Asset Pricing and Prediction with Time-Varying Betas

by

Petros A. Messis

PhD Dissertation

Submitted to the
Department of Accounting and Finance of the
University of Macedonia
Economic and Social Sciences

Thessaloniki, 2015

This page intentionally left blank

Asset Pricing and Prediction with Time-Varying Betas

by

Petros A. Messis

Members of Review Committee

Achilleas Zapranis (Thesis supervisor)

Professor of the Department of Accounting and Finance of the University of Macedonia

Athanasios Noulas (Member of the advisory committee)

Professor of the Department of Accounting and Finance of the University of Macedonia

Ioannis Papanastasiou (Member of the advisory committee)

Professor of the Department of Accounting and Finance of the University of Macedonia

Christos Kollias

Professor of the Department of Economics of the University of Thessaly

Dimitrios Soubeniotis

Professor of the Department of Business Administration of the University of Macedonia

Stefanos Papadamou

Assistant Professor of the Department of Economics of the University of Thessaly

Symeon Papadopoulos

Assistant Professor of the Department of Accounting and Finance of the University of Macedonia

Asset Pricing and Prediction with Time-Varying Betas

The approval of this dissertation from the Department of Accounting and Finance of the University of Macedonia does not necessarily denote the acceptance of the author's opinions on behalf of the department.

I dedicate this dissertation to my son Andreas, to my daughter Sofia, and last but not least to my wife Christina.

ACKNOWLEDGEMENTS

First of all I would like to thank my supervisor, Professor Achilleas Zapranis, who guided me during this journey as a great mentor both in knowledge learning and in mentality training. I would like to express my gratitude to my committee members, Professors Athanasios Noulas and Ioannis Papanastasiou for their valuable support.

I would also like to thank, Professor Christos Kollias and Assistant Professor Symeon Papadopoulos for their constructive suggestions and advices. Many thanks belong of course to all my colleagues past and present and especially to Antonis Alexandridis, Prodromos Tsinaslanidis and Anestis Ladas for their help, friendship and encouragement. A special mention goes to the academic and administrative staff of the department of Accounting and Finance for providing me a friendly working environment.

Finally, the last in order but the foremost in importance, I owe the deepest gratitude to my wife and my parents for their love and support throughout these five constructive and unforgettable years.

ABSTRACT

The theory of asset pricing relies heavily on the principles of present value calculations and the hypothesis of efficient capital markets. The former implies that the price of an asset, not necessarily stock, is a function of the expected future yields discounted to the current data. However, in the field of investments, there seems to be an important but unanswered question. This particular question is concerned with why some assets earn substantially higher average returns. Financial economists have developed different models to address this question in the context of theoretically or empirically motivated asset pricing models. The CAPM is considered to be the most widely used asset pricing model. However, in view of its empirical shortcomings, researchers have made many attempts to refine the theoretical foundations and improve its empirical performance.

One of the main assumptions of the CAPM is the stability of beta coefficients. Because this assumption does not hold in reality, in this thesis we develop a novel approach for capturing the time variation of betas by treating the pattern as a function of market return. To do so, we construct a new two-factor model (TFM) which incorporates variables targeting to absorb the information conveyed by betas' instability. The model is free from subjective bias problems related to the selection of a critical threshold. In addition, the important implications of predicting betas motivated us to examine empirically the accuracy of our TFM's betas. Our analysis uses stocks traded on S&P 500 and covers a long period of time and different kinds of portfolios. The tests for finding out the model's performance along with other well-known models proposed in the literature indicate that this novel approach is very promising.

In addition, in this thesis we examine the existence of herding behaviour in different financial markets. Herding behaviour can have significantly consequences

on the market efficiency, since it might aggravate volatility of returns destabilizing financial markets. Furthermore, nonlinearities of stock prices have been attributed to the existence of herding. Hence, in order to obtain a better understanding of herding, we examine its effects on market volatility. Furthermore, we seek for the existence of herding in factors other than the market risk such as co-skewness and co-kurtosis. Finally, we explore the existence of contagion effects of herding as well as if the measure of herding is affected by various unexpected macroeconomic shocks. We believe that the empirical findings reported in this thesis will help market participants and investors in many ways.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

All models are wrong but some are useful.

GEORGE E. P. BOX
(1919-2013)

CHAPTER 1

INTRODUCTION

1.1 Motivation and Scope

The theory of asset pricing relies heavily on the principles of present value calculations and the hypothesis of efficient capital markets. The former implies that the price of an asset, not necessarily stock, is a function of the expected future yields discounted to the current data. However, in the field of investments, there seems to be an important but unanswered question. This particular question is concerned with why some assets earn substantially higher average returns. Financial economists have developed different models to address this question in the context of theoretically or empirically motivated asset pricing models. A common practice in the literature is to take the models to the data and perform different tests among competitive models. A good model should accompanied by small pricing errors and economic significant risk premia.

The Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965) is by far the most famous model for asset pricing. The model predicts that the expected return of an asset is proportional to its beta coefficient. The coefficient measures the sensitivity of an asset's return to the aggregate market return. However, the considerable evidence against the CAPM points to the fact that variables other than the market portfolio accommodate significant risk premia.

Over the years, researchers have made many attempts to refine the theoretical foundations and improve the empirical performance of the CAPM. Among others, popular extensions include the Arbitrage Pricing Theory (APT), developed by Ross (1976), the Intertemporal CAPM (ICAPM), developed by Merton (1973), the Fama and French three-factor model (FF3FM) (Fama and French, 1993), or the conditional CAPM of Jagannathan and Wang (1996). The APT model relates to the use of multiple factors that capture the asset risk exposure. The underlying concept is that asset prices are formulated by several factor prices, which have some fundamental and plausible relationship with the underlying company (Maringer 2004). In the ICAPM, it is assumed that investors are concerned not only with their end-of-period returns as in the CAPM, but also with the opportunities they have to consume or invest the payoff. In relation to the FF3FM, the authors argue that the spread observed in returns between small and big firms as well as between high book-to-market stocks and low book-to-market stocks are able to capture return variations. Because these spreads produce undiversifiable risks, the formulated factors can be regarded as state variables. As far as the conditional CAPM is concerned, the central idea lies on the fact that assets' market betas vary through time. Chan and Chen (1988) and Ferson and Harvey (1991) show in their studies that market betas exhibit a significant amount of time variation. Hence, Jagannathan and Wang (1996) develop a model by arguing that the CAPM holds in a conditional sense that betas and the market premium vary over time.

Furthermore, there is strong evidence the assumption of CAPM constant betas does not hold, while at the same time a number of studies depict the need of calculating separately beta coefficients for bull and bear markets (Levy, 1974). Fabozzi and Francis (1977) developed a dual-beta model that takes into consideration the market conditions. This way, the model allows investors to differentiate downside risk from upside risk.

In view of the strong evidence of betas' instability, the scope of this thesis is to develop a novel approach for capturing the time variation of betas by treating the pattern as a function of market return. To do so, we construct a new two-factor model (TFM) which incorporates variables targeting to absorb the information conveyed by betas' instability. The model is free from subjective bias problems related to the selection of a critical threshold. The results are very promising both in the times series

(Messis and Zapranis, 2014a) and in the cross-sectional contexts (Messis, Alexandridis and Zapranis, 2014). In addition, the important implications of predicting betas motivated us to examine empirically the accuracy of our TFM's betas with other well-known techniques developed in the literature.

Finally yet importantly, our scope of this thesis is to examine the existence of herding behaviour in financial markets for two particular reasons. First, investors and financial managers are concerned about the way information is reflected in stock market prices. The efficient market hypothesis states that market participants form rational expectations of future prices discounting all market information into expected prices. However, the existence of herding might aggravate volatility of returns destabilizing financial markets (Demirer and Kutan, 2006). Second, the existing findings of nonlinearities in stock prices have been attributed to various behavioural dynamics of investors. In turn, the instability of betas has long been recognised as a result of the instability of asset returns (Groenewold and Fraser, 1999). For example, Hwang and Salmon (2004) show that the estimated CAPM betas of individual assets will be biased and away from their equilibrium values when herding towards market portfolios exists. Hence, we empirically test the existence of herding in different financial markets and report its effects on different aspects of financial activity.

1.2 Thesis Overview

This section provides the manner this thesis is constructed into four parts and eight chapters and gives an overview for each one.

Part I presents the main theoretical background of this thesis. The description of this background starts by presenting some fundamental concepts on general equilibrium and the way it has been made applicable to finance. We continue by reporting the two distinctive groups of models that characterize neoclassical finance (i.e. absolute pricing models and relative pricing models). Subsequently, our focus is on the description of different extensions of the CAPM, the most widely used asset pricing models. In particular, static and dynamic asset pricing models are presented as well as models developed based on the time variability of betas. Finally, we introduce and develop our new approach of asset pricing which primarily draws information conveyed by time varying betas. Thus, in this first part, we gradually focus our attention from a wider theoretical background to the main topic of this thesis, which relates to asset pricing and prediction with time varying betas. Part I consists of Chapters 2 and 3.

