recession and expansion periods, separately. This allows downside risk premium to vary with the business cycle conditions. Post and Vliet (2005) indicate that they conduct the conditioning test by splitting sample period into two periods of good and bad times and then re-conduct the test for these two periods separately and argue this is a simple conditioning approach.

Therefore, this chapter contributes to downside risk literature by first examining Ang, Chen and Xing's (2006) downside risk premium conditional on business cycle conditions and secondly, by providing an out-of-sample test for Ang, Chen and Xing's (2006) study. This is an important robustness exercise. Ang, Chen and Xing (2006) point out that the investor in their downside risk model is more concerned about losses than is attracted to gains. However, there is no reason to believe that investors in the UK market have such preferences. Blake (1996) reports that he finds a 35.04 weighted–average coefficient of relative risk aversion in UK. In addition Blake (1996) points out that Mankiw and Zeldes (1991) finds a 26.3 coefficient for USA. Black and Fraser (2000) point out that they find the UK investors are highly affected by future economic uncertainty, and different from investors in the other countries including the US[27].

[27] Black and Fraser's (2000) study sample includes UK, Germany, USA, Australia, and Japan.

The remainder of the chapter is organized as follows: Section (4.2) includes the relevant literature review on downside risk and time-varying risk premium. Section (4.3) develops the chapter's testable hypotheses. Section (4.4) discusses the data and the methodology, followed by Section (4.5) which discusses the findings. Finally Section (4.6) concludes.

4.2 Literature Review

4.2.1 Downside Beta

Sharpe (1964) states that, in developing his CAPM, investor's preference is summarized by the expected return and its square root of variance (standard deviation). Markowitz (1959) points out that the positive and negative extreme returns are treated similarly under the variance. Bawa and Lindenberg (1977) use the lower partial movement as measure of risk. They indicate that a criterion that uses this measure of risk along with the mean to be the measure of return works under any distribution of returns on stocks and the mean-variance framework becomes a special case of this mean-lower partial moment rule when normality assumption holds. Nawrocki[28] (1999) points out that the lower-partial moment accommodates different types of utility functions of Von Neumann- Morgenstern as well as different risk attitudes and hence does not restrict the analysis to the quadratic utility function as in the case of variance and semi-variance measures of risk.

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[28] Available at http:// www56.homepage. villanova.edu/david.nawrocki/ Brief%20History %20of %20 Downside%20Risk%20-%20Nawrocki.pdf

For the definition of downside risk, Price, Price and Nantell (1982) define the lower partial moment as a risk measure that is function of the returns dropping below a particular target, where the reference is to portfolio's risk and return. Bawa and Lindenberg (1977) define the lower-partial moment risk as the risk that occurs when the market return falls below the risk-free rate of return. They point out that this latter rate of return is an opportunity cost that results form investor's choice of making risky investment.[29] Ang, Chen and Xing (2006) use average market excess returns as well as zero return and risk free rate of return as cutoff points for measuring downside risk. In addition, Ang, Chen and Xing (2006) define upside risk as the covariance of stock's return with the market return when the latter is above the cutoff point.

As mentioned earlier, Bawa and Lindenberg (1977) developed an equilibrium capital asset pricing model which employs the mean-lower partial moment. Bawa and Lindenberg (1977, p.196, Eq.4 and Eq.5) derive the model as

$$E(R_j)-r_F=\beta_j^{MLPM_n}(E(R_M)-r_F) \qquad j=1,2,\ldots,M. \tag{1}$$

$$\beta_j^{MLPM_n}=\frac{CLPM_n(r_F;M,j)}{LPM_n(r_F;M)} \tag{2}$$

Equations (1) and (2) above are in Bawa and Lindenberg's (1977) notations. They define the notations in the above equations as follow: $CLPM_n(r_F;M,j)$ as colower partial moment (n), M, R_M, R_j *as* market portfolio, its return, and stock's j return, respectively, r_F as risk-free rate, and)$LPM_n(r_F;M$ as market portfolio's lower partial moment (n) at

[29] Harlow and Rao (1989) point out that they find the target rate based on empirical data is the average market returns

r_F[30]. Bawa and Lindenberg (1977) point out that in this framework if market return is lower than the riskless rate of returns, then market portfolio will have risk.

In a recent study, Post and Vliet (2006) pointed out that they find the proxy for market portfolio is inefficient based on mean-variance rule but it is third-order stochastic dominance efficient and this mean-variance inefficiency can be explained by downside risk. They mention that the strong case for the mean-variance rule to be substituted with general rule comes from the empirical findings of the non-normality of returns on stocks' distribution and the psychological evidence of risk perception. Furthermore, they point out that although the issue of mean-variance inefficiency can be accounted for by other possible explanations, still a downside risk-based generalized CAPM can capture a number of financial anomalies.

Price, Price and Nantell (1982) formulate a theorem, in which they point out that when returns are lognormal, a risk measure that is based on variance or lower-partial moment will be equal only for stocks with average systematic risk, but for stocks with high (low) systematic risk the former will be higher (lower) than the latter. They reported that they find empirical differences between these two measures of risk for the last two groups of stocks. They point out that this finding supports the model of Bawa and Lindenberg. Kim and Zumwalt (1979) developed what they call a two-beta model. They point out that this model divides the systematic risk in the single-market model into two components; down-market systematic risk and up-market systematic risk. They reported

[30] See Bawa and Lindenberg (1977, p.192) for technical details of LPM_n definition.

that they find that down-market beta is compensated with positive risk premium but up-market beta has a negative price of risk. They point out that this is interpreted as while investors are ready to pay for taking upside risk, they require for downside risk a positive premium. Chen (1982) points out that Kim and Zumwalt's model suffers from heteroskedasticity that results from time-varying betas and from multicolinearity and these problems can be overcome by Bayesian time-varying beta model. He points out that the two-beta model is still valid under time-varying betas. He reports that he finds this time-varying model's findings confirm those of Kim and Zumwalt that investors ask for a positive premium for down-market risk while accept a negative premium for up-market risk. Furthermore, Chen (1982) points out that these results verify that downside beta is a better risk measure than the single market beta.

On the other hand Jahankhani (1976) indicates that the appropriateness of portfolio's variance as its risk measure needs to be studied in the light of the unsupportive findings for the mean-variance CAPM. He reports that he finds empirically the two models; mean – variance and mean semivariance, fail to produce an intercept's and slope's coefficients that are in agreement with the underlying framework. Post and Vliet (2005) point out that the inability of Jahankhani (1976) to find supportive evidence to the mean-semivariance CAPM over its variance counterpart is a result of not examining the bear markets years. In a recent study, Ang, Chen and Xing (2006) point out that Jahankhani (1976) and other early studies have not actually provided a direct examination of the risk premium that is associated with bearing downside risk and have not employed all individual stocks and therefore fail to find supportive evidence.

Ang, Chen and Xing (2006) propose a downside risk model. They point out that they assume investor's preferences are descried by Gul's (1991) rational disappointment aversion utility function. They point out that in their model and framework, the risk is asymmetric and investors worry about downside risk and require compensation for bearing it and the CAPM beta is not the appropriate measure of risk. Furthermore, they indicate that under this utility function and assuming all other things are equal investors are prepared to give up part of the return, in form of a negative risk premium, for investing in stocks that have high potential of upside risk. They point out that they examine the contemporaneous relationship between downside risk and the cross-section of US stock returns using portfolio formation as well as using individual stocks with Fama and MacBeth's (1973) cross-sectional regressions. They report that they find around 6% annual downside risk premium in the cross-section of US returns on stocks, which is robust for controlling for other effects, while robust results for a negative upside risk premium is not supported empirically. Furthermore, they point out that they find that except for highly volatile stocks, future downside beta is predicted by past downside beta. They point out that their methodology has a high statistical power as they use daily returns daily returns over short 12- month periods instead of monthly returns over longer periods which suits the situation when betas are time varying.

However, there is shortcoming in Ang, Chen and Xing's (2006) study which is pointed out by Post and Vliet (2005). Post and Vliet (2005) point out that Ang, Chen and Xing (later published as Ang, Chen and Xing's (2006)) do not employ conditional tests for downside risk. As mentioned earlier Ang, Chen and Xing (2006) allow for risk measures to be time-varying but not downside risk premium.

Post and Vliet (2005) point out that they use a different methodology from that of Ang, Chen and Xing's (later published as Ang, Chen and Xing's (2006)) and use unconditional tests as well as also conditional tests to allow for time-variation in risk and downside risk premium conditional on economic states. Post and Vliet (2005) use the stochastic discount factor representation of asset pricing models and GMM, instead of beta representation. They point out that difference between the mean-variance CAPM and mean-semivariance CAPM is that in the latter model, the pricing kernel is linear in market return over losses and flat over gains. They point out that in light of the evidence of time-variation in risk and risk-aversion, the conditional asset pricing models is the appropriate choice. Furthermore, they state that they conduct the conditional test by using the median of a conditioning variable to split the full sample period into good times and bad times and then re-conduct the GMM chi square test for the two good and bad periods individually and also measure the fit of entire sample. They point out that they find the unconditional and conditional (on state of the economy) mean- semivariance CAPM do better in explaining the cross-sectional returns on stocks than its mean-variance counterpart, and US stock returns are driven by conditional downside beta. In addition they state that these results are robust for controlling for other effects including value and size among others. More importantly they point out that they find downside risk – return relationship particularly is near-perfect during high market risk premium time which is the bad states of the economy

As cited above Ang, Chen and Xing (2006) and Post and Vliet (2005) provide support to downside risk in the US stock market. However, Post and Vliet (2005) point out that they find over the sample period of Ang, Chen and Xing (later published as Ang, Chen and Xing's (2006)), the results that the mean-semivariance CAPM is better than the mean-variance CAPM is not strong and the strong evidence occur during bad economic conditions. Post and Vliet (2005) criticize Ang, Chen and Xing's (later published as Ang, Chen and Xing's (2006)) study as using a questionable downside risk's definition, in-sample estimates, Fama and MacBeth's (1973) methodology, and unconditional test which led to their findings.

Bali, Demirtas and Levy[31] study the inter-temporal relationship. They point out that the importance of downside risk stems from different reasons; one of these is the empirical failure of supporting a normal distribution for stock returns. They report that they find downside risk is positively related to the expected market returns regardless of the how downside risk is measured whether it is measured using value-at-risk, tail risk or expected shortfall.

4.2.2 Downside Risk in UK

Pedersen and Hwang (2007) point out that the problem of variance as symmetrical measure of risk can be overcome by the lower partial moment of Bawa and Lindenberg (1977) which is asymmetrical. They state that their study examines the percentage of UK

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[31] Available at: http://w4.stern.nyu.edu/finance/docs/pdfs/Seminars/061f-bali.pdf. Final Access on 18 September 2008.

individual stocks that downside risk, measured by the lower-partial moment CAPM, better describe than CAPM beta. They point out that this is essential in order to know how downside risk affects individual stocks and whether it is a potential risk factor. They indicate that they use different return frequencies on the largest stocks (FTSE100), as well as on the (FTSE250) constituents and on the small stocks (FTSE SmallCap) that are available over the entire sample period. They point out that they find normality assumption is not appropriate for high frequency (weekly and daily) returns. They report that they find 23% more of small stocks for daily frequency are explained by the lower partial moment CAPM compared with the CAPM. They point out that the results imply that measuring risk should be customized to asset classes such as small stocks with daily frequency. Furthermore they point out that downside beta is better than CAPM beta, but its additional value may not justify using it in asset pricing models and the CAPM is the recommended model for normal returns.

Olmo (2007) formulate an economy in which investors are mean-variance-downside risk averse. He points out that in his model the stock's risk measure is the weighted sum of its CAPM beta and its comovement with downturn markets and this extends the CAPM model by considering downside risk. He point out that even upside movement still can have effect on investment. He indicates that he uses weekly returns on UK sectoral indices and FTSE 100. He points out that he finds that stocks that covary positively (negatively) with the down market such as Chemical (Telecommunications) have higher (lower) returns than estimated under the CAPM, while other stocks are not affected by down market such as Oil and Gas.

4.2.3 Business Cycle and Time-Varying Risk

Fama and French (1989) report that they find there is a negative relationship between expected stock returns and business conditions. They point out that this is in agreement with the consumption smoothing of asset pricing models, where investors increase (decrease) their saving in times of high (low) income which results in lower (higher) expected returns. Nevertheless, they indicate that this time-variation in returns may reflect changes in the risks of stocks. Furthermore, Fama and French (1989) point out that their findings are supportive to Chen, Roll and Ross's (1986) findings that small stocks have higher expected return and risk than large stocks. Perez-Quiros and Timmermann (2000) reported that they find the conditional distribution of returns on stocks is asymmetrical between expansion and recession periods and it is more asymmetrical for small stocks than large stocks. They point out that this is because during recession the tighter credit conditions have more adverse effect on small stocks' risk than large stocks which results in an increase in small stocks' expected returns in this bad time of the economy. In addition they pointed out that the increase in expected stocks returns (for both small and large) during recession reflects an increase in both the level and expected price of risk. Furthermore Perez-Quiros and Timmermann (2000) state that their results indicate that asymmetries in the stocks' risk and their expected returns over the business cycle should be modeled in the cross-sectional returns on stock studies.

Lettau and Ludvigson (2001) reported that they find their conditional (scaled) version of the consumption CAPM matches the performance of Fama and French's (1993) three factor model. They point out that risk (risk level or risk aversion) is higher during bad times of the economy than during good times. Furthermore, they point out that some stocks covary more with the growth in consumption during weak economic conditions than during strong economic conditions which makes the conditional version of the model more appropriate to describe the cross-section of returns on portfolios of stocks as the conditional model captures this time-varying risk premia. Furthermore, they point out that the risk of a stock is economic state-dependent as it varies over the state of the economy.

In addition, Ferson and Harvey (1991) point out that according to asset pricing the variations in the measure of risk and price of risk cause the predictable changes in the returns on the stocks. They point out that however less work is done on the latter source of variation. They report that they find the stocks returns' predictable variation is mostly captured by the market risk premium. Furthermore, they point out that they find the return's predictability results mainly from time-varying expected price of risk rather than the measure of risk. In addition, they indicate that their findings imply that the market risk premium is time varying conditional on the business cycle conditions.

Also Campbell (1998) points out that in the pricing model the risk-factor premium should be conditional on the state of the economy. Furthermore, Boyd, Hu and Jagannathan (2005) report that they find the reaction of stock market to the news of unemployment differs based on the state of the economy. They point out that they find stock prices increase (fall) when unemployment increases in expansion (recession) periods. In addition, they point out that the information contained in unemployment news differs based on the state of the economy and hence the return's sensitivity to such news is dependent on the economic state. In addition, Yogo (2006) points out that he finds the equity premium is countercyclical as returns on stocks are low during recession periods when investor's marginal utility is high and the value and small stocks have more procyclical returns than their counterparts.

4.3 Hypotheses Development

This chapter attempts to contribute to the literature of downside risk and asset pricing by examining Ang, Chen and Xing's (2006) downside risk study conditional on the state of the economy. This is also important in the light of Post and Vliet's (2005) argument who pointed out that the superiority of downside risk over CAPM beta occurs mainly during bad times of the economy.

First, Post and Vliet (2005) point out that Ang, Chen and Xing (later published as Ang Chen and Xing (2006)) use a questionable downside risk's definition. However, it could be argued that, Ang, Chen and Xing (2006) use a measure of downside risk that is consistent with their assumption of investor's disappointment utility function. Ang, Chen and Xing (2006) point out that under this utility function there is a positive (negative) downside (upside) risk premium. This is different from Post and Vliet (2005). Post and Vliet (2005) point out that their pricing kernel is flat over gains. Second; Ang, Chen and Xing (2006) state that the basis of the return and risk cross sectional relationship is to be contemporaneous; hence using in-sample tests is not a drawback as suggested by Post and

Vliet (2005). Even more Ang, Chen and Xing (2006) report that they find past downside beta is positively related to future returns except for highly volatile stocks.

Third, Ang, Chen and Xing (2006) report that their findings based on the Fama and MacBeth's (1973) regression support their findings based on portfolio formations. Therefore their support for downside risk is not dependent on Fama and MacBeth's (1973) methodology as criticized by Post and Vliet (2005).

In addition, Ang, Chen and Xing (2006) employ daily returns to estimate downside beta whilst Post and Vliet (2005) use monthly returns. Pedersen and Hwang (2007) point out that lower partial moment CAPM is preferable for high frequency data in the UK. Therefore this chapter applies Ang, Chen and Xing's (2006) study to the UK market. Then, it allows their downside risk premium to vary over the business cycle by splitting the full sample period into two periods following Post and Vliet (2005) and then reapplies Ang Chen and Xing's (2006) study over both periods separately. Post and Vliet (2005) argue that this is a simple conditioning approach and point out that this, what they call a "split sample approach", overcomes a number of problems which are related to conditional models

4.3.1 Is Downside Risk a Significant Beta Factor in the UK?

The first step in this chapter is to examine downside risk in the UK market. Pedersen and Hwang (2007) point out that they study the percentage of UK stocks whose returns are better captured by downside beta compared with CAPM beta. They point out that downside risk additional value does not justify using it in pricing models. Olmo (2007) proposes a model with investors who are mean-variance-downside risk averse and applies it to UK sectoral indices over a short period of time. Therefore, this chapter attempts to examine whether downside risk is able to explain the cross section of UK stock returns by applying Ang, Chen and Xing (2006) study to London Stock Exchange.

This provides an out-of-sample test for Ang, Chen and Xing's (2006) study. This is important as Ang, Chen and Xing (2006) point out that the assumption of disappointment aversion utility function leads to a priced downside risk in the cross-section of returns on stocks. They also report that the US investor's price downside risk. On the one hand, Blake (1996) points out that he finds a 35.04 average coefficient of relative risk aversion in the UK. Also Blake (1996) points out that Mankiw and Zeldes (1991) find in US a 26.3 coefficient. Furthermore, Black and Fraser (2000) report that they find UK investors behave differently from other investors including the US investors. On the other hand Pedersen and Hwang (2007) report that they find high frequency (including daily) returns on UK stocks are not normal. Furthermore, they point out downside beta is better than CAPM beta but it is doubtful that it can be a risk factor that can significantly improve the pricing models. In light of this, the first hypothesis is stated as:

Hypothesis 1: Downside beta is a significant risk factor in the UK cross-sectional returns on stock.

4.3.2 Downside Risk and Firm Characteristics

If the relationship between downside risk and the cross sectional returns exists in UK; i.e. if the first hypothesis holds, then the chapter examines the robustness of downside risk in the UK market. Ang, Chen and Xing (2006) report that they find downside risk is robust in the US cross-section of returns for controlling for several cross sectional characteristics such as size and book-to-market value among others.

In addition, Post and Vliet (2006) point out that an empirical shortcoming of the mean-variance principle is that stock returns are not normal, and Pedersen and Hwang (2007) report that they find the UK small stocks are more non-normal than large stocks and downside beta has an important role for small size stocks which are the main benefited of this measure of risk. Furthermore, they point out that estimating risk has to be customized to small stocks with daily returns. Even more, they point out there is a relationship between size and downside risk and the former is important in deciding what model to use for risk (downside beta or CAPM beta). In addition Perez-Quiros and Timmermann (2000) point out that returns on small stocks and their risks are more asymmetrical than for large stocks across the business cycle. Moreover, Ferson and Harvey (1991) pointed out that during recession times, the betas of small stocks are high while those of large stocks are low in this time of high expected premium. In addition, Yogo (2006) reports that he finds the small and value stocks have more procyclical returns compared with their counterparts. Therefore the second hypothesis is stated as follows;

Hypothesis 2: Firm's size and book-to-market value are important factors in deciding the existence and significance of downside beta and its superiority to CAPM beta.

Therefore, hypothesis (2) tests the robustness of downside risk in the UK. Furthermore, Post and Vliet (2005) report that they find downside risk is better than CAPM beta in each section of the market (divided based on size, book-to-market or momentum) in the US. Similarly, Hypothesis (2) tests whether the cross-sectional downside risk-return relationship in UK is different across market capitalization and book-to-market stock categories and whether downside risk-returns is better than CAPM beta-return relationship across these categories as Pedersen and Hwang (2007) report that small stocks are the main benefited from downside beta.

4.3.3 Downside Risk and Business Cycle

Post and Vliet (2005) criticize Ang Chen and Xing's (later published as Ang Chen and Xing (2006)) study as for not examining conditional downside risk. In addition they report that they find bad times of the economy have higher return and risk than good times. Pereze-Quiros and Timmermann (2000) point out that Fama and MacBeth's (1973) method tests an average price of risk whilst the price of risk could be state-dependent and takes a significant value in one or more states of the economy while has a zero average. Furthermore, they point out that it is important to model the asymmetries in stocks' risk and return across the business cycle. Therefore, based on this, despite the fact that Ang, Chen and Xing (2006) report that they find downside beta is robustly and positively related to average returns, if downside risk premium is time-varying, then similar results may not be found in other markets without allowing for downside risk premium to vary over the business cycle as Pereze-Quiros and Timmermann (2000) stressed. Furthermore Perez-Quiros and Timmermann (2000) point out that risk premia in the pricing model should vary substantially across (conditional on) the expansion and recession times in order for the model to have explanatory ability for the time-varying expected returns.

In addition, Fama and French (1989) report that they find expected returns on stocks are higher during weak economic conditions and lower during strong conditions of the economy. Post and Vliet (2005) point out that they perform conditional tests of downside risk, conditional on the state of the economy, to allow for time-variation in the risk, risk aversion and risk premium. They report that they find downside risk is superior to CAPM beta in describing the US cross-sectional returns on stocks. However they point out that they find an almost perfect relationship between the two variables (downside risk and return) occurs during bad economic times which are characterized by high equity premium. Furthermore, Post and Vliet (2005) point out that during the sample period of Ang, Chen and Xing's (later published as Ang Chen and Xing (2006)) study the evidence is not strong for the relative superiority of downside risk. Consequently, hypothesis (3) of this chapter examines the downside risk premium of Ang, Chen and Xing's (2006) model conditional on the state of the economy. Therefore, the third hypothesis is

Hypothesis 3: The risk premium of downside risk is time-varying conditional on the state of the economy and it is higher during recession than during expansion.

4.3.4 Downside Risk and Industry

The case for the potential importance of the industry in deciding the significance of the downside beta in explaining stock's returns is strong. Yogo (2006) point out that the marginal utility is countercyclical and value and small stocks have high returns because they have more procyclical returns than growth and large stocks. Furthermore, Perez-Quiros and Timmermann (2000) point out that stock returns are asymmetrical between expansion and recession and this asymmetry is larger for small stocks than for large stocks. Black and Fraser (2000) point out that there the UK stock market may have higher cyclical stocks' percentage than other markets. Olmo (2007) reports that he finds for the UK sectoral indices, industries that co-vary positively (negatively) with downturn market have higher (lower) returns than that under the CAPM while downside beta is not priced in industries that do not move with the down market. Therefore, the fourth hypothesis is stated as follows;

Hypothesis 4: Downside beta is priced within some industries but not within every industry.

Olmo (2007) uses sectoral indices and very short weekly sample period from 11-2003 to 4-2006. This chapter is different from his study in that it examines downside risk-return relation within each industry using individuals stocks and a different framework to that of Olmo. It applies the model and methodology of Ang, Chen and Xing (2006) within each industry. Ang, Chen and Xing (2006) predict as a positive downside risk premium and a negative upside risk premium while Olmo (2007) points out that his model extends the CAPM to include in addition to the CAPM beta a measure of downside beta. He points out that his measure of stock's risk is a weighted sum of both stock's CAPM beta and stock's comovement with down markets.

4.4 Data and Methodology

4.4.1 Data

Daily and monthly data on 2020 UK common stocks traded on LSE for the period of July 1981 to December 2005 are obtained from Datastream. These are the same 2020 stocks used in Chapter (3) of the thesis. Daily and monthly returns on FTSE-all share as a proxy for the return on the market is also obtained from Datastream. Also book-to-market value (book value divided by price) and market capitalization for each stock at monthly frequency are obtained from Datastream. Industry code for each individual stock also obtained from Datastream. The industry code from the Datastream for each company is used to group the stocks into their corresponding industries. In addition, the dates of the UK recession and expansion periods are obtained from the ECRI- Economic Cycle Research Institute's website (http://www.businesscycle.com) and these dates are used to split the sample period into expansion and recession periods. The business cycle dates obtained from ECRI that occur during the sample period of the chapter (July -1981 to December-2005) are Peak (May-90) and Trough (March -1992).

The UK coincident index (UKCI) is also provided by the Economic Cycle Research Institute (ECRI[32]) and Figure (4.1) depicts the changes in this UK coincident index (UKCI). The Figure shows the biggest negative change in this index appeared to have happened during the recession period where the latter is identified by the dates from the ECRI as mentioned above.

Table (4.1) shows descriptive statistics for the sample over the period July-1981 to December-2005. The FTSE-all share is used as proxy for the value-weighted average return on the UK stock market. In addition an equally-weighted market portfolio is constructed using all the stocks in the sample. Fama and French (1989) point out that value-weighted portfolio attaches more importance to large stocks' returns while equally-weighted portfolio attaches more importance to small stocks' returns.

The descriptive statistics displayed in Panel (A) is for daily frequency while Panel (B) displays the statistics for monthly frequency. Jarque-Bera test is used for testing normality following Pedersen and Hwang (2007). Normality assumption for the distribution of returns on the UK stock is rejected by Jarque-Bera test for both value-weighted and equally-weighted market returns, for monthly and daily frequencies. Although both daily and monthly UK returns are found to be non-normal, the daily returns show more deviation from normality than the monthly returns. Daily market returns have higher kurtosis than monthly market returns for both value-weighted and equally weighted market portfolios and the equally-weighted daily market returns have

[32] We are grateful to the Economic Cycle Research Institute (http://www.businesscycle.com) for providing us with the UK Coincident index (UKCI) index.

higher negative skewness than the equally-weighed monthly returns. On the other hand, while the equally-weighted daily market returns have higher kurtosis and negative skeweness than the value-weighted daily market returns. For monthly frequency, the value-weighted market returns have higher kurtosis and negative skewness than the equally-weighted market returns.

Pedersen and Hwang[33] (2007) report the UK daily and weekly returns are non-normal. They point out that the FTSE-all share daily returns' non-normality arises from their fat tails. By examining Panel (A) of Table (4.1) of this chapter, it appears that the non-normal daily returns are kurtoic and negatively skewed especially for the equally-weighted market returns. Furthermore, Pedersen and Hwang (2007) report that they find the normality is appropriate assumption for monthly returns on FTSE all share, while Panel (B) of Table (4.1) of this chapter rejects the normality assumption for both monthly value-weighted and equally-weighted market returns.

Fama and French (1989) point out those large stocks are relatively more represented in value-weighted portfolio while the small stocks are more represented in the equally weighted portfolio. Pedersen and Hwang (2007) point out that the UK small stocks with daily returns are the most benefited from downside risk while CAPM is appropriate for large stocks with monthly returns. Furthermore, they point out when returns' normality does not hold, then the lower partial moment CAPM is a better choice over the CAPM. In light of this, Table (4.1) supports using downside beta in this chapter for UK daily and monthly returns, as both of them are non-normal, and for the daily

[33] Pedersen and Hwang (2007) sample period is from the first of August, 1991 until the 31 of July, 2001.

returns on small stocks as the small stocks, consistent with Pedersen and Hwang (2007), show more non-normality than large stocks, this is implied by the equally-weighted market returns results compared those with the value-weighted market returns[34]. In deed, Pedersen and Hwang (2007) point out that the frequency of return and stock's size are important in determining whether returns on stocks are normal and when daily frequency is combined with small stocks the lower partial moment CAPM is the proper model.

4.4.2 Methodology

4.4.2.1 The Downside Risk Model of Ang, Chen and Xing (2006)

This chapter applies Ang, Chen and Xing's (2006) model. Ang, Chen and Xing (2006) assume an investor has Gul's (1991) rational disappointment aversion utility function. Ang, Chen and Xing (2006) point out that under this utility function, investor is more concerned about downside risk and this results in downside risk being priced in the cross sectional expected returns on stocks and CAPM beta is not the adequate measure of stock's risk. They point out that they use as downside risk's measure that of Bawa and Lindenberg's (1977) downside beta.

Ang, Chen and Xing (2006, p. 1197, Eq.5) define their downside beta as:

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[34]Similarily, Bali, Demirtas and Levy (Available at http://w4.stern.nyu.edu/finance/docs/pdfs/Seminars/061f-bali.pdf . Final Access on 18 September 2008.) point out that they find, VaR is better in predicting returns on the equally-weighted index as small stocks have more non-normal returns than larger stocks. They comment further that is because equally weighted index weighs smaller stocks more than value weighted index.

$$\beta^{-} = \frac{\mathrm{cov}(r_i, r_m \setminus r_m < \mu_m)}{\mathrm{var}(r_m \setminus r_m < \mu_m)} \tag{3}$$

Equation (3) above is in Ang Chen and Xing's (2006) notations. They define the notations in the above equation as follows r_i , r_m and μ_m are the excess return on security *i*, the excess return on the market portfolio and the cut-off point between down and up markets. They use for the latter i.e. the cut-off point, the average market excess return, although they use alternatives to is as a robustness check.

Ang, Chen and Xing (2006) point out that the disappointment aversion investors are prepared to invest in stocks that produce high return at times of high wealth (i.e. have high positive covariation with the upside market), assuming all other thing are equal, at a discount Ang, Chen and Xing (2006, p.1199, Eq.9) estimate upside risk as:

$$\beta^{+} = \frac{\mathrm{cov}(r_i . r_m \setminus r_m > \mu_m)}{\mathrm{var}(r_m \setminus r_m > \mu_m)} \tag{4}$$

Equation (4) above is in Ang Chen and Xing's (2006) notations.

Then this chapter aims at examining the downside risk premium of Ang, Chen and Xing (2006) conditional on business cycle conditions. The approach used is applying Ang, Chen and Xing's (2006) model of downside risk and their study and methodology to the UK market over the full sample period following them and then over the recession and expansion periods separately. This conditioning approach is applied following Post and Vliet (2005) which splits sample period into two periods of good and bad times and reapply the test over the periods individually. Ang, Chen and Xing (2006) use both portfolio formation and Fama and MacBeth's (1973) cross sectional regressions on individual stocks.