Chapter 2, after describing concepts of general equilibrium in introduction, it presents some of the most cited static asset pricing models in finance. The specific models ignore consumption decisions and treat asset prices as being determined by the portfolio choices of investors who have preferences over wealth just only one period in the future. The section of static models starts with the CAPM, which marks the birth of asset pricing. The model's attraction according to Fama and French (2004) is its powerful and pleasing predictions about how to measure risk and return. We continue by introducing the reader to some alternative univariate models such as the Black Zero-beta CAPM and the International CAPM (ICAPM). The Arbitrage Pricing Theory (APT) constitutes the first multifactor model of the static models being considered. The APT attempts to overcome the anomalous empirical evidence that has plagued the CAPM while this equilibrium model generates fewer and more realistic assumptions than the CAPM. Subsequently, the FF3FM and the higher moment CAPM are described. The former adds two additional variables other than the market risk that takes into consideration the spread between small and big in size stocks and the spread between high book-to-market and low book-to-market stocks. The latter model has been developed after demonstrating in international literature that apart from the pricing of the first co-moment of stock returns with the market return, differences in average returns across assets are related to systematic third and fourth moments of the return distribution. The third section of this chapter deals with dynamic asset pricing models. The models of this category adopt a more realistic assumption about investors. They accept that in the real world investors consider many periods in making their portfolio decisions and thus consumption and portfolio choices should be treated simultaneously. The Intertemporal CAPM (ICPM) and the Consumption CAPM (CCAPM) belong to this category. The ICAPM adopts a different assumption about investor objectives. In this model, investors are concerned not only with their end-of-period payoff, but also with the opportunities, they have to consume or invest the payoff. As a result, a second type of risk is included in the analysis. It may concern changes in the instantaneous investment opportunity set, as its variation alters the expected risk-return trade-off in the future. The CCAPM involves a single consumption beta relative to a specific variable, and thus it makes easier its empirical examination. The third section of chapter 2 relates to models developed based on the time varying nature of betas. The conditional CAPM and the Dual-Beta model are presented. The former model though a dynamic model, we chose to incorporate it into this category in order to emphasize its main idea that assets' betas vary through time. The latter model is not an equilibrium model but a model that informs investors about the magnitude of betas in bull and bear markets.

Chapter 3 introduces our novel approach of asset pricing. It starts by presenting some of the main drawbacks of CAPM and continues reporting the literature about the most famous studies regarding betas' behavior in up and down markets. Subsequently, we focus on the advantages of our new approach and in section 2 we develop the main steps for constructing our new Two Factor Model (TFM). This model constitutes two variables, which relate to the information obtained after running a nonlinear regression. The first variable aims at capturing the risk associated with 'Superior' and 'Inferior' stocks whereas the second variable contains the remaining stocks with constant betas.

Part II presents the main empirical findings regarding the performance of the TFM. Tests of the CAPM are based on three implications of the relation between expected return and market beta implied by the model. First, expected returns on all assets are linearly related to betas and no other variable. Second, the beta premium is positive, and third assets uncorrelated with the market have expected returns equal to the risk-free interest rate. Most tests of these predictions use either time series or cross-section regressions (Fama and French, 2004). Thus, the purpose of Part II is to use both approaches for testing our model in order to have a better understanding of the TFM's performance. Finally, the last chapter of Part II shows the results associated with the accuracy of beta predictions by employing the TFM and other well-known models that treat systematic risk as time varying. Part II is being composed by Chapters 4, 5 and 6.

Chapter 4 reports the empirical findings coming from the time series regressions. The TFM is tested and compared against CAPM and FF3FM on five different kinds of portfolios. These portfolios are formed using the estimated coefficients of a nonlinear regression and each one of them accommodates different properties. The regression tests also concern momentum portfolios that found to be the main drawback in FF3FM tests. The dataset used concerns securities traded on the S&P 500. The choice to form portfolios at the start of each year ensures that we will not face the look-ahead bias problem (Banz and Breen, 1986). The risk free rate is a 3-month Treasury bill for the US market. The findings show that neither CAPM nor FF3FM explain the variation of portfolio returns and the superiority of the TFM is apparent. The portfolios used to construct the variables of the TFM do not accommodate higher fundamental risk. The aggregate z-scores, which help to combine all variables and give more consistent explanations, show that 'Superior' portfolio dominates 'Inferior' at least for the years preceding the formation period. In addition, the observed differences in returns between extreme deciles of the estimated portfolios are not associated with higher risk when different states of the world are considered. After verifying that the model better explains portfolio returns, we compare the power of the explanatory variables using the residuals that come from the time series regressions. The results show that the SMISI factor seems to explain information left on the FF3FM residuals.

Chapter 5 describes the findings related to the cross-section regressions. The cross sectional approach is to regress the average returns of assets or portfolios on their estimated betas. Our effort is to test the TFM both conditionally and unconditionally. The competitive models are the CAPM, the FF3FM and the P-L model of Jagganathan and Wang (1996). These models are examined on two different portfolios sorted on the historical beta coefficients and the Book Value per share. The findings exhibit that in the cross-sectional analysis both conditionally and unconditionally, the stock market prices different risk factors. In the unconditional setting and regarding the BVps portfolios, the SMISI factor is priced and the market risk premium has the expected positive sign. The conditional cross-sectional regressions in the case of BVps portfolios identify the power of the TFM variables in explaining asset returns even though a proportion of them left unexplained. For the beta-sorted portfolios, we should refer that almost no risk premia are priced apart from the case of the PL-model. In extreme market conditions, the lowest portfolios seem to be influenced less than the highest ones by downward movements of the market. The findings of the models' performance in extreme conditions present that all models in down moths leave unexplained returns but they do better in up months.