4.4.2.2 Risk Measures

To examine the relationship between risk and average stock returns, Ang, Chen and Xing (2006) estimate CAPM beta (β), downside beta (β^-) and upside beta (β^+) of individual stocks, Ang, Chen and Xing (2006, p.1236, Eq.B-7 and Eq.B-8):

$$\hat{\beta} = \frac{\sum(\tilde{r}_{it}\tilde{r}_{mt})}{\sum\tilde{r}_{mt}^2}, \hat{\beta}^- = \frac{\sum_{\{r_{mt}<\hat{\mu}_m\}}(\tilde{r}_{it}^-\tilde{r}_{mt}^-)}{\sum_{\{r_{mt}<\hat{\mu}_m\}}\tilde{r}_{mt}^{-2}}, \hat{\beta}^+ = \frac{\sum_{\{r_{mt}>\hat{\mu}_m\}}(\tilde{r}_{it}^+\tilde{r}_{mt}^+)}{\sum_{\{r_{mt}>\hat{\mu}_m\}}\tilde{r}_{mt}^{+2}} \tag{5}$$

Equation (5) above is in Ang Chen and Xing's (2006) notations, they define the notations in the above equation as follows; $\tilde{r}_{mt}$ and $\tilde{r}_{it}$ as the demeaned excess returns on the market portfolio and stock *i*, respectively, $\tilde{r}_{mt}^-$ ($\tilde{r}_{mt}^+$) and $\tilde{r}_{it}^-$ ($\tilde{r}_{it}^+$) as the demeaned excess returns on the market portfolio and stock *i*, respectively, when the excess return on the market is below (above) the cutoff point or target ($\hat{\mu}_m$). Ang, Chen and Xing (2006) use as cut-off point between down and up markets the average excess return on the market portfolio, the zero rate of return and risk-free rate of return and point out that the results are robust to the cut-off point. Furthermore, Ang, Chen and Xing (2006) point out that that they use a 12-month (t - t_{+12}) interval, i.e annual horizon, of stock's daily returns to estimate stock's betas as this compromises between an enough number of observations for estimating the risk measures conditional on the down or the up markets and not too long period for not allowing for time-variation in the risk measures. They point out that those stocks with a number of missing observations that exceed five are excluded. Furthermore, Ang, Chen and Xing (2006) estimate CAPM beta (β), relative downside beta, which they define as ($\beta^- - \beta$) the difference between downside beta and CAPM beta, and relative upside beta, which they define as ($\beta^+ - \beta$), the difference between upside beta and CAPM beta.They predict a positive relation between downside risk and stocks returns and a negative relation between upside risk and stocks returns. This chapter follows Ang, Chen and Xing (2006) in estimating all the above betas following their procedures using only zero rate of return as the cut-off point.

4.4.2.3 Portfolio Formation

4.4.2.3.1 Risk Sorted Portfolios

Ang, Chen and Xing (2006) point out that to examine the contemporaneous relationship between average excess returns and downside risk they form equally-weighted five quintile portfolios by sorting all the stocks on the basis of their estimated risk characteristcis – or what they call it realized – CAPM betas (β), downside betas (β^-) or upside betas (β^+), relative downside beta $\beta^- - \beta$ among other measures, at the beginning of the 12-month interval which is used for estimating these risk measures. They point out that then they calculate the equally-weighted realized excess returns on each of the five portfolios over these very same period of 12 months that is used to estimate the betas by calculating the cumulative excess return on each individual stock. Furthermore, Ang, Chen and Xing (2006) point out that these step are repeated at the beginning of each month, even though 12-month of daily return is used as (horizon) a base for estimating betas. They indicate that for this reason they adjust for the overlapping in the sample periods by calculating Newey-West (1987) with 12 lags based t-statistics for the difference between the average excess return on the highest beta portfolio and the average excess return on the lowest beta portfolio. Furthermore, Ang, Chen and Xing (2006) point out that they also used monthly returns with 60-month interval as estimation period for betas and returns and found similar results. This chapter follows Ang, Chen and Xing (2006) in forming the portfolios as described above and estimating the risk measures using both daily returns and monthly returns.

The importance of the effect of return frequency on downside risk – average return relationship in UK is stressed by Pedersen and Hwang (2007) who point out that frequency has a significant role in deciding the normality of stock returns and report that that they find for the monthly frequency of returns and especially for large stocks CAPM beta is appropriate.

In addition Ang, Chen and Xing (2006) point out that to make use of downside risk relationship with contemporaneous average stock returns, downside beta should be predicted. Ang, Chen and Xing (2006) point out that in order to examine this they employ Fama and MacBeth (1973) cross-sectional regressions, in which they regress realized relative downside beta measure to be predicted on a number of stock characteristics that are the investor's information set beforehand, which include[35], among others, stock's (1)

[35] Ang, Chen and Xing (2006) use in addition to firm characteristics other risk variables to predict downside risk measure.

past downside beta measure, (2) past standard deviation, (3) logarithm of market capitalization (size), (4) book-to-market value, (5) past 12-month excess returns. They point out that the first two variables are calculated over the preceding 12 months using daily returns and the next three variables are calculated at the beginning of the period. They explain that they run different monthly cross sectional regression specifications which include regressing realized relative downside beta measure on one firm characteristic at a time with industry dummies and then they run one regression of realized downside beta measure on all firm characteristics and industry dummies all together. They point out that because these regressions are carried out on a monthly basis, they use Newey-West (1987) with 12 lags to correct for overlapping. This chapter follows them and applies their procedure to predict UK downside beta and CAPM beta.

This chapter also follows Ang, Chen and Xing (2006) in forming what they call investable portfolios. They point out that they form five quintile portfolios at the beginning of the month by sorting all the stocks on the basis of their past downside beta estimated over the previous 12-month interval of daily returns. Then they calculate the equally-weighted (average) realized excess return on each of these portfolios over the next month, in addition they calculate the difference between average excess return on the highest past downside beta portfolio and average excess return on the lowest past downside beta portfolio with Newey and West (1987) t-statistics. This chapter follows them and estimates the average portfolio excess returns over the next month as well as over the next 12 months and average returns are reported on annual basis.

4.4.2.3.2 Accounting for Size and Book-to-Market Value Effects

Post and Vliet (2005) point out that they use the double sorting procedure to control for size and book-to-market among other effects. They explain that they first form two portfolios by sorting the stocks based on one of the characteristics and then within each of the two portfolios, stocks are sorted into 10 portfolios based on either their CAPM beta or downside beta. In addition, Ang, Chen and Xing (2006) use this procedure to control for, for example, co-skewness, They explain the details as follows; they first sort all stocks into quintile portfolios based on their co-skewness at the beginning of every 12-month period where the latter measure is estimated over this subsequent one year period. They point out that then in the second step, within each of these five portfolios, they sort all stocks based on their downside beta into equally weighted five quintile portfolios and then the realized excess return on each downside beta portfolio is averaged over the first-step five quintile co-skewness portfolios to form downside beta portfolios that control for co-skewness. They point out that the co-skewness measures, downside betas and realized excess returns all are calculated over the same 12-month period using daily returns and they calculate Newey-West (1987) with 12 lags to compute the t-statistics for the difference between average excess returns on the highest and the lowest downside beta portfolios within each of the five co-skewness portfolios and for the co-skewness controlled five downside beta portfolios. This chapter applies this quintile double sorting procedure as in Ang, Chen and Xing (2006) to control for size and book-to-market value; i.e. the stock's market capitalization or book-to-market value replaces the co-skewness. The market capitalization or book-to-market value calculated at the beginning of the 12-month period, the reason for this is because when Ang, Chen and Xing (2006) control for these characteristics in the Fama and MacBeth's (1973) cross-sectional regression, they calculate the log size and book to market at the beginning of the 12-month period (see next sub-section).

4.4.2.4 Fama and MacBeth's (1973) Cross-Sectional Regression

Ang, Chen and Xing (2006) point out that they use Fama and MacBeth's (1973) cross-sectional regressions on individuals stocks to show that downside risk is in fact not the same as other firm's effects that are found empirically to explain the cross sectional returns on stocks. Ang, Chen and Xing (2006) point out that they run Fama and MacBeth's (1973) cross sectional regressions of 12-month excess returns of individual stocks calculated over the subsequent 12 months on (1) stock's characteristics including, among others, logarithm of market capitalization and book-to-market ratio, both calculated at the beginning of every period and (2) contemporaneous risk measures including, among others, CAPM beta or downside beta and upside beta, calculated over the same 12 month period) and this regression is repeated at monthly frequency. They point out for this overlapping they use Newey-West (1987) with 12 lags is to calculate the t-statistics. This chapter follows them in their application of Fama and MacBeth's (1973) cross-sectional regressions to control for these two characteristics.

In detail, Ang, Chen and Xing (2006) run different specifications of Fama and MacBeth's (1973) regression, among these which are applied in this chapter are; individual stock annual realized excess return on (1) downside beta and upside beta (2) downside beta, upside beta, logarithm of market capitalization and book-to-market, among other variables (3) CAPM beta and (4) CAPM beta and logarithm of market capitalization and book-to-market, among other variables.

4.4.2.5 Downside Risk Premium and Business Cycle

After applying Ang, Chen and Xing's (2006) model and methodology to the UK market over the full sample period following them, this chapter proceeds to its main contribution which is examining if the risk premium of downside risk of Ang, Chen and Xing (2006) is conditional on the business cycle and whether it provides different results from that of the unconditional risk premium. It does so by reapplying their model and methodology (both portfolio formation and Fama and MacBeth (1973) cross sectional) regression over expansion and recession periods, separately.

To condition downside risk premium of Ang, Chen and Xing (2006) on business cycle conditions, this chapter divides the full sample period into two periods as in Post and Vliet (2005) who carry out the conditional downside risk tests by splitting the sample period into two periods. However, Post and Vliet (2005) use the median of a conditioning variable (dividend yield, credit spread or earnings yield) to split the full sample period into bad and good times, but this chapter splits the sample into recession and expansion periods following Antoniou, Lam and Paudyal (2007). They point out that they use the Economic Research Cycle Institute's dates of the business cycle to split their sample period into recession and expansion in the UK to study the momentum over the business cycle. Therefore, this chapter, as mentioned in the Data section above, splits the sample period into two economics states; i.e. recession and expansion guided by the business cycle dates from the Research Cycle Institute[36]. Furthermore, as 12 months of daily returns is used to estimate the betas, it is difficult to restrict the recession and expansion periods exactly to the months obtained form the ECRI. Therefore, the rule applied is if any of the months used to calculate the beta happened to be during the recession period, then that beta is considered to be part of the recession periods.

4.5 Results

4.5.1 Downside Beta and Realized Returns

This sub-section tests the first hypothesis which examines the significance of downside risk in the UK market. Table (4.2) presents the results of portfolios formed on CAPM betas (Panel A) downside betas (Panel B) relative downside betas (Panel C), and upside betas (Panel D), for the whole sample period using daily returns over 12-month period. Ang, Chen and Xing (2006) report for each portfolio the equally weighted excess return (realized), CAPM beta, downside beta, upside beta, where they calculate the three measures over the same one year period, the difference between the beta of quintile (5) and quintile (1) portfolios and the difference between the average excess return on the highest risk portfolio and average excess return on the lowest risk portfolio. Similar calculations are presented in this chapter or the UK market.

[36] We thank the Economic Research Cycle Research Institute for providing this information.

Panel (A) shows a positive relationship between CAPM beta (β) and average excess returns from the lowest CAPM beta portfolio (quintile 1) to the fourth CAPM beta portfolio (quintile 4). However, the relationship breaks for the fifth highest CAPM beta portfolio which provides lower average excess returns than the previous lower risk (fourth) portfolio. In addition the difference between the yearly average excess return on the highest and yearly average excess return on the lowest CAPM beta portfolios is 4.02% which is positive but marginally insignificant at the 10% level. Higher CAPM beta is associated with both higher downside beta and higher upside beta and the difference between the beta of the highest CAPM beta portfolio and the beta of the lowest CAPM beta portfolio is positive and takes the values of 1.11, 1.14, 1.12 for CAPM beta, downside beta and upside beta respectively, which are very similar in magnitudes.

Panel (B) shows similar findings for downside beta (β^-) and the average excess returns on portfolios sorted on downside beta. There is a positive relationship between downside beta and average excess return from the lowest to the second highest downside beta portfolios and then the relationship breaks for the riskiest (quintile 5) downside beta portfolio, which has lower returns than the previous lower risk downside beta portfolio. However the difference between the average excess return on the highest downside beta portfolio and the average excess return on the lowest downside beta portfolio is 3.91% which is positive and significant at 10%. This is unlike the spread for the CAPM beta portfolios which is marginally significant as mentioned above. This may indicate a potential slight improvement when using downside beta as measure of risk over CAPM beta, although the positive risk-return relation has not been restored for the riskiest stocks. This significant difference in returns between downside beta portfolios is also accompanied by larger difference between downside beta of the highest downside beta portfolio and downside beta of the lowest downside beta portfolio, which is 1.62, compared with a corresponding differences for CAPM betas and upside betas of 0.80 and 0.62 respectively, which is consistent with Ang Chen and Xing's (2006) findings for USA. However, the findings so far UK is slightly different from US, in Ang, Chen and Xing (2006) report that they find for the US stock market a strictly positive and increasing relationship between downside beta and average excess return for the five quintile portfolios.

Figure (4.2) depicts visually the relation between the different risk measures and the corresponding portfolios' average excess return that are reported in Table (4.2). It shows that downside beta –return relationship (Downside) appears to be smoother than CAPM beta-return relationship (CAPM). Indeed the relationship between downside beta and average excess return for the first four portfolios (quintile 1 to quintile 4) is almost linear while this is not the case of CAPM beta portfolios.

Although the results show downside risk is positively related to the cross section of stock returns except for the riskiest stocks, CAPM beta provides, to some extent, similar results so far. Ang, Chen and Xing (2006) point out that one potential explanation for the positive association between downside risk and average excess return is that investors are indifferent to downside risk and this positive relationship is a result of the high correlation between downside beta and CAPM beta which occurs by construction, as downside beta sorted portfolios produce spread in both downside beta and CAPM beta. They point out to examine that they construct portfolios by sorting stocks on relative downside beta (β^{-}-β) to gauge how much downside beta provides incremental influence over CAPM beta. This chapter applies their exercise on the UK stocks are reports the results in Panel (C) of Table (4.2).

The results in Panel (C) shows that sorting on relative downside beta does not change the previous findings, reported in Panel (B), for the existence of a positive relationship between downside beta and average excess return for the first four downside beta portfolios; i.e. except for the riskiest portfolio. This relationship is also depicted visually in Figure (4.2) (RelDwn). Furthermore the difference between the average excess returns on the highest relative downside beta portfolio and the average excess returns on the lowest relative downside beta portfolios is more significant now at 5%. In addition and although, the spread in average excess returns between the third and second highest relative downside beta portfolios is small, the difference between downside beta of the highest relative downside beta portfolio and downside beta of the lowest relative downside beta portfolio is 1.11 while the corresponding difference in CAPM beta and upside beta are -0.02 and -0.36 respectively. This confirms that downside beta is behind the positive relationship between downside risk and returns. These findings are consistent with Ang, Chen and Xing (2006) for the US. In fact Ang, Chen and Xing (2006) report that downside beta and not CAPM beta is driving the positive relationship as sorting on relative downside betas produces no spread in CAPM betas over relative downside beta portfolios.

Panel (D) of Table (4.2) presents the results of sorting stocks into upside beta portfolios. It shows no obvious relationship between upside beta and average excess returns and although the difference between average excess returns on the highest upside beta portfolio and the lowest upside beta portfolio is negative, it is insignificant. However, Ang, Chen and Xing (2006) report that they find a positive relationship between upside beta and average excess return on the US stocks and indicate that this is not in agreement with disappointment aversion investors who are prepared to invest in high upside variation stocks at discount. They point out that this is because upside beta is contaminated with CAPM beta or downside betas effects and therefore they study relative upside beta portfolios. This chapter does not perform this exercise on UK market as Fama and MacBeth's (1973) cross sectional regressions show that upside beta is not priced in UK at all as shown below.

Table (4.3) presents the results of Fama and MacBeth's (1973) cross-sectional regressions. The first regression shows that the results of regressing individual stocks excess returns on CAPM beta, is a positive market risk premium which is significant at 10%. The third regression shows downside and upside risk premia that results from regressing individual stocks average excess returns on stock's downside and upside betas. Downside risk premium is 4.3%, which is positive and significant at 5%. This is consistent with portfolio formations findings in Table (4.2) and supports the potential that downside risk is better than CAPM beta. However, upside beta premium is positive with a very small magnitude and is statistically insignificant. Hence, although downside risk premium is in line with Ang, Chen and Xing's (2006) predictions of positive downside risk premium, upside risk premium in UK is not negative as Ang, Chen and Xing (2006) predict for disappointment aversion maximizers. They argue that under such utility function investors are prepared to sacrifice part of the returns on stocks that have high upside betas as this is the time of low marginal utility of wealth and this results in a negative sign to the risk premium associated with upside beta. And even more it is not priced. When size and book-to-market are included in the regression to control for size and value effects, downside risk premium remains significant at 5%. On the other hand, upside risk premium becomes also significant at 5% but positive and not negative. Nevertheless, the magnitude of upside risk premium is smaller than downside risk premium which, in terms of magnitudes, supports Ang, Chen and Xing's (2006) model and findings for the US that price of risk is asymmetrical between down and up markets and the latter is smaller in magnitude than the former. Despite the fact that this chapter finds the sign of upside risk premium in UK is not negative as they expect. Ang, Chen and Xing (2006) also report that the sign of upside risk premiums in US is not robust and not stable as it changes after controlling for other variables and becomes insignificant. This chapter does not control for all the variables that are controlled for by Ang, Chen and Xing (2006) but for their regression that includes size and book-to-market as control variables the sign of upside risk premium is negative and significant. Finally the second regression of Table (4.3) shows that the market risk premium is also robust to size and book-to-market value effects and it becomes more significant.

In summary, the results in this chapter accept the first hypothesis that downside risk is a priced risk factor in the UK market with a 4.9% annual risk premium. This positive relationship between downside risk and the cross-section of stock returns is not due to the CAPM beta but results from the additional power of downside beta over CAPM beta. Furthermore, the results support that downside beta is potentially a better measure of risk than CAPM beta in UK. This is evidenced by the significant spread between average returns on the highest downside beta portfolio and the average returns on the lowest downside beta portfolios, while the corresponding spread for CAPM beta portfolios is only marginally significant. In addition, the visual depiction of the risk-returns relationships suggests an almost linear relationship between downside risk and average excess returns for the first four downside beta portfolios while the relationship is not such smooth for CAPM beta portfolios, although it is positive. However, the difference in the performance between the two models is not that significant and both models fail to price the riskiest stocks (quintile 5) in line with a positive risk-return relationship. This is in contrast with Ang, Chen and Xing (2006) findings for US stocks market of a positive relationship between downside risk and average returns over the five quintile portfolios. Nevertheless the results support Pedersen and Hwang (2007) who point out that asset pricing models will not improve significantly by downside beta as risk factor.

4.5.2 Downside Beta and Size and Book-to-Market Value

This section examines the second hypothesis of the chapter which test whether book-to-market and market capitalization are important determinants of downside risk – return relationship and its superiority over CAPM beta. Specifically it examines if downside risk is a better driving risk factor of returns on stocks for a particular category of stocks rather than for all stocks. This is motivated by the findings of Pedersen and Hwang (2007). They point out that downside beta is more important for small UK stocks as these are more skewed and indicate that this clarifies the association between size and downside beta. Indeed Ang, Chen and Xing (2006) point out that the small stocks are exposed to more risk that results from asymmetries. In addition they point out that there is a possibility that the results of downside risk are driven by small stocks and equally weighted returns and therefore they check that this is not the case using different robustness checks. In addition, this exercise provides, similar to Post and Vliet (2005), a further check that downside beta is robust to the size and book-to-market effects. They point out that they use the double sorting procedure to examine if downside beta captures these and other effects, by studying downside risk within different segments (small versus large, value versus growth, among others) and also compare downside beta performance with CAPM beta performance within each of these segments.

4.5.2.1 Downside Beta and Size

Table (4.4) presents the average yearly excess returns on the 25 portfolios resulting from first sorting on stock's market capitalization and then on stock's CAPM beta (Panel A) or downside beta (Panel B). In addition it presents the average excess returns on the five beta portfolios that control for size in the last row of each Panel.

Panel (B) shows the robustness of downside beta to size. It shows the same positive relationship between downside beta and average excess returns from the lowest downside beta portfolio to the second highest downside beta portfolio, which then breaks for the riskiest downside stocks. The difference between the average excess return on the highest downside beta portfolio and the average excess return on the lowest downside beta portfolio is positive but now is insignificant. Nevertheless, the difference between the average excess returns on quintile (4) portfolio and the average excess return on quintile (1) portfolio is 4.58, which is positive and significant at 1%. These findings of the robustness of downside risk to size effect, is consistent with the findings in Table (4.3) of Fama and MacBeth's (1973) cross sectional regression

By examining the relationship between downside risk and average excess return within each size quintile portfolio, a number of points appear. A positive relationship between downside risk and average excess returns generally holds within the smallest three size portfolios (except for either the lowest or highest downside beta portfolios). The difference between the average excess return on the highest downside beta portfolio and the average excess returns on the lowest downside beta portfolio is positive and significant within the two smallest size portfolios but the difference for the third portfolio, although positive it is insignificant. Within the second largest portfolio, the relationship between downside beta and average excess return is bell-shaped and the difference between the average excess return on the highest downside beta portfolio and average excess return on the lowest downside beta portfolio is negative but insignificant. Finally within the largest size portfolio, the corresponding difference is negative and significant and the relationship between downside beta and average excess return is negative except for the lowest downside beta portfolio. Panel (A) shows qualitatively similar results for CAPM beta.

In summary, first, the relationship between downside beta and stock returns holds for small to middle size stocks but not for large stocks. This is consistent with Pedersen and Hwang (2007) who point out that downside beta, in the UK market, is significant for high frequency returns on stocks of small size to middle size. In addition they point out that although downside beta is superior to CAPM beta its additional value possibly does not provide better ability for explaining the variation in the cross section of returns on stocks. Again this seems to be supported by this chapter's finding when it examines the unconditional downside risk premium of Ang, Chen and Xing (2006) on UK market as shown above. Second, the negative relationship between downside beta or CAPM beta and average excess return within large stocks may suggest that investors are more concerned with the movements of small stocks than large stocks in line with Perez-Quiros and Timmermann (2000). They point out that the small stocks are more subject to deteriorating credit conditions in the market during recession and small stock returns and risk are more asymmetrical than for large stocks. So this could be the interpretation of why downside beta and indeed CAPM beta works for small but not large stocks. Finally, downside beta and CAPM beta show similar performance within each size portfolios. This is different from Pedersen and Hwang's (2007) findings. They point out that size is a crucial factor in deciding the suitability of CAPM relative to downside beta and an asymmetrical model, for high frequency returns. However, the results, presented in this sub-section, suggest that although size is important in deciding whether the risk factors studied here are suitable for explaining the cross section of returns, this applies to both CAPM beta and downside beta against a potentially other asset pricing model.

4.5.2.2 Downside Beta and Book-to-Market

Table (4.5) presents the average yearly excess return on the 25 portfolios resulting from, first sorting stocks' on their book-to-market value and then on stock's CAPM beta (Panel A) or downside beta (Panel B). In addition it presents the average excess return on the five beta portfolios that control for book-to-market value in the last row of each Panel. Panel (B) shows the relationship between downside beta and average excess return is robust to book-to-market value. As before, there is a positive relationship between downside beta and average excess return from the lowest downside beta portfolio to the fourth downside beta portfolio and the relationship breaks for the riskiest downside beta stocks. The difference between the average excess return on the highest downside beta portfolio and the average excess return on the lowest downside beta portfolio is positive and significant at 5%. These findings are consistent with Table (4.3).

Examining downside risk - return relationship within each book-to-market portfolio reveals that downside risk is significant within middle to high book-to-market value stocks; the highest book-to-market portfolios. The difference between the average excess return on the highest downside beta portfolio and the average excess return on the lowest downside beta portfolio is positive and significant for the highest two book-to-market portfolios, while positive but insignificant for the middle book-to-market portfolio. In addition, although the positive relationship between downside risk and return breaks for the lowest downside beta portfolio within the highest book-to-market portfolio and also breaks for the highest downside beta portfolio within the middle book-to-market portfolios, there is a strict positive relationship between downside beta and average excess returns on the five portfolios within the second highest book-to-market portfolio. Within growth stocks, there is no obvious relationship between downside beta and average returns, this suggest that returns on these stocks may be driven by other risk factors.

Panel (A) of Table (4.5) presents the findings for CAPM beta. By examining the downside beta portfolios that control for book-to-market (last row in Panel B) and the corresponding portfolios for CAPM beta (last row in Panel A), it is obvious that downside beta produces, on average, larger spread in portfolios' average excess returns. In addition, the difference between the average excess return on the highest CAPM beta portfolio and the average excess return on the lowest CAPM beta portfolio is positive but insignificant for the CAPM while as shown above, it is significant for downside beta portfolios. In addition downside beta does a better job in maintaining the positive risk-return within the second lowest and middle book-to-market portfolios. These findings may indicate that downside beta is a better measure of risk than CAPM beta.

In summary, although the relationship between downside risk and returns is robust to book-to-market value, within book-to-market categories, the results indicate that downside beta is not a priced factor for all the stocks. Downside beta is a driving risk factor for return on value stocks but not growth stocks, and still there is a problem of pricing the highest or lowest risk stocks even within value stocks[37].

4.5.3 Downside Risk and Economic Conditions

The third hypothesis of this chapter is tested in this section. This hypothesis examines whether downside risk premium of Ang Chen and Xing's (2006) is varying over the state of the economy. To examine this hypothesis, the full sample period is split into recession and expansion times as described under the methodology section. Then after splitting the sample period into recession and expansion, Ang, Chen and Xing's (2006) model and methodology reapplied on each state of the economy; i.e. on the recession period and the expansion periods instead of just over the full sample period.

Panel (C) of Table (4.6) presents the results of forming downside beta portfolios during expansion periods. It shows a strict positive relationship between downside risk and portfolio's average excess returns from the lowest risk stocks (lowest downside beta portfolio) to the riskiest stocks (highest downside beta portfolio). The difference between the average excess return on the highest downside beta portfolio and the average excess return on the lowest downside beta portfolio is positive and significant at 5%. This is also consistent with the Fama and MacBeth's (1973) cross-sectional regression in Panel (A) of Table (4.7). It shows downside risk has a significant positive price of risk of 6.0% in the cross-section of the UK stock returns during expansion, which is robust to stock's size

[37] Ang Chen and Xing (2006) report that they find that downside beta is able to explain the cross sectional returns on the Fama and French's (1993) 25 size and book-to-market portfolios.

and book-to-market characteristics. Upside beta is not significantly priced when it exists in the regression with downside beta, however, when size and book-to-market variables are included in the regression, it becomes significant but again with positive and not negative risk premium. Nevertheless, as for the unconditional downside and upside risk premia, upside risk premium is smaller in magnitude than downside risk premium during expansion.

Panel (D) of Table (4.6) presents the results for downside beta portfolios during recession period. There is a bell-shaped relationship between downside risk and the average excess return, and the difference between the average excess return on the highest downside beta portfolio and the average excess return on the lowest downside beta portfolio is positive but insignificant. In addition Fama and MacBeth's (1973) cross sectional regression results, which are reported in Panel (B) of Table (4.7), show that neither downside beta nor upside beta are priced in the UK cross sectional returns during recession period when no other variables exist in the regression. However when size and book-to-market exist in the regression, both downside risk and upside risk premia became significant but negative. These results combined with the portfolio formation results, indicate that there is no clear and robust relationship between downside risk and stock's excess returns during recession.

Table (4.6) also presents the results for CAPM beta during expansion (Panel A) and recession (Panel B). During expansions, despite the fact that the relationship between CAPM beta and average excess returns on portfolios is positive and increases over the first four portfolios, it breaks for the riskiest stocks (highest CAPM beta portfolio). This is similar to the relationship over the full sample period. However, during the recession, similar to downside beta results, there is no clear relationship between CAPM beta and portfolios' average excess returns. The results of Fama and MacBeth's (1973) cross sectional regression for CAPM beta during expansion and recession are reported in Table (4.7). These results support the findings based on portfolio formation in Panel (A) of Table (4.6) for expansion. But for the recession, it shows a negative risk premium for the market portfolio which is robust to controlling for size and book-to-market value effects. Figure (4.3) depicts the risk – return relationships visually.

From the above analysis, a number of important insights arise; first downside risk premium is positive and significant during expansions and larger in magnitude than downside risk premium during recession period. However, downside risk premium during recession is negative and becomes significant only when other stock's characteristics exist in the regression. Furthermore, downside risk – return relationship is almost linear during expansion, as shown in Figure (4.3) while this relationship does not hold during recession. These findings are opposed to Fama and French (1989) who report that stock returns are higher during bad times than good times of the economy. Also contradict Post and Vliet (2005) who report that they find the outstanding performance of downside risk over CAPM beta in the US occurs, in particular, during bad economic states which are the times of higher return and risk. They report that they find that bad economic times have higher return and risk than good times.

Furthermore, Perez-Quiros and Timmermann (2000) point out that returns on stocks are cyclical as a result of changes in both their risks and the price of risk over the business cycle, which are higher during recession and also small stocks returns' premium over large stocks increase in recession.

Second, it seems that using unconditional downside risk premium estimated over the full sample period causes the break of downside risk - return relationship for the riskiest stocks. However, when downside risk is estimated over expansion and recession separately; i.e. it is allowed to vary over the business cycle, downside beta outperforms CAPM beta in explaining the cross-section of the UK stock returns and the improvement comes from pricing the riskiest stocks.

In summary, allowing for downside risk premium of Ang, Chen and Xing's (2006) to vary with business cycle conditions, is important for uncovering the risk-return relationship in the UK market during expansion times. However, during recession, neither downside beta nor CAPM beta, is priced based on portfolio formation, although they are negatively priced based on Fama and MacBeth's (1973) cross sectional regression. One possible reason for the lack of a stable significant role for downside risk during recession in the UK is the short recession period in the chapter's sample. In fact Post and Vliet (2005) point out that the bear market in their sample is important for downside risk.

4.5.4 Downside Risk and Industry

This section tests the fourth hypothesis, which examines whether downside beta is a priced measure risk of for stocks within some industries but not within every industry. Ang, Chen and Xing (2006) point out that they find downside risk of utilities industry is lower compared with other industries whereas there is little pattern among the industries. They point out further that the finding for the utilities industry is in agreement with this industry being defensive in down markets.

To examine the above hypothesis, Ang, Chen and Xing's (2006) model and their methodology of portfolio formation and Fama and MacBeth's (1973) cross sectional regression are conducted within each industry instead of using all the stocks in the sample as before. Table (4.8) presents the results of sorting stocks into five downside beta portfolios, and separately into five CAPM beta portfolios within each industry. The findings indicate that downside beta seems to have explanatory power for the average excess returns on Travel and Leisure, Personal and Households Goods, Technology and Retail industries. Within each of these industries, there is a positive relationship between downside risk and average excess return from the lowest downside beta portfolio to the fourth (second highest) downside beta portfolios. However, for Retail industry, the relationship is strictly positive over the five downside beta portfolios. The difference between the average excess return on the highest downside beta portfolio and the average excess return on the lowest downside beta portfolio is positive and significant for all those industries except for the Technology industry where the difference is positive but insignificant. Although CAPM beta performs similar to downside beta for Travel and

Leisure and Personal and Household Goods, for the Retail industry, it has a negative relationship with the average excess returns, and the difference in average excess returns on the highest CAPM beta portfolio and the average excess return on the lowest CAPM beta portfolio is negative but insignificant.

On the other hand, CAPM beta seems to have better explanatory power for the cross section of returns on stocks within Media industry, although the positive relationship between CAPM beta and average excess returns is not maintained for the riskiest stocks. Furthermore, CAPM beta seems to be slightly better for stocks within Industrial Goods and Services, as downside beta has a bell-shaped relationship with the average excess returns while CAPM beta has a positive relationship with the average excess returns for all stocks except for the highest beta stocks. However, the difference between the excess returns on the highest beta portfolio and the average excess return on the lowest beta portfolio is positive and significant for both downside and CAPM betas. Within Healthcare industry, CAPM beta shows a positive relationship with average excess return. Finally, neither downside beta nor CAPM beta has an explanatory power for returns on stocks within Other Industries[38] which include Automobiles and Parts, Construction and Materials, Telecommunications, Basic Resources, Oil and Gas, Chemicals, Food and Beverages and Utilities. This is not surprising, as these are not homogenous industries.