The fact that that all models accommodate the market risk, we have proceeded with the estimation of risk premium when beta sorted portfolio returns were used as dependent variables in the conditional-cross sectional regressions. In this analysis, the TFM gave the most accurately results.

Chapter 6 aims at testing the predictive accuracy of three different in nature models designed to capture time variation in beta coefficients and compare them with the estimated coefficients of our new TFM. In particular, different models from the GARCH family are employed along with the Kalman filter algorithm and the Schwert and Seguin (1990) model. In this chapter, we also present the estimating results of various out of sample beta forecasts using nine consecutive years and three different in magnitude samples. With the large number of years forecasting we try to ensure the results' consistency so that any model's performance to be independent on the particularities of a given period. Furthermore, we focus on a more closely examination on the parameters of the models with the best and worst results in order to be capable of selecting the best model (or some of the best models) at an earlier stage. Finally, it is worth mentioning that in this chapter we perform some diagnostic tests to find out if the normality of returns is accompanied by better predictions. The results show that the accuracy of estimating out of sample betas differentiates according to the selected period of the sample. For the two largest samples, the new method works well enough, while the Kalman filter algorithm takes the advantage of accuracy at the smallest sample. As for the asset returns, as expected, they do not follow the normality assumption. However, the average J-B test is smaller for stocks with better accuracy predictions than the worst ones. At the same time, significant differences in predictive accuracy are apparent in tests related to autocorrelation and heteroskedasticity.

Part III introduces the reader to concepts of herding behavior. The efficient market hypothesis states that market participants form rational expectations of future prices discounting all market information into expected prices. However, the existence of herding might aggravate volatility of returns destabilizing financial markets (Demirer and Kutan, 2006). A small volatility in the prices of financial assets is acceptable due to the process of allocating funds among competing uses. However, excessive or extreme market volatility could lead to structural or regulatory changes (Becketti and Sellon, 1989). Hence, this part of this thesis exhibits the results of the effects of herding on different volatility measures. We continue by reporting the reasons of selecting the herding model of Hwang and Salmon (2004) among other competitive models. Furthermore, in the light of the empirical evidence that higher co-moments are capable of explaining asset returns, we firstly investigate whether herding also matters towards higher co-moments in five major developed markets (i.e. USA, UK, Germany, France and China). Finally, in this part, we explore the existence of contagion effects of herding as well as the effects of unexpected macroeconomic shocks on herding. Part III is being composed by Chapters 7 and 8.

Chapter 7 justifies the choice of the herding measure considered and examines the effects of herding on market volatility (Messis and Zapranis, 2014b). In empirical studies, the estimation of herding can be classified into two main categories (Spyrou, 2013). The first one investigates the existence of herding on specific investor types such as money managers. The herding measure of this category was first proposed by Lakonishok et al. (1992) and improved by Sias (2004). The second category investigates herding towards market consensus by relying on aggregate price and market activity data. This category is primarily based on measures proposed by Cristie and Huang (1995), Chang et al. (2000) and Hwang and Salmon (2004) and it is widely used in the literature (Spyrou, 2013). In addition, the measures of the latter category are relatively easy to calculate since they are based on observed returns data and not on detailed records of individual trading activities such as the measure proposed by Lakonishok et al. (1992) (Hwang and Salmon, 2004). The investigation of the effects of herding on volatility has been conducted for the Greek stock market. Four different measures of volatility have been employed. The first one is the standard GARCH(1,1) model, the second is the TGARCH model that incorporates asymmetries in asset returns, and third is the volatility measure of French et al. (1987) which takes into account the autocorrelation in daily returns. This latter measure is also decomposed into upside and downside volatilities by estimating the summation of positive and negative daily market returns respectively.