[38] The reason for combining all these industries in one category "Other Industries" is that the number of stocks in each industry is not enough to form portfolios.

To shed more light on the role of downside beta in explaining returns on the stocks within each industry, Fama and MacBeth's (1973) cross sectional regressions is run for the one year excess returns on individual stocks on their CAPM beta and then on their downside beta and upside beta (Ang Chen and Xing's (2006) model) just as before for the full sample. However, the results should be interpreted with caution as the number of stocks for some industries is small. Table (4.9) presents the results. The results show that downside beta has a positive and significant price of risk in the following industries; Automobiles and Parts (8%), Travel and Leisure (12%), Personal Households and Goods (5%), Retail industry (9%), Food and Beverages (6%) and marginally insignificant at the 10% level in Construction and Material (4%). The portfolio formation results in Table (4.8) show that downside risk and average returns have no relationship within the Healthcare industry. However, surprisingly, downside beta, upside beta and CAPM beta, all are have significant risk premiums in the Fama and MacBeth's (1973) cross sectional regressions for the stocks within this industry, with the signs of these risk premia being consistent with Ang, Chen and Xing's (2006) model. Furthermore, within the utilities industry, downside risk has a negative risk premium, although insignificant. This is could be seen as consistent with Ang Chen and Xing (2006). They point out that they find, in unreported findings, utilities are less exposed to downside risk.

In addition, the results of the chapter show that CAPM beta has a positive and significant price of risk within the following industries; Industrial Goods and Services (5.3%), Media (8%), Travel and Leisure (16%), Personal and Households Goods (12%), Technology (13%), Healthcare (15%). For the Basic Resources, CAPM beta has a negative and significant risk premium (-9%).

Even though both CAPM beta and downside beta have signifincat risk premiums in the cross sectional regressions within Travel and Leisure industry, downside beta performs better in the portfolio formation. Downside beta has a strict positive relationship with the average excess returns over the five downside beta portfolios while CAPM beta does not maintain its positive relationship with average excess returns for the highest beta portfolio.

A general conclusion that can be drawn for the above results is that downside beta seems to a better measure of risk for stocks in some industries but not for all industries which is line with Olmo's (2007) findings. He reports that stocks with positive covariation (negative) with the down market have higher (lower) returns than estimated under the CAPM, while other stocks are not affected by down market. This chapter, though, studies the relationship at individual stock level and it does not focus on the magnitude of returns under CAPM compared with that using downside beta. It focuses on whether downside risk as an appropriate measure of risk is industry-dependent.

These findings have important implications for the participants in the London Stock Exchange. First, the choice between CAPM or downside beta as a risk factor – possibly along with other risk factors - depends on the industry of the firm. Pedersen and Hwang (2007) also call for paying attention to stock category when choosing the appropriate pricing model, although their focus is on the size category combined with the return frequency. Second it seems there are missing factors that influence stock returns which need to be considered in order to successfully describe the behavior of all stocks' prices. This is consistent with the first chapter of this thesis.

4.5.5 Is Past Downside Beta a Good Proxy for Future Downside Beta?

The results presented so far are for downside risk's contemporaneous relationship with the average excess returns on stocks. Ang, Chen and Xing (2006) point out that to practicalize this contemporaneous risk-return relationship, downside beta need to be predicted using previous information. This section presents the results of applying Ang, Chen and Xing's (2006) methods for examining the relationship between downside risk and future stocks returns on the UK market. Table (4.10) presents the results. It shows the average excess returns on portfolios sorted on their past downside beta and separately on their past CAPM beta. Panel (A) presents the average excess returns on these portfolio over the next month and Panel (B) presents the average excess returns calculated over the next 12-month, both are on yearly basis. Unlike the contemporaneous case, there is a negative relationship between downside risk and portfolio's future excess returns. And the difference between the average excess return on the highest downside beta and the average excess return on the lowest downside beta is negative and significant. Similar results are found to CAPM beta portfolios.

The negative downside risk – return relationship can be consistent with the positive contemporaneous risk – returns found earlier if past downside beta is negatively related to future downside beta. Ang, Chen and Xing (2006) use Fama and MacBeth's (1973) cross sectional regressions to predict future relative downside beta using a number of predictor variables each once a time and then all in one regression. The results of applying their procedure for a number of predictors to predict future UK downside beta are presented in Panel (A) of Table (4.11). The slope of Regression (1) is 0.30 (coefficient on past downside beta) which is positive and significant, therefore it rejects the potential explanation that the negative relationship between past downside beta and average excess returns is due to the negative relationship between past and future downside betas. This has an important warning for the investors, they cannot use past downside beta as a proxy for future downside beta. In fact Ang, Chen and Xing (2006) report that they find that future downside beta cannot be predicted only by past downside beta. However, they report that they find there is a positive relationship between past downside beta and future returns except for the highly volatile stocks. So the negative relationship between past downside beta and future returns found here in the UK market, remains a puzzle. Similar results are found for CAPM beta in Panel (B) of Table (4.11).

Regression (2) in Panel (A) of Table (4.11) shows that past book-to-market is positively related to future downside beta. Panel (B) of Table (4.5) shows that the highest returns is achieved by the highest downside beta portfolio within the highest book-to-market portfolio. The positive relationship between book-to-market value and future downside beta is similar to Ang, Chen, and Xing's (2006) findings for the US relative downside beta. They point out that their results show that the value stocks have higher relative downside risk than the growth stocks (note that in this chapter downside beta is predicted and not relative downside beta) when book-to-market value is the only predictor in the regression but the opposite occurs in a regression that includes all other predictors together. However for the UK, Regression (6) in Panel (A) of Table (4.11) confirms that the UK value stocks have higher downside risk than the growths stocks.

Regression (3) shows the past logarithm of stock's market capitalization (size) is positively related to future downside beta, which indicates that larger firms have higher downside risk than smaller stocks. However, Panel (B) of Table (4.4) shows that the highest return is achieved by the highest downside beta portfolio within the smallest size portfolio and the smallest stocks have higher average returns than the largest stocks. These findings taken altogether contradict a positive risk-return relationship. On the other hand, Ang, Chen and Xing (2006) report that they find for the US, a negative relationship between past logarithm of market capitalization and future relative downside beta.

Regression (4) shows that past standard deviation is positively related to future downside beta. Regression (5) shows that the past 12 month returns have no relationship with future downside beta. The findings of Regression (4) is consistent with Ang, Chen and Xing's (2006) results for US relative downside beta, while for the past 12 month they report a positive relationship between past 12 month excess return and future relative downside beta. However, this positive relationship is consistent with the findings for the UK in Regression (6), which shows that when all variables are included altogether, the past 12 month return becomes significant and positively related to future downside beta. In addition all other variables remain significant. Similar results are found for predicting CAPM beta as Panel (B) of Table (4.11) shows.

4.5.6 Monthly Return and Downside Risk

Ang, Chen and Xing (2006) point out that their results for downside risk is robust to using monthly returns over 60 month interval period. On the other hand, Pedersen and Hwang (2007) point out the normality could fit the UK monthly return and CAPM works for normal returns. Table (4.1) of this chapter rejects the normality assumption for monthly returns, however, it still requires examining whether using monthly returns over the 60 month, as Pedersen and Hwang (2007) point out, would result in CAPM beta be a good measure of risk compared with downside beta for the UK stock returns. Table (4.12) presents the results of portfolios sorted on their downside beta and separately on their CAPM beta, estimated using monthly returns. It shows that there is a bell-shaped relationship between downside beta and average excess returns, and the difference between the average excess return on the highest downside beta portfolio and the average excess return on the lowest downside beta portfolio is positive and significant. For CAPM beta, a similar bell-shaped relationship exists between CAPM beta and average excess returns, however, the difference between the average excess return on the highest CAPM beta portfolio and the average excess return on the lowest CAPM beta portfolio is negative but insignificant.

These results show the importance of return frequency in deciding the significance of downside risk as well as the CAPM beta in explaining the cross section of returns. Pedersen and Hwang (2007) point out that returns frequency is important in deciding whether to use downside risk and whether returns' normality holds. However, the results in this chapter show that both CAPM beta and downside beta fail to price the highest two CAPM beta portfolios and the highest two downside beta portfolios, respectively.

In summary, it is found that, using monthly returns to estimate downside beta, the relationship between downside beta and average excess return is much weaker than using daily return and similar results found for the CAPM beta. This implies that the UK investors have to use daily data and not monthly data to estimate the measure of risk when using downside beta (or CAPM beta) as a risk factor in their asset pricing models.

4.6 Conclusion

This chapter applies the model of downside risk and methodology of Ang, Chen and Xing (2006) to the UK market, and then it contributes to the literature by allowing their risk premium of downside beta to vary with the business cycle conditions.

A number of important findings have been presented. First it has been shown that when the risk premium of downside risk is estimated unconditionally over the full sample period, downside beta has a positive relationship with stock's returns but it fails to price the riskiest stocks and it does not improve significantly upon the CAPM beta which shows similar results. Second, the relationship between downside risk and the returns on stocks is robust to a number of effects which are the size and the book-to-market value. Third, it has been found that both downside beta and CAPM betas explain the cross sectional returns on the UK small and value stocks but not on large and growth stocks and although both measures show similar performances, downside beta seems to be a slightly better measure of risk for some stocks. In addition, the findings suggest that downside beta is a better measure of risk for some industries. Fourth, when the risk premium is allowed to vary over the business cycle's expansion and recession periods, a strictly positive relationship between downside risk and stocks returns has been found during expansion. However during recession times, it has been found no robust relationship between downside risk and stock returns, with a potential negative downside risk premium. Finally, the results show that in order for downside risk and market risk (CAPM beta) to be priced in the cross sectional returns of the UK stocks with the correct sign, they should be estimated using daily and not monthly data.

This chapter concludes that although the performances of downside beta and CAPM beta are largely similar when their corresponding risk premiums are estimated unconditionally, once the risk premium becomes time varying conditional on the economic conditions, it has been shown that downside beta is better in pricing the return on high risk stocks. In addition downside and CAPM betas have different performances in explaining the returns within industries, especially the Retail industry and Construction and Material industry. For these two industries the results show while downside beta has a positive risk premium which is significant for Retail industry and marginally significant for Construction and Material, CAPM beta has negative reward, although it is not significant. Indeed among the different variables that are studied in this chapter, industry is the only factor that distinguishes between CAPM beta and downside beta.

The findings in this chapter also suggest that there may be other factors that drive returns on large and growth stocks that need to be considered. The negative relation between downside beta and future excess return remains a puzzle for this study.

Important implications have arisen from the results of this chapter for the investors who trade stocks on the London Stock Exchange. First, investors should estimate a risk premium for downside risk that is state-dependent, although a search for a better measure of risk during recession might be needed. Second, investors should use downside risk and CAPM beta as risk factors only for small and value stocks but not for large and growth stocks and they should use daily returns and not monthly returns to estimate the risk measures.

Table 4.1 Descriptive Statistics

	Daily Frequency		Monthly Frequency	
Market Return	Value-Weighted	Equally-Weighted	Value-Weighted	Equally-Weighted
Mean	0.051	0.058	1.073	1.233
Standard Deviation	0.93	0.588	4.746	5.089
Skewness	-0.825	-3.642	-1.511	-1.012
Kurtosis	13.213	63.203	9.977	6.609
Normality *(Jarque-Bera)*	0.00	0.00	0.00	0.00

This Table presents the average return, standard deviation, skewness, kurtosis and Jarque-Bera test for normality for (1)value weighted UK market returns proxied by the return on FTSE-all share and (2) equally weighted market returns proxied by the return on portfolio constructed from all the stocks in the chapter's sample. The sample period is July – 1981 to December – 2005. Panel (A) presents the statistics for daily returns and Panel (B) presents the statistics for the monthly returns.

Table 4.2 Annual Excess Returns on Risk Characteristic Based Portfolios

Panel A: Portfolios based on CAPM β						
CAPM-beta Portfolios	Low	2	3	4	High	High - Low
Average Excess Return	5.82%	9.33%	10.43%	11.09%	9.85%	4.02% (1.62)
CAPM β	-0.03	0.18	0.35	0.57	1.08	1.11
Downside Beta β^-	0.11	0.35	0.55	0.79	1.25	1.14
Upside Beta β^+	-0.10	0.09	0.26	0.49	1.02	1.12
Panel B: : Portfolios based on Downside Beta β^-						
Downside beta Portfolios	Low	2	3	4	High	High - Low
Average Excess Return	6.13%	9.16%	10.30%	10.96%	10.04%	3.91% (1.69)*
CAPM β	0.10	0.23	0.37	0.56	0.90	0.80
Downside Beta β^-	-0.12	0.29	0.54	0.84	1.50	1.62
Upside Beta β^+	0.11	0.18	0.30	0.45	0.72	0.62
Panel C: : Portfolios based on Relative Downside Beta $\beta^- - \beta$						
Relative downside beta Portfolios	Low	2	3	4	High	High - Low
Average Excess Return	7.74%	9.22%	10.03%	10.15%	10.03%	2.28% (1.98)**
CAPM β	0.51	0.39	0.37	0.40	0.49	-0.02
Downside Beta β^-	0.15	0.39	0.53	0.73	1.26	1.11
Upside Beta β^+	0.59	0.37	0.30	0.27	0.23	-0.36

Table (4.2) continued

Panel D: : Portfolios based on Upside Beta β^{+}						
Upside beta portfolios	Low	2	3	4	High	High - Low
Average Excess Return	9.00%	8.88%	10.14%	10.49%	8.69%	-0.31% (-0.21)
CAPM β	0.14	0.22	0.34	0.53	0.93	0.79
Downside Beta β^{-}	0.43	0.42	0.52	0.69	1.00	0.57
Upside Beta β^{+}	-0.37	0.05	0.27	0.56	1.24	1.61

This Table presents the portfolios constructed from sorting all the stocks in the chapter's sample, at the beginning of every month, into five quintile portfolios based on their CAPM beta (Panel A), downside beta (Panel B), relative downside beta (Panel C) and upside beta (Panel D). The sample period is July – 1981 to December 2005. The measures of risk (the betas) are computed using daily return over the subsequent one-year period and the equally weighted annual excess returns on the portfolios (Average excess Return) are calculated over the same one-year period. CAPM β, Downside Beta β^{-} and Upside Beta β^{+} are the averages of the betas of the individual stocks in each portfolio, all computed over the same one-year period. Newey- West (1987) based t-statistics are reported in parenthesis. ***significant at 1%, ** at 5% and * at 10%

Table 4.3 Cross-Sectional Regressions

	Intercept	CAPM β	Downside beta β^-	Upside beta β^+	Logarithm market Capitalization (Size)	Book-to-Market
Regression (1)	0.109 (3.97)***	0.074 (1.87)*				
Regression (2)	0.234 (4.47)***	0.131 (2.31)**			-0.086 (-3.85)***	0.001 (1.09)
Regression (3)	0.111 (4.09)***		0.043 (2.53)**	0.004 (0.37)		
Regression (4)	0.236 (4.68)***		0.049 (2.25)**	0.030 (2.19)**	-0.078 (-4.29)***	0.001 (1.29)

This Table presents the coefficients from monthly Fama and MacBeth's (1973) cross sectional regressions. The sample period is July-1981 to December – 2005. The annual excess return on the individual stock is calculated over the same one year-period used to calculate its measures of risk, which are calculated using daily returns. The excess returns on individual stocks are regressed on their measures of risk and size and book-to-market variables. The logarithm of the market capitalization (size) and book-to-market are calculated at the beginning of every period. Newey- West (1987) based t-statistics are reported in parenthesis, ***significant at 1%, ** at 5% and * at 10%

Table 4.4 25 Size and CAPM or Downside Beta Portfolios

Panel A: CAPM Beta						
Beta Portfolios / Size Portfolios	Low	2	3	4	High	High-Low
Small	8.69	7.83	11.05	14.64	24.97	16.29 (5.48)***
2	1.50	5.63	10.31	9.70	11.85	10.35 (3.39)***
3	4.55	8.69	9.61	10.74	7.31	2.75 (0.80)
4	6.42	8.33	9.56	8.75	2.97	-3.45 (-0.95)
Large	8.34	9.02	8.63	5.23	0.39	-7.95 (-2.26)**
Average	5.90	7.90	9.83	9.81	9.50	3.60 (1.32)
Panel B: Downside Beta						
Beta Portfolios / Size Portfolios	Low	2	3	4	High	High-Low
Small	9.01	7.30	11.11	16.13	24.14	15.13 (5.54)***
2	0.71	6.73	8.89	11.51	11.40	10.69 (4.11)***
3	5.57	8.59	9.37	10.44	7.64	2.07 (0.71)
4	6.24	9.25	9.45	9.04	2.34	-3.89 (-1.19)***
Large	8.46	8.61	7.72	5.80	1.25	-7.22 (-2.1)**
Average	6.00	8.09	9.31	10.58	9.35	3.36 (1.42)

This Table presents results of the 25 portfolios that result from sorting all the stocks in the sample into five portfolios based on their size (market capitalization) and then within each size portfolio, stocks are sorted into five portfolios based on their CAPM betas (Panel A) or downside betas (Panel B). The sample period is July – 1981 to December – 2005. The average (equally weighted) annual excess returns, which are reported in the Table, and the betas are calculated using daily returns over the same subsequent one-year period. The market capitalizations are calculated at the beginning of the period to match those in Table (4.3). This formation of the 25 portfolios is carried out at the beginning of every month. Newey- West (1987) based t-statistics are reported in parenthesis, ***significant at 1%, ** at 5% and * at 10%. The last row of each Panel shows the average annual excess return on portfolios that control for size.

Table 4.5 25 Book-to-Market and CAPM or Downside Beta Portfolios

Panel A: CAPM Beta						
Beta Portfolios / Book-to-Market Portfolios	Low	2	3	4	High	High-Low
Low Book-to-Market	-0.76	5.40	2.81	3.64	-1.79	-1.04 (-0.35)
2	4.98	9.06	8.30	5.43	4.00	-0.97 (-0.42)
3	6.54	9.77	10.58	10.47	8.70	2.17 (0.94)
4	7.85	9.48	10.70	12.03	12.72	4.87 (2.29)**
High Book-to-Market	12.97	12.27	15.50	17.68	20.60	7.63 (3.22)***
Average	6.32	9.20	9.58	9.85	8.85	2.53 (1.33)
Panel B: Downside Beta						
Beta Portfolios / Book-to-Market Portfolios	Low	2	3	4	High	High-Low
Low Book-to-Market	-2.97	4.31	3.81	4.36	-0.47	2.50 (0.82)
2	3.56	7.27	8.74	7.66	4.48	0.93 (0.40)
3	7.71	8.68	9.99	10.55	9.26	1.56 (0.66)
4	7.60	9.84	10.94	12.08	12.41	4.82 (2.58)**
High Book-to-Market	12.76	12.74	15.03	17.74	20.98	8.21 (3.87)***
Average	5.73	8.57	9.70	10.48	9.33	3.60 (2.02)**

This Table presents the results of the 25 portfolios that result from sorting all the stocks in the sample into five portfolios based on their book-to-market value and then within each book-to-market portfolio stocks are sorted into five portfolios based on their CAPM betas (Panel A) or downside betas (Panel B). The sample period is July – 1981 to December – 2005. The average (equally weighted) annual excess returns, which are reported in the Table, and betas are calculated using daily returns over the same subsequent one-year period. The book-to-market values are calculated at the beginning of the period to match those in Table (4.3). This formation of the 25 portfolios is carried out at the beginning of every month. Newey-West (1987) based t-statistics are reported in parenthesis, ***significant at 1%, ** at 5% and * at 10%. The last row of each Panel shows the average annual excess return on portfolios that control for book-to-market.

Table 4.6 Annual Excess Return on Risk Characteristics Based Portfolios in Expansion and Recession

Panel A: Portfolios based on CAPM β Expansion						
CAPM-beta Portfolios	Low	2	3	4	High	High - Low
Average excess Return	8.87	11.62	13.02	13.68	13.19	4.33 (2.33)**
CAPM β	-0.03	0.18	0.34	0.57	1.07	1.10
Downside Beta β^-	0.11	0.35	0.55	0.79	1.25	1.14
Upside Beta β^+	-0.11	0.08	0.24	0.46	0.99	1.10
Panel B: : Portfolios based on CAPM β Recession						
Downside beta Portfolios	Low	2	3	4	High	High - Low
Average excess Return	-17.38	-8.17	-9.24	-8.66	-15.51	1.87 (0.77)
CAPM β	0.01	0.21	0.37	0.61	1.15	1.15
Downside Beta β^-	0.13	0.38	0.58	0.82	1.28	1.15
Upside Beta β^+	0.00	0.20	0.40	0.66	1.26	1.26
Panel C: : Portfolios based on Downside beta β^- Expansion						
Relative downside beta Portfolios	Low	2	3	4	High	High - Low
Average excess Return	9.59	11.31	12.35	13.37	13.92	4.33 (2.55)**
CAPM β	0.10	0.22	0.37	0.55	0.90	0.80
Downside Beta β^-	-0.12	0.29	0.54	0.84	1.50	1.62
Upside Beta β^+	0.09	0.16	0.28	0.43	0.70	0.61

Table (4.6) Continued

Panel D: : Portfolios based on Downside beta β^- Recession						
Relative downside beta Portfolios	Low	2	3	4	High	High - Low
Average excess Return	-20.02	-7.16	-5.25	-7.29	-19.33	0.70% (0.24)
CAPM β	0.13	0.26	0.40	0.60	0.96	0.82
Downside Beta β^-	-0.07	0.32	0.56	0.86	1.54	1.61
Upside Beta β^+	0.25	0.32	0.44	0.61	0.90	0.65

This Table presents results of splitting the sample period into expansion and recession period based on the dates of the business cycle from the Economic Cycle Research Institute. Then for each economic state separately, portfolios are constructed from sorting all the stocks in the chapter's sample, at the beginning of every month, into five quintile portfolios based on their CAPM beta (Panel A for expansion and Panel B for recession) and downside beta (Panel C for expansion and Panel D for recession). The sample period is July – 1981 to December 2005. The measures of risk (the betas) are computed using daily returns over the subsequent one-year period and the equally weighted annual excess returns on the portfolios (Average excess Return) are calculated over the same one-year period. CAPM β, Downside Beta β^- and Upside Beta β^+ are the averages of the betas of the individual stocks in each portfolio, all computed over the same one-year period. Newey- West (1987) based t-statistics are reported in parenthesis, ***significant at 1%, ** at 5% and * at 10%.

Table 4.7 Cross –Sectional Regression in Expansion and Recession

Panel (A): Expansion

	Intercept	CAPM β	Downside beta β^-	Upside beta β^+	Logarithm market Capitalization (Size)	Book-to-Market
Regression (1)	0.134 (4.73)***	0.087 (2.00)**				
Regression (2)	0.284 (5.21)***	0.164 (2.63)***			-0.108 (-4.62)***	0.001 (0.92)
Regression (3)	0.135 (4.72)***		0.051 (2.67)***	0.005 (0.42)		
Regression (4)	0.285 (5.42)***		0.060 (2.5)**	0.040 (2.63)**	-0.098 (-5.15)***	0.001 (1.15)

Panel (B): Recession

	Intercept	CAPM β	Downside beta β^-	Upside beta β^+	Logarithm market Capitalization (Size)	Book-to-Market
Regression (1)	-0.083 (-1.75)*	-0.024 (-1.77)*				
Regression (2)	-0.145 (-2.26)**	-0.124 (-6.36)***			0.082 (6.19)***	0.001 (4.15)***
Regression (3)	-0.075 (-1.80)*		-0.017 (-1.21)	-0.004 (-0.70)		
Regression (4)	-0.134 (-2.26)**		-0.033 (-1.79)*	-0.042 (-9.84)***	0.066 (4.91)***	0.001 (3.94)***

This Table presents the coefficients from monthly Fama and MacBeth's (1973) cross sectional regressions for expansion period (Panel A) and recession period (Panel B). The sample period is July-1981 to December – 2005. The sample period is split into expansion and recession based on the dates of the business cycle from the Economic Cycle Research Institute. Then for each economic state separately, the annual excess return on the individual stock is calculated over the same one year-period used to calculate the measures of risk, which are calculated using daily returns. The excess returns on individual stocks are regressed on their measures of risk and size and book-to-market variables. The logarithm of the market capitalization (size) and book-to-market are calculated at the beginning of every period. Newey- West (1987) based t-statistics are reported in parenthesis, ***significant at 1%, ** at 5% and * at 10%.

Table 4.8 Annual Excess Return on Risk Characteristics Based Portfolios within each Industry

	Low	2	3	4	High	High - Low
			Panel A: Ind. Goods & Services			
	Low	2	3	4	High	High - Low
CAPM-beta	4.80	8.93	9.12	9.46	8.55	3.75 (2.24)**
Downside -beta	4.94	9.02	9.08	8.81	8.59	3.65 (1.99)**
			Panel B: Media			
	Low	2	3	4	High	High - Low
CAPM-beta	4.89	8.91	11.22	11.79	8.61	3.72 (1.79)*
Downside -beta	5.76	10.86	12.56	11.47	4.36	-1.40 (-0.49)
			Panel C: Travel & Leisure			
	Low	2	3	4	High	High - Low
CAPM-beta	1.15	3.95	7.80	9.15	9.03	7.88 (2.6)***
Downside -beta	1.30	4.87	7.36	7.84	10.03	8.73 (2.98)***
			Panel D: Pers & Househld Goods			
	Low	2	3	4	High	High - Low
CAPM-beta	1.65	6.04	8.61	11.15	9.03	7.38 (3.34)***
Downside -beta	2.79	6.46	8.03	10.60	8.82	6.03 (2.73)***
			Panel E: Technology			
	Low	2	3	4	High	High - Low
CAPM-beta	1.09	9.14	12.96	11.32	7.32	6.23 (1.45)
Downside -beta	1.97	8.84	11.43	13.34	7.88	5.91 (1.46)
			Panel F: Healthcare			
	Low	2	3	4	High	High - Low
CAPM-beta	5.08	7.20	6.57	7.72	14.24	9.16 (2.01)**
Downside -beta	5.24	9.88	8.11	10.57	7.65	2.41 (0.7)

Table (4.8) continued

	Low	2	3	4	High	High - Low
			Panel G: Retail			
	Low	2	3	4	High	High - Low
CAPM-beta	11.50	13.65	13.42	12.11	10.71	-0.79 (-0.25)
Downside -beta	9.59	11.32	13.04	12.98	14.48	4.88 (1.72)*
			*Panel H: Others**			
	Low	2	3	4	High	High - Low
CAPM-beta	7.59	9.49	11.20	11.08	8.25	0.66 (0.33)
Downside -beta	8.02	10.08	10.28	10.13	9.02	1.00 (0.48)

This Table presents the portfolios constructed from sorting the stocks within each industry, at the beginning of every month, into five quintile portfolios based on their CAPM beta (first row of each Panel) and separately their downside beta (second row in each Panel). The sample period is July – 1981 to December 2005. The measures of risk (the betas) are computed using daily returns over the subsequent one-year period and the equally weighted annual excess returns on the portfolios, which are reported in the Table, are calculated over the same one-year period. Newey- West (1987) based t-statistics are reported in parenthesis, ***significant at 1%, ** at 5% and * at 10%.

* Automobiles & Parts, Construct. & Material, Telecommunications, Basic Resources, Oil & Gas, Chemicals, Food & Beverage, Utilities

Number of stock in each industry is; Ind. Goods & Services (569), Media (163), Automobiles & Parts (19), Travel & Leisure (168), Pers & Househld Goods (201), Technology (206), Construct. & Material (79), Healthcare (105), Telecommunications (25), Basic Resources (66), Oil & Gas (64), Chemicals (51), Retail (187), Food & Beverage (82), Utilities (35)

Table 4.9 Cross –Sectional Regression within each Industry

	CAPM β	Downside beta β^-	Upside beta β^+
Panel (A): Ind. Goods & Services			
Regression (1)	0.053 (1.95)*		
Regression (2)		0.024 (1.23)	0.022 (1.85)*
Panel (B): Media			
Regression (1)	0.08 (2.30)**		
Regression (2)		0.015 (0.76)	0.016 (0.97)
Panel (C): Automobiles & Parts			
Regression (1)	0.07 (1.52)		
Regression (2)		0.08 (2.70)***	-0.002 (-0.04)
Panel (D): Travel & Leisure			
Regression (1)	0.16 (2.55)**		
Regression (2)		0.12 (2.78)***	-0.017 (-0.54)
Panel (E): Pers & Househld Goods			
Regression (1)	0.12 (2.66)***		
Regression (2)		0.05 (2.37)**	0.017 (0.88)
Panel (F): Technology			
Regression (1)	0.13 (1.63)		
Regression (2)		0.05 (1.27)	0.019 (0.40)
Panel (G): Construct. & Material			
Regression (1)	-0.01 (-0.29)		
Regression (2)		0.04 (1.60)	-0.02 (-1.12)

Table (4.9) Continued

	CAPM β	Downside beta β^-	Upside beta β^+
Panel (H): Healthcare			
Regression (1)	0.15 (2.47)**		
Regression (2)		0.12 (1.94)*	-0.10 (-1.65)*
Panel (J): Telecommunications			
Regression (1)	0.001 (0.01)		
Regression (2)		-0.04 (-0.47)	0.25 (1.05)
Panel (I): Basic Resources			
Regression (1)	-0.09 (-3.09)***		
Regression (2)		-0.02 (-0.78)	-0.028 (-1.12)
Panel (K): Oil & Gas			
Regression (1)	0.05 (0.95)		
Regression (2)		-0.03 (-0.97)	0.11 (2.68)***
Panel (L): Chemicals			
Regression (1)	-0.09 (-1.30)		
Regression (2)		-0.08 (-1.55)	-0.12 (-1.27)
Panel (M): Retail			
Regression (1)	-0.07 (-1.32)		
Regression (2)		0.09 (1.77)*	-0.04 (-1.32)
Panel (N): Food & Beverage			
Regression (1)	-0.001 (-0.03)		
Regression (2)		0.06 (2.02)**	-0.027 (-0.93)

Table (4.9) Continued

Panel (O): Utilities			
	CAPM β	Downside beta β^-	Upside beta β^+
Regression (1)	0.02 (0.16)		
Regression (2)		-0.20 (-0.90)	-0.02 (-0.51)

This Table presents the coefficients from monthly Fama and MacBeth (1973) cross sectional regressions within each industry. The sample period is July-1981 to December – 2005. Within each industry, the annual excess return on the individual stock is calculated over the same one year-period used to calculate the measures of risk, which are calculated using daily returns. The excess returns on individual stocks are regressed on their measures of risk. Newey- West (1987) based t-statistics are reported in parenthesis, ***significant at 1%, ** at 5% and * at 10%.