Chapter 8 investigates the existence of herding towards market, co-skewness and co-kurtosis in five major developed markets (i.e. USA, UK, Germany, France and China). To our knowledge this is done for first time as most of the papers test herding towards the factors of Fama and French (1993) model. Furthermore, we examine the effects of unexpected variations in different macroeconomic variables on the estimated herding measures. To achieve our goal and catch any macroeconomic shocks we make use of the Box-Jenkins methodology. Finally, we investigate whether contagion of herding between the selected countries exists. If this happens, the benefits of international portfolio diversification diminish. We extend the analysis by investigating whether contagion of herding matters due to macroeconomic shocks or crises period. Estimated conditional correlations are used for this purpose. Moreover, we examine whether specific crises happened in these markets affect the China's market herd measure. This particular country is used here as another candidate country, apart from the three European countries and the US market, for international portfolio diversification purposes since it accommodates some specific characteristics such as its significant economic growth and the attraction of international investors (Valukonis, 2013). The results demonstrate the existence of herding not only towards market index but also towards the factors of co-skewness and co-kurtosis. Most of the herding measures follow their own patterns particularly towards the market index, while the herding patterns towards co-skewness and co-kurtosis reveal an opposite direction in relation to their corresponding market behavior. In addition, turbulent periods in the EU and the US markets and extreme negative shocks on the expected values of their macroeconomic variables influence the China's herding measure as the conditional correlation indicates. (Messis and Zapranis, 2014c).

Part IV contains the conclusions of this thesis, the Appendices and the corresponding bibliography. As for the conclusions, a summary of our main contributions to academia and market participants is also provided, along with a discussion of directions for further work. In appendices are presented the main theoretical steps used in the development and empirical examination of the CAPM.

1.3 Contributions

Our thesis, with its findings and proposals, can be very useful not only to researchers but also to traders, hedging companies and new investors. In view of the strong evidence of betas' instability, we develop a novel approach for capturing their time variation by treating the pattern as a function of market return. Our new two factor model (TFM) incorporates variables targeting to absorb the information conveyed by betas' instability. Although different models and procedures have been developed in the literature for splitting betas in up and down markets, this is the first time where this betas' characteristic is used for the construction of a compact model. The model is free from subjective bias problems related to the selection of a critical threshold. Our results indicate that this specification outperforms alternative models such as CAPM and FF3FM in explaining returns in time series regressions. Furthermore, we provide evidence that the particular portfolios used to model's construction are not being necessarily riskier. The strong performance of the model also holds in the cross-sectional analysis. Thus, the new risk factors which found to be significant both in time series and cross section analyses, give valuable information of better understanding the characteristics of returns, targeting the reinforcement of stock market efficiency.

After the successful empirical implementation of the TFM in the above two testing approaches, we assess the predictive accuracy of the model and compare it along with other modelling techniques that rely heavily on time series regressions. The different versions of the GARCH models and the Kalman filter algorithm are two of the most documented methods. As far as this part of this thesis is concerned, the contribution to the international literature is multiple. First, the predictive accuracy of betas is examined by employing different versions of the reported models. Second, we use nine out of sample consecutive years and three different samples of returns intervals. This way, we are in a position of selecting the best fitted time interval and use it for future predictions without wondering what time interval is the most appropriate. According to the empirical findings, a five years period gives the most accurate predictions while at the same time our new model is very competitive though not the best one. However, even though the new model does not seem to be the best one among the examined models its sufficient accuracy prediction and its use for pricing assets enables it a useful tool at investors' hands. Third, we provide evidence that the estimated models' parameters vary significantly not only from period to period but also among the best and worst groups sorted on the models' predictive accuracy. Finally, the fact that the CAPM model is firmly based on the assumption that asset returns are iid normal (i.e. identically, independently and normally distributed) motivates us to apply a few diagnostic tests for finding out if the existence of iid normal returns is accompanied by better results. As expected, asset returns do not follow the normality assumption. However, the average J-B test is smaller for stocks with better accuracy predictions than the worst ones. At the same time significant differences are also observed on the tests related to autocorrelation and heteroskedasticity. Hence, the different results reported here give valuable information for those investors and hedging companies that wish to use the aforementioned models for predicting betas. We also supply them with a new approach that may be used in many different financial applications.

Furthermore, this thesis sheds light to various aspects of herding behavior in financial markets. To begin with, we explore the existence of herding in the Greek stock market, and examine whether its presence influences market volatility. The measurement of herding has been conducted using the model of Hwang and Salmon (2004). With this particular model, we are able to detect herding not only in periods of extreme market movements but also during normal market conditions. Hence, it provides a more detailed analysis of herding over time (Demirer et al., 2010). In addition, the model is free from the influence of idiosyncratic components as it focuses only on the variability of factor sensitivities (Hwang and Salmon, 2004). This part of this thesis adds to the literature on the herding behaviour of investors with different ways. First, it extends investor herding studies to an emerging market by using state space models not previously applied in this specific market. Second, it employs different portfolios formed on the basis of the magnitude of beta and the size designed to identify whether herding is differentiated across these portfolios. Last but not least, it examines the implications of herding on market volatility. Generally speaking, traders use different models to evaluate stock market volatility. From this point of view, the results could provide a better understanding of which variables affect market volatility resulting in to much more accurate forecasting and, furthermore, to the adoption of new hedging strategies for more integrated risk management. We also contribute with our findings to the growing literature on the ASE. Diacogiannis et al. (2005) claim that studying the Athens Stock Exchange (ASE) can offer useful inferences due to the regulatory regime and practices characterizing the Greek market. The authors report that in the ASE, despite the influence of institutional investors, traders are mainly small investors and from this point of view the ASE employs no specialists. However, the regulatory authority monitors trading activities and controls insider trading by targeting on the restriction of excessive volatility.