Table 4.10 Future Annual Excess Return on Past Risk Characteristics Based Portfolios

			Panel A:			
	Low	2	3	4	High	High - Low
CAPM-beta	12.23	10.64	10.60	8.87	3.22	-9.01 (-2.55)**
Downside -beta	10.87	10.21	9.43	9.44	5.81	-5.06 (-1.72)*
			Panel B:			
	Low	2	3	4	High	High - Low
CAPM-beta	13.49	11.16	10.68	8.99	4.01	-9.48 (-4.59)***
Downside -beta	12.38	10.96	9.83	9.85	5.60	-6.78 (-3.93)***

This Table presents the portfolios constructed from sorting all the stocks in the chapter's sample, at the beginning of every month, into five quintile portfolios based on their past CAPM beta (first row of each Panel), and past downside beta (second row of each Panel). The sample period is July – 1981 to December 2005. The measures of risk (the betas) are computed using daily returns over the past one-year period and the equally weighted annual excess returns on the portfolios, which are reported in the Table, are calculated over the next one month (Panel A) and next one year (Panel B). Newey- West (1987) based t-statistics are reported in parenthesis, ***significant at 1%, ** at 5% and * at 10%.

Table 4.11 Does Past Information Predict Downside Beta?

	Downside Beta					
	Reg. (1)	Reg. (2)	Reg. (3)	Reg. (4)	Reg. (5)	Reg. (6)
Downside Beta	0.30 (14.77)***					0.15 (9.95)***
BMV		0.01 (2.25)**				0.003 (1.95)*
SIZE			0.17 (11.95)***			0.19 (15.09)***
STDEV				7.77 (12.83)***		12.51 (10.69)***
RET					-0.001 (-0.04)	0.07 (3.2)***
R^2	9.42%	0.38%	8.44%	4.37%	1.68%	21.42%
	CAPM Beta					
CAPM Beta	0.60 (24.28)***					0.39 (15.58)***
BMV		0.003 (2.6)***				0.002 (2.19)**
SIZE			0.23 (16.21)***			0.17 (15.31)***
STDEV				4.72 (9.77)***		6.25 (8.41)***
RET					0.013 (0.66)	0.043 (2.91)***
R^2	35.88%	0.63%	25.03%	3.98%	2.01%	47.98%

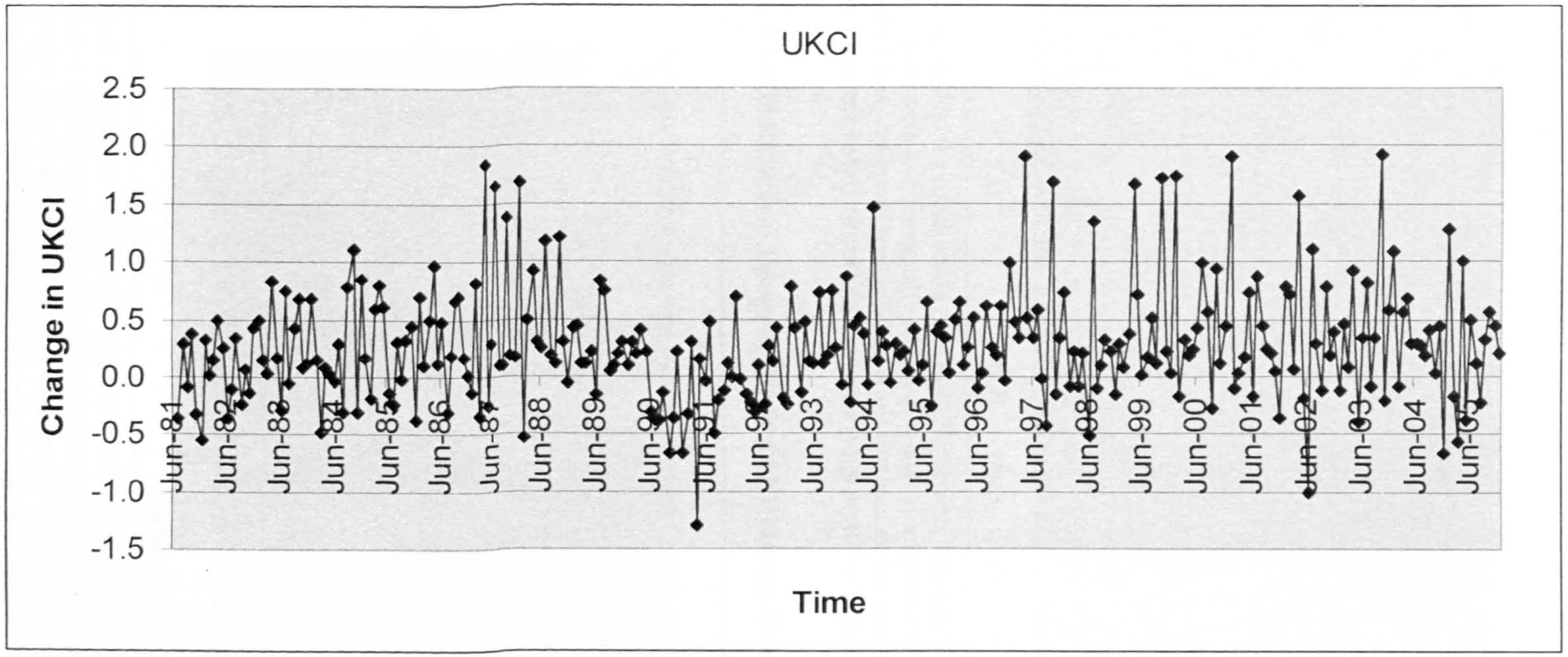
This Table presents the coefficients of monthly Fama and MacBeth's (1973) cross sectional regression for predicting downside beta (Panel A) and predicting CAPM beta (Panel B). Downside beta (CAPM beta) is regressed on past downside beta (past CAPM beta), past book-to-market value (MBV), past logarithm of market capitalization (SIZE), past standard deviation (STDEV) and past one year excess returns (RET). Dummies for industries are included in every regression. Downside beta and CAPM beta to be predicted are calculated over the subsequent one-year using daily returns. Past downside and CAPM betas and past standard deviation are calculated using daily returns over the past one-year while past book-to-market, past size and past one year excess returns are calculated at the beginning of the period. R^2 is the adjusted R^2 from the regression. Newey- West (1987) based t-statistics are reported in parenthesis, ***significant at 1%, ** at 5% and * at 10%. The sample period is July 1981 to December – 2005.

Table 4.12 Annual Excess Return on Risk Characteristics Based Portfolios – Monthly Frequency

	Low	2	3	4	High	High - Low
CAPM-beta	4.56	6.09	7.06	5.53	3.14	-1.42 (-1.26)
Downside –beta	2.81	6.12	6.82	6.29	4.62	1.81 (2.81)***

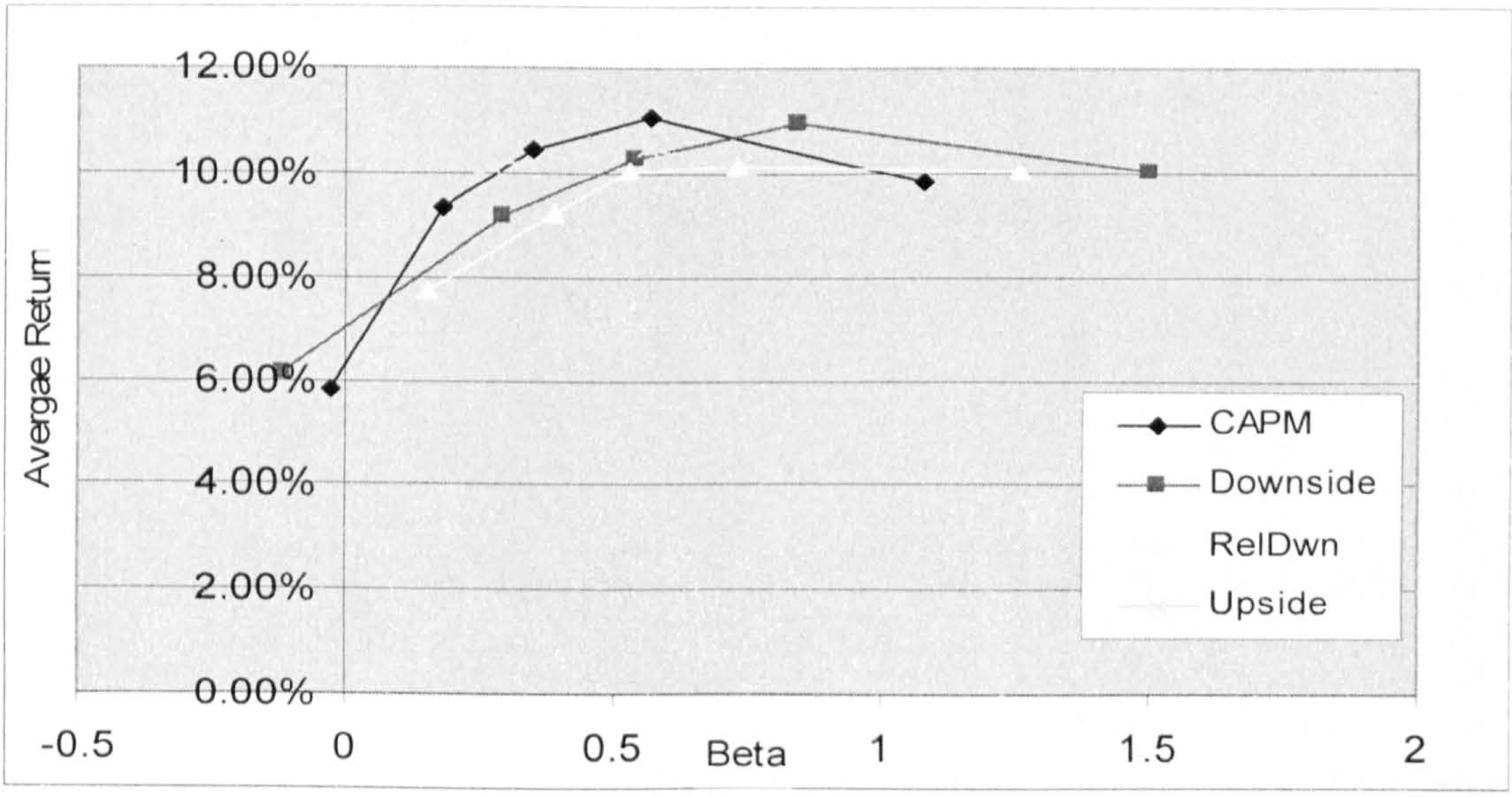
This Table presents the portfolios constructed from sorting all the stocks in the chapter's sample, at the beginning of every month, into five quintile portfolios based on their CAPM beta (first row) and downside beta (second row). The sample period is July – 1981 to December 2005. The measures of risk (the betas) are computed using monthly returns over the subsequent 60 month- period and the equally weighted annual excess returns on the portfolios, which are reported in the table, are calculated over the same period. Newey- West (1987) based t-statistics are reported in parenthesis, ***significant at 1%, ** at 5% and * at 10%..

Figure 4.1 Changes in UK Coincident Index



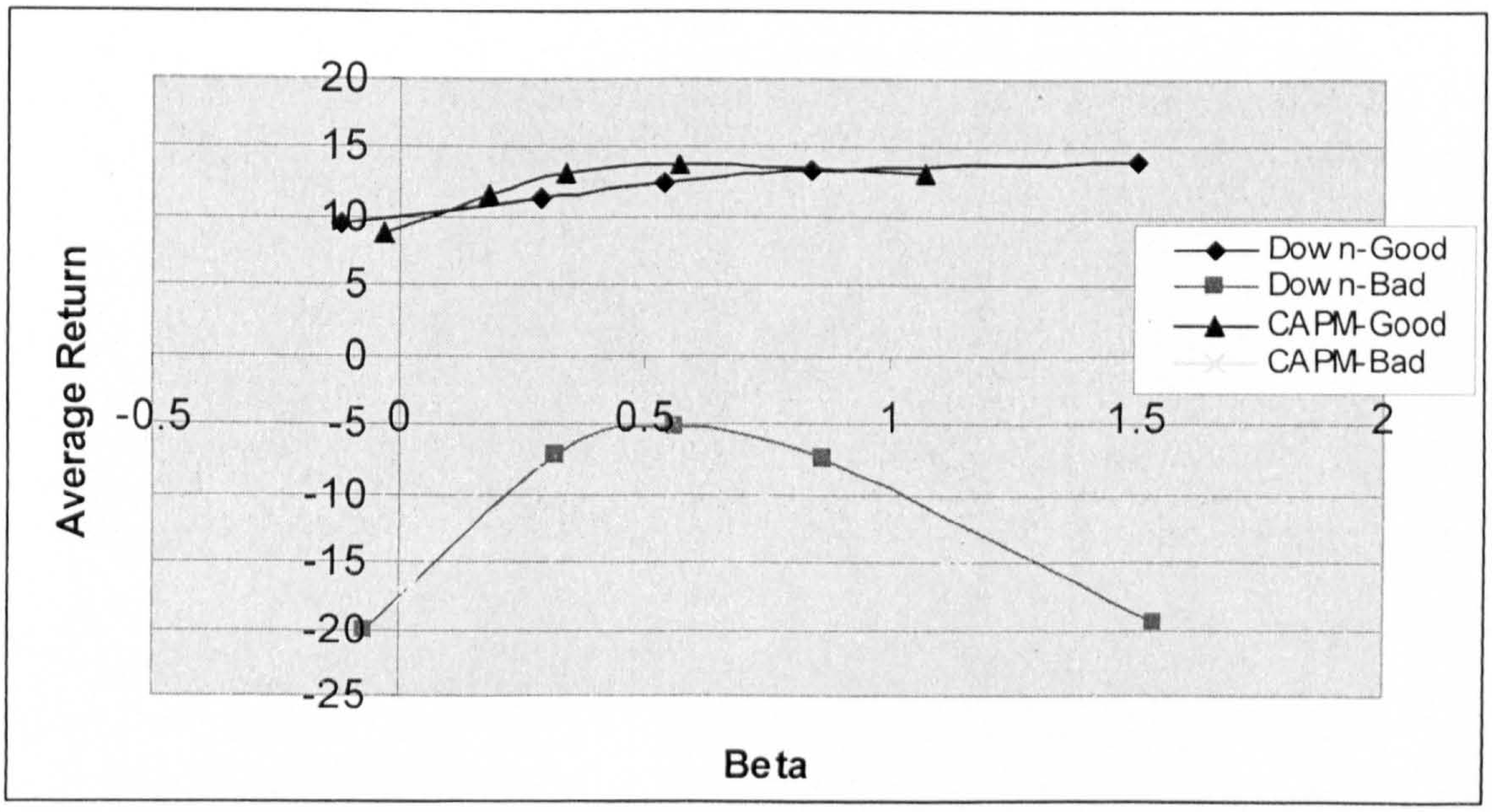
This Figure depicts the changes in the UK coincident index over the sample period, July 1981 to December -2005. The UK coincident index is provided by the Economic Research Cycle Institute (http://www.businesscycle.com)

Figure 4.2 Relationship Between Risk and Returns



This Figure depicts the relationship between CAPM beta, Downside beta, Relative Downside (RelDwn) Beta, or Upside beta and the equally weighed annual average excess returns on five portfolios sorted by their CAPM beta, downside beta, relative downside beta and upside beta, respectively. The y-axis is the portfolio's average excess return and the x-axis is the portfolio's beta.

Figure 4.3 Relationship Between Risk and Returns Over the Business Cycle



This Figure depicts the relationship between CAPM beta (CAPM-Good) and Downside beta (Down-Good) during expansions and the average annual returns on the five portfolios sorted by their CAPM beta and downside beta respectively. Also it depicts the relation between CAPM beta (CAPM-Bad) and Downside beta (Down-Bad) and average excess return during recession. The y-axis is the portfolio's average excess return and x-axis is the portfolio's beta.