Furthermore, we explore the existence of herding towards factors other than the market and contribute in the literature with different ways. In the light of the findings that higher co-moments are capable of explaining asset returns, we investigate whether herding also matters towards co-skewness and co-kurtosis in five major developed markets (i.e. USA, UK, Germany, France and China). To our knowledge this is done for first time since most of the papers test herding towards the factors of Fama and French (1993) model. In addition, a number of studies have documented that unexpected variations in different macroeconomic variables or uncertainty shocks such as the 9/11 terrorist attacks influence stock prices and increase volatility (*inter alia*: Fama, 1981; Pearce and Roley, 1985; Wasserfallen, 1989; Gjerde and Saettem, 1999; Hondroyiannis and Papapetrou, 2001, Bloom, 2009). This fact motivates us to empirically examine their effects on the estimated herding measures. Finally, we investigate whether contagion of herding between the selected countries exists. If this happens, the benefits of international portfolio diversification diminish.

1.4 Summary

In this chapter we presented subsequently our main motivations, the scope, an overview and the main contributions to the academia and financial industry in general of this thesis. As we already mentioned, although different pricing models have been developed, and different approaches try to split betas in up and down markets, there is not a comprehensive model for pricing assets based on this latter characteristic. The TFM seems to work reasonably well both in time series and in cross-sectional regressions, while at the same time its accuracy in predicting betas is not disappointing. In this thesis we also address the effects of herding in financial markets, since the literature demonstrates its consequences in market efficiency in general. Thus, we explore the different aspects of herding and hope the findings of this thesis to help all participants in financial markets in many ways.

PART I: ASSET PRICING MODELS

This part provides the theoretical background and gives the most cited asset pricing models in financial markets. The theory of asset pricing tries to shed light on the relation between prices or values of claims to uncertain payments. A low price of an asset implies a high rate of return. However, some assets pay higher average returns than others, and from this point of view it could be said that the asset pricing theory examines the possible reasons hidden behind this notion. Pricing an asset based on its exposure to fundamental sources of macroeconomics risk constitutes the most common practice in academic settings (Cochrane, 2005). The CAPM and its successor factor models of equilibrium are paradigms of this approach. Chapter 2 describes the different approaches of static and dynamic asset pricing models as well as models developed based on the time variability of betas. This part of the dissertation ends with the introduction and development of our new approach of asset pricing.

CHAPTER 2

EQUILIBRIUM MODELS IN ASSET MARKETS

2.1 Introduction

The asset pricing theory along with general equilibrium theory and macroeconomics constitute three fields in economics that have converged and continue so over the last three decades or more (Lengwiler, 2004). The theory of general equilibrium tries to describe the behaviour of an economy as a whole, by searching for compatibility and consistency points among its members. In this economy, individuals interact with each other only indirectly and prices of exchange rates for different commodities are posted. In addition, the influence of each individual on prices is negligible due to the small fraction they possess on the market. This model, which holds these two particular assumptions (i.e. anonymity and perfect competition), was firstly formulated by Walras (1874). The economy is in equilibrium when each individual, at a certain price, buys or sells the optimal quantities and the total supply equals to the total demand. However, the model left unspecified who posts the prices, an issue solved later by Arrow and Debreu (1954). The authors established the conditions that guarantee the equilibrium existence, and hence modern general equilibrium theory accommodates a large number of different goods and different preferences of individuals. Hirshleifer (1965, 1966) and Radner (1972) made general equilibrium theory applicable to finance by building financial markets into the model. Although the theory was pushed aside by advances in game theory and information economics in 1970s, its applications to the theory of asset pricing gave it new dynamic. However, the empirical investigation of general equilibrium requires the use of equilibrium consumption values something difficult in practice since we have to model the investor's entire environment such as the specification of all the assets he has access or what his labour income process looks like. Thus, despite the fact that consumption-based model is a complete answer to all asset pricing questions, it works poorly in practice. This motivates factor pricing models such as CAPM, APT and ICAPM to constitute a sensible response to bad consumption data (Cochrane, 2005).

In neoclassical finance, the models are separated into two distinctive groups: absolute pricing models and relative asset pricing models. In absolute pricing, each price is determined by reference to its exposure to fundamental sources of macroeconomic risks. The consumption-based and general equilibrium models are the purest examples of this approach. This particular approach of asset pricing is most common in academic setting. In other words, asset pricing theory is positively used to give an explanation in order to predict how prices might change if policy or economic structure changed.

In relative pricing, the asked question is what we can learn about an asset's value given the prices of some other assets. The information used in this approach relatively to fundamental risk factors is as little as possible. A well known example of this approach is Black and Scholes (1973) option pricing and its extension Contingent Claim Analysis (CCA) developed for crediting a country's default risk (Celik, 2012).

In building a framework for the study of financial markets, academics face a number of fundamental choices. They need to choose a set of assumptions about the judgments, preferences, and decisions of participants in financial markets. For example, financial decision-makers posses von Neumann-Morgenstern[1] (1953) preferences over uncertain wealth distributions, and use Bayesian techniques to make appropriate statistical judgments from the available data. These assumptions hold in the neoclassical framework. On the other hand, there is the theory of behavioral finance in which people do not have von Neumann-Morgenstern preferences, and do not form judgments based on Bayesian principles. The prospect theory is the counterpart to von Neumann-Morgenstern theory and the 'heuristics and biases' is the

[1] For more details on von Neumann-Morgenstern preferences see Appendix A.

behavioral counterpart to Bayesian theory. Shefrin (2005) presents very analytically models related to behavioral finance. However, the scope of this work is not to cover in depth the behavioral counterparts.

The work proceeds as follows. Next two sections discuss the theoretical framework of static and dynamic asset pricing models. Section 4 reports two widely used models built on time varying betas and section 5 concludes.

2.2 Theoretical background of static models

This section gives a description of static asset pricing models most presented in the international literature (Celik, 2012). These specific static asset pricing models ignore consumption decisions and treat asset prices as being determined by the portfolio choices of investors who have preferences defined over wealth one period in the future (Campbell et al., 1997).

2.2.1 The Capital Asset Pricing Model (CAPM)

The Capital Asset Pricing Model (CAPM) developed by Sharpe (1964) and Lintner (1965) marks the birth of asset pricing theory. The model is still widely used in estimating the cost of capital for firms and evaluating the performance of managede funds. According to Fama and French (2004), the model's attraction is its powerful and intuitively pleasing predictions about how to measure risk and the relation between expected return and risk.

The CAPM is the extension of one period mean-variance[2] portfolio model of Markowitz (1952, 1959), which in turn is built on the expected utility model of von Nuemann and Morgenstern (1953). The Markowitz's model is concerned with how investors should allocate their wealth among the various assets available in the market, given that they are one-period utility maximisers. Investors care only about the mean and variance and as a result, they choose mean-variance efficient portfolios,

[2] A detailed description of the mean-variance rule is presented in the Appendix B.

in the sense that the portfolios 1) minimize the variance of portfolio return, given expected return, and 2) maximize expected return, given variance.

The CAPM is derived from a set of assumptions in order to define the relationship between risk and return that determines security prices. For example, the Sharpe-Lintner derivation of the CAPM assumes that a) all investors are risk-averse individuals, who maximise the single-period expected utility of wealth b) the investors have homogenous expectations of the end-of-period joint distributions of returns c) all investors can borrow or lend unlimited amounts at the risk-free rate, and there are no restrictions on short sales, d) securities markets are frictionless and perfectly competitive, and e) the quantities of asset are fixed while all assets are marketable and perfectly divisible.

Based on these assumptions the CAPM can be written as

$$E(R_i) = R_f + \beta_i((E(R_m) - R_f)\,. \qquad 2.1$$

In words, R_i is the return of asset i, R_f is the risk-free rate, R_m is the market return, β_i is the market sensitivity parameter defined as $cov(R_i,R_m)/var(R_m)$ and $E(\cdot)$ is the expectation operator. According to the assumption that investors are risk adverse, it seems reasonable that high beta stocks should have higher expected returns than low beta stocks. In fact, this is what equation 2.1 implies. In equilibrium, an asset with zero systematic risk (β=0) will have expected return equal to the risk less asset. Intuitively, when markets are frictionless, investors price assets according to their systematic or nondiversifiable risk. This way, the model invalidates the traditional role of standard deviation as a measure of risk. In addition, this is a natural result of the rational expectation hypothesis applied to asset markets.

Most tests of the asset pricing models have been performed by estimating the cross sectional relation between average return on assets, and their betas over some time interval and comparing the estimated relationship implied by CAPM. The empirical estimation is also conducted using time series regressions. More on these empirical testing procedures are discussed in Part II of this dissertation. However, it is worth mentioning that the CAPM and capital market efficiency are joint and inseparable hypotheses (Copeland et al., 2005). If capital markets are inefficient, then the assumptions of the CAPM are invalid and a different model is required. The remaining section of this chapter will give an overview of the extensions of CAPM as well as alternative approaches.