Chapter 5 Conclusion

5.1 Conclusion

This thesis has studied the relationship between stock return and risk motivated by the recent developments in the area. It has examined the relationship in the light of a number of adjustments that have recently been re-examined by researchers. These include advancing from a static to an inter-temporal model (Merton (1973)); from pricing systematic risk to testing whether both systematic risk and idiosyncratic risk have significant effects on stock returns (e.g. Merton (1987)); and from CAPM beta risk to downside risk (e.g. Bawa and Lindenberg (1977) and Ang, Chen and Xing (2006)). The evidence from this thesis provides useful insights to add to other researchers' efforts toward understanding the relationship between stock rerun and risk.

5.2 Macroeconomic Factors and Fama and French Asset Pricing Model

In light of Campbell's (2000) and Cochrane's (2006) emphasis on the importance of macroeconomic variables to stock returns, the second chapter started by applying Petkova's (2006) study to UK. It examined the performance of the Fama and French's (1993) three-factor model on the UK Fama and French (1993) 25 size and book-to-market portfolios. It found both the SMB (negatively) and HML (positively) are robustly priced in the cross section of returns on stocks. Then it applied Petkova's (2006) model that includes excess market return and innovations to dividend yield, term spread, default spread and one-month T-Bill as well as her model that includes in addition to the above five variables the HML and SMB. The findings showed that innovations to dividend yield and term spread are significantly priced, and that the results are robust to innovation estimation technique and model estimation method. These results when taken as a whole are in line with Petkova's (2006) findings for US. She reports that innovations to term spread and one-month T-Bill are priced. In addition she reports that HML is positively priced while the SMB is not significant. However this chapter's results showed, unlike hers, the priced risk factors are not able to suppress the HML and SMB factors. Griffin (2002) points out that countries SMB and HML correlations that he finds are unlike those that would be found if they were driven by similar state variables.

Therefore, motivated by this lack of association between Fama and French's (1993) SMB and HML factors and the above risk variables selected by Petkova (2006), this chapter made use of the dynamic factor model and principal components method of Stock and Watson (2002a, b) to augment Petkova's (2006) model with innovations in factors estimated from a large set of macro variables. This is also motivated by the findings of Mönch (2004, 2006) and Ludvigson and Ng (2007). These studies applied this method and reported that such estimated factors add information over and above the variables generally used in asset pricing models literature. This augmenting step is important in light of the challenge that are put forward by Campbell (2000) and Cochrane (2006) that macro variables which influence stock return need to be unearthed and the call by Cochrane (2006) among others, to link the SMB and HML to macroeconomic variables. Therefore, confining the analysis to a few macro variables will not provide a definitive answer to these challenges.

The results showed that the innovations to two estimated factors (the first and the sixth factors) are priced in the cross sectional returns on stocks. Mönch (2004) also reported that two estimated factors are priced in the cross section of return in the US. However, the final results showed that Petkova's (2006) model, that includes excess market returns and innovations to dividend yield, term spread, and the HML and the SMB [retaining only priced factors] augmented with innovations to the second estimated factor, is potentially the best choice to describe stock returns in the UK.

The results suggested that this second estimated factor, which is found to be associated with employment and term spread, may add information beyond those captured by innovations to dividend yield and term spread. The ability of the estimated factors from a large set of data to add additional information is consistent with Mönch (2004) who augments Campbell's (1996) model with two estimated factors, and Ludvigson and Ng (2007) and Mönch (2006) who augment the conditional information set with estimated factors. Nevertheless, the results showed, this second estimated factor does not eliminate the effect of the SMB and HML and therefore it remains unclear what exactly these two factors do represent in the UK market.

Having employed a large set of macro variables reduces the possibility of finding an interpretation of Fama and French's (1993) HML and SMB in the context of the macroeconomic variables in the UK. Despite the fact that Liew and Vassalou (2000) report that there is a link between the SMB and HML in the UK and GDP growth and

Kelly (2003) also reports that these two factors are connected to the real GDP growth in the UK. Furthermore, he reports that the HML is also linked to unexpected inflation.

5.3 Idiosyncratic Risk and Time-Varying Betas

The previous chapter examined whether a number of systematic risk factors were priced in the cross section of stock returns. However, there is recent evidence pointing the finger at idiosyncratic risk as a potential factor in capturing changes in stock prices (e.g. Ang, Hodrick, Xing, and Zhang (2006, 2008), Spiegel and Wang (2005) and Fu (2007)) while others reject such findings (see Bali and Cakici (2008) and Huang et al (2006)). Therefore, the third chapter of this thesis examined whether idiosyncratic risk is priced in the cross section of UK stock returns. It examined idiosyncratic risk effect by following Ang, Hodrick, Xing, and Zhang (2006, 2008) and Spiegel and Wang (2005), in order to establish whether it is a sustained effect or not robust as found by Bali and Cakici (2008). This is important as there has been evidence of significant idiosyncratic risk effect in the UK documented by, for example, Guo and Savickas (2006), Angelidis and Tessaromatis (2008b), Ang, Hodrick, Xing, and Zhang (2008) and Fletcher (2007).

The results showed, consistent with Bali and Cakici's (2008) conclusion, that idiosyncratic risk effect is not robust. The results showed negative, positive or insignificant effects in the cross section of UK stock returns for idiosyncratic risk. In detail, when idiosyncratic risk is examined based on daily returns with OLS following Ang, Hodrick, Xing, and Zhang (2006, 2008), the relationship between stock returns and idiosyncratic risk is negative and significant as reported by Ang, Hodrick, Xing, and Zhang (2006, 2008). However these findings, unlike the previous studies are not robust to the testing procedure. Fama and MacBeh's (1973) cross sectional regression show a negative idiosyncratic effect while portfolios formed on their idiosyncratic risk show insignificant effect. Furthermore, the results suggested an association between idiosyncratic risk and small stocks which is consistent with other studies such as Bali and Cakici (2008), Angelidis and Tassaromatis (2008b) for the UK and Diavatopoulos et al., (2007).

When lagged idiosyncratic risk is measured based on monthly returns with OLS following Spiegel and Wang (2005), the results suggested that idiosyncratic risk could be positively priced in the cross section of returns only in the presence of other effects, also there is connection between small and value stocks and idiosyncratic risk effect. Furthermore, this chapter calculated idiosyncratic risk from monthly returns using EAGARCH (1,1) following Spiegel and Wang (2005). The results showed, in contrast to the above findings for the OLS monthly idiosyncratic risk, that when idiosyncratic risk exists alone in the relationship it is found to be significant and negative in the cross section of returns, while when other effects exist, EAGARCH (1,1) idiosyncratic risk effect vanishes. These findings are in contrast with Spiegel and Wang (2005) and Fu (2007) who reported significant positive idiosyncratic risk effect when the latter estimated from EGARCH models. All in all, these findings are line with the Baly and Cakici (2008) who conclude that idiosyncratic risk effect in the cross sectional return of US stocks is not robust.

In light of these confusing findings of the importance of idiosyncratic risk in the UK stock return which are consistent with the documented confusing evidence, this chapter proceeded to examine the relationship between stock returns and idiosyncratic risk using the time-varying beta (conditional) model and methodology of Avramov and Chordia (2006) who point out that the advantage of their modelling of the variation in the stock betas is that it is explicit. Fletcher (2007) also uses conditional asset pricing model in studying idiosyncratic risk in the UK. The application of Avramov and Chordia's (2006) time-varying beta model and methodology was also motivated by Chen and Keown (1981) and Malkiel and Xu (2006) who point out that the residuals may include other effects. In fact, Malkiel and Xu (2006) point out that Miller and Scholes (1972) argue that the significant idiosyncratic risk could be due to errors in betas.

The results showed that once the time variation in betas is accounted for, no significant effect for idiosyncratic risk remains in the cross section of returns, regardless of idiosyncratic risk measure (monthly OLS or EGARCH) or the testing procedure (Fama and MacBeth (1973) or portfolios formation). However, this chapter did not examine the effect of the time-varying betas on idiosyncratic risk when the latter is calculated based on the daily returns. The reason for this is the daily book value does not change within a month's time period. Nevertheless, the results from portfolios formed based on daily OLS idiosyncratic risk are less supportive to idiosyncratic risk effect which may support that idiosyncratic risk is not really priced in the cross section of returns.

5.4 Downside Risk and Business Cycle

Fama and French (2004) point out that theoretical shortcoming could be behind the CAPM failure. Furthermore, there is recent evidence of the significance of downside risk in the cross sectional returns. Therefore, and in light of these recent promising studies of downside beta such as those by Ang, Chen and Xing (2006) and Post and Vliet (2005), the fourth chapter sets the following objective: examining downside risk in the cross sectional returns on UK stocks following Ang, Chen and Xing (2006). This was also motivated by the evidence of Pedersen and Hwang (2007) and Olmo (2007) for downside risk in the UK market.

The results showed that downside risk is significant in explaining UK stock returns with a positive price of risk, a finding that is generally consistent with Ang, Chen and Xing (2006) and Post and Vliet (2005) for the US. However, the findings showed that downside risk has a problem pricing the riskiest stocks and did not improve significantly over CAPM beta. Pedersen and Hwang (2007) study downside risk in the UK and point out that based on their findings downside beta will not result in great improvement for asset pricing models. These findings of this chapter are not consistent with Ang, Chen and Xing (2006) for US market. They reported great explanatory power for downside risk in the cross section of returns. In addition, the results in this chapter showed that the return – risk (whether downside beta or CAPM beta) relationship is significant with the correct sign of risk premium only for small size to middle size and value stocks but not for large and growth stocks. The finding of an association between small and middle stocks and downside risk is in line with Pedersen and Hwang (2007). Pedersen and Hwang (2007) report downside beta is essential for the small size to middle stocks in UK.

In the next stage, then the risk – return relationship was studied over the business cycle by dividing the study period into recession and expansion periods following Post and Vliet (2005) and then reapplying Ang, Chen and Xing's (2006) downside risk model and methodology over recession and over expansion separately. The recession and expansion periods are identified following Antoniou et al (2007) using the Economic Research Cycle Institute's dates of the business cycle. The results showed, during expansion, a strict positive relationship between downside risk and stock returns whilst CAPM beta still fails to price the riskiest stocks. On the other hand, during recession this chapter found no conclusive relationship between risk and return which could be attributed to the small recession period in this study. These findings support Post and Vliet (2005) who studied and emphasized the importance of time-variation in downside risk. But at the same time it supports the findings of Ang Chen and Xing (2006) that their measure of downside risk is robust and not weakened by allowing for time variation in the risk- return relationship over the business cycle, on the contrary it uncovers a better relationship. This is despite the fact that this chapter found no relationship during recession while Post and Vliet (2005) point out that they find downside beta's superiority is more apparent in bad economic times.

Furthermore, the results of the chapter suggested that industry could be an important distinguisher between downside risk and CAPM beta performances where the former appears to be more suitable for some industries. This is consistent with the findings of Olmo (2007) for UK.

5.5 Implications

The evidence from this thesis has important implications for understanding the behaviour of stock returns, which is a necessity for every investor and researcher in finance who need to make decisions about changes in stock prices. The former group of beneficiaries includes management, stock holders, bankers etc., who need to make the decision to invest or not based on the risk-return aspects of their investment options. On the other hand researchers need to be aware of what factors are important to price stocks, whether they directly study asset pricing or merely employ these models as a tool to adjust the return on their investing strategies which may change the findings on the empirical grounds. Although this thesis provides evidence that is generally in line with the literature, it also gives some insights related to some unresolved issues.

First, it strongly supports Campbell (2000) and Cochrane (2006) that macroeconomic factors are crucial in shaping stock returns and it is important for LSE investors not to overlook any potential macro variable that may have association with stock returns. It also supports the importance of HML in particular and SMB as pricing factors in the UK stock market, although it does not find any direct association between them and the macroeconomic variables. Second, it joins those who very much doubt that idiosyncratic risk has any real ability to explain stock returns and stresses the importance of accounting for time variation correctly in risk measures which seems to help resolve this issue. Finally, it supports the importance of downside risk for stock returns and that allowing for time variation in the relationship strengthens it.

5.6 Further Area for Research

5.6.1 Idiosyncratic Risk and Time-Varying Betas

Chapter (3) of this thesis studied idiosyncratic risk in the cross section of UK stock returns. Fama and French's (1993) three factor model is used as the asset pricing model to calculate idiosyncratic risk measure. This was done following other studies in this area, as explained in detail in the chapter, which employ this model as the underlying asset pricing model. The results of the chapter showed that there is mixed and inconsistent evidence as to whether idiosyncratic risk is priced in the UK or not. Furthermore, the results show that the UK Fama and French's (1993) three risk factors are not significant in the Fama and MacBeth's (1973) cross sectional regression of daily returns.

However, when Avramov and Chordia's (2006) conditional Fama and French's (1993) three-factor model, which accounts for time-variation in beta risk, is used as the underlying asset pricing model, the results showed that idiosyncratic risk, based on monthly frequency, becomes insignificant in the cross sectional returns. On the other hand, the findings of chapter (2) of this thesis showed a number of factors are priced in the UK stock market. These include Petkova's (2006) model augmented with innovations to an estimated factor that relates to unemployment. At the same time Petkova (2006) reported that her model succeeds as a conditional model while Fama and French's (1993) model does not. In light of this, it would be interesting to apply this model as the underlying model in studying idiosyncratic risk. The hypothesis here is that if this model succeeds in capturing idiosyncratic risk, then this confirms that it is also a conditional model. This is because this hypothesis examines if this model really captures time variation in risk without an explicit modelling of beta risk as has been done in chapter (3) using Avramov and Chordia's (2006) methodology and their conditional Fama and French's (1993) model.

5.6.2 Downside Risk and Business Cycle

Chapter (4) of this thesis studied downside risk in the UK cross section of returns by applying Ang Chen and Xing's (2006) study. The results of the chapter showed that downside risk premium, when examined over the full sample period (unconditionally), does not show significant improvement over the CAPM. Furthermore, within the largest stocks, it was found that there is, generally, a negative relationship between downside risk and stock returns. In addition within the growth stock, it was found that there is no clear relationship between stock returns and downside risk. Therefore, it would be interesting to examine if downside risk modelled using Avramov and Chordia's (2006) conditional methodology, which accounts for time varying beta, would improve the performance of downside risk within large and growth stocks.

Furthermore, it has been shown that there are some inconsistent findings for the relationship between downside risk and stock average returns in the Healthcare industry when the results obtained from portfolio formation are compared to those using Fama and MacBeth's (1973) cross sectional regression. it has been found that, using portfolio formation, there is no relationship between downside risk and returns. However, using Fama and Maceth's (1973) cross sectional regression produced a significant positive downside risk premium and a significant negative upside risk premium. In addition, for some industries such as; Telecommunications, Chemicals and Utilities, the results based on Fama and McBeth's (1973) cross sectional regression showed that neither CAPM beta nor downside beta is priced. This may suggest that there may be other risk factors affect stocks in these industries. In addition, the results could be affected by the fact that the number of the stocks available within some of these industries is not sufficiently large. Therefore, it would be interesting to split the full sample of stocks into groups of industries based on their covaraition with the business cycle, instead of working within each individual industry. The split based on the covaraition of the stock's industry with business cycle is justified as Ang, Chen and Xing (2006) point out that they find the utilities industry is less exposed to downside risk which is in agreement with the fact that these stocks protect their value in the down market. Furthermore, Olmo (2007) reported that he finds that downside beta is not priced for stocks that are not affected by the downturn market in the UK stocks, while stocks that have positive (negative) covariation with downturn market have higher (lower) returns compared with the CAPM.

In addition, the results showed inconclusive findings concerning the relationship between stock returns and downside risk for the recession period. This could be due to the short sample period; therefore, it would be interesting to split the full sample as in Post and Vliet (2005) who split their sample period into equal size sub-samples using the median of a conditioning variable.

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