2.2.2 The Black Zero-beta CAPM

The assumptions underlying the CAPM are violated in reality. For example, Farrell (1997) reports that empirical tests have shown that the line (i.e. Security Market Line) did not intercept the vertical axis at the risk-free rate, thus indicating a potential deficiency in one of the main assumptions of the CAPM. Black (1972), realizing this problem and observing empirical evidence, showed that the major results of the CAPM do not require the existence of a risk-free asset that has constant returns in every state of nature. His analysis indicated that it was possible to substitute the risk-less asset with a zero beta asset or portfolio. Such a portfolio is designed to have zero covariance with the market portfolio. The zero beta CAPM has a structure similar to the original with the difference being that the risk-free rate (R_f) is replaced by the portfolio return (R_z) in the following equation:

$$E(R_i) = E(R_Z) + \beta_i [E(R_m) - E(R_Z)] . \qquad 2.2$$

2.2.3 The International CAPM

International diversification studies date from the 1970s, when globalization and international investing became important (You and Daigler, 2010). If the universe of assets available for investment is larger than just the assets in one country, investors may be able to reduce the risk of their investments through diversification. Solnik (1974a, 1974b) developed an international asset pricing model (ICAPM) and tested it. In his model, a market portfolio is constructed by using market value-weighted stocks, and a portfolio of risk-free assets of different countries in the world. The portfolio weights depend on net foreign positions in each country and the relative risk aversions[3] of the countries' citizens. The ICAPM has the following form:

$$E(R_i) = R_{fi} + \beta_i((E(R_{WM}) - R_{fW}) \qquad 2.3$$

where

R_i denotes the return on security i,

R_{fi} denotes the riskless rate in the country of security i,

R_{WM} denotes the return o

n the world market portfolio,

R_{fW} denotes the riskless rate of the average worldwide risk-free asset, and

β_i denotes the international systematic risk coefficient of security i.

2.2.4 Arbitrage Pricing Theory (APT)

The APT developed by Ross (1976) attempts to overcome the anomalous empirical evidence that has plagued the CAPM (Lehmann and Modest, 1988). This equilibrium model generates fewer and more realistic assumptions than the CAPM. Copeland et al. (2005) report several reasons according to which APT is more robust than the CAPM. These reasons can be summarized as follows:

- The APT makes no assumptions about the returns distribution.
- The APT makes no strong assumptions about individuals' utility functions.
- The APT allows the equilibrium returns of assets to be dependent on many factors other than the market risk.
- The APT does not require that the market portfolio is efficient.
- The APT can be easily extended to a multiperiod framework.

The APT is based on the law of one price, which states that two otherwise identical assets cannot sell at different prices. The basic assumptions of the model are that the capital markets are perfectly competitive, and that, under conditions of economic certainty, investors would always prefer more wealth to less. The following equation illustrates the general form of the model, assuming that there are several factors generating returns for the securities (Bodie et al., 2002):

---

[3] The relative risk aversion (RRA) can be defined as: $RRA = -W\frac{U''(W)}{U'(W)}$, where $U''(W)$ and $U'(W)$ are the second and first derivatives of a utility function respectively.

$$R_i = a_i + \beta_{i1}\Pi_1 + \beta_{i2}\Pi_2 + ... + \beta_{ik}\Pi_k + e_i \quad \text{for i=1,2,…N.} \qquad 2.4$$

In the above equation, Ri, is the return of asset I while it is linearly related to a set of factors $\Pi_j (j = 1, 2, ..., k)$. The beta coefficients show the sensitivity of the asset to each factor. Again, higher values of beta coefficients indicate greater sensitivity, whereas lower values indicate lesser sensitivity of the stock return to a particular factor. The last term of equation 2.4, e_i, is a random variable and it is expected to average zero over time (i.e. $E(e_i) = 0$) as well as to be uncorrelated across securities (i.e. $E(e_i, e_j) = 0$). In a well-diversified economy with no arbitrage opportunity, the equilibrium expected return on asset i, with the presence of a risk free rate, is given by the following equation (Groenewold and Fraser, 1997):

$$E(R_i) = R_f + \beta_1(\lambda_1 - R_f) + \beta_2(\lambda_2 - R_f) + ... + \beta_k(\lambda_k - R_f) \qquad 2.5$$

Where λ_k has the interpretation of the expected return to an asset or portfolio with unit sensitivity to factor k and zero sensitivity to all other factors. If there is only one factor and that is the market risk, then the APT is equal to CAPM.

The main drawback of the APT is primarily that it does not specify the number or type of factors that are important in determining security returns. Modern financial theory focuses upon systematic factors, as sources of risk, and suggests that macroeconomic variables systematically affect stock market returns. The inflation rate is the most common factor that influences the returns of a portfolio, and is found to be significant in Chen et al., (1986) for the US stock market, and Beenstock and Chan (1988) and Clare and Thomas (1994) for the UK stock market. Other factors that are found to be significant in these studies are industrial production index, interest rate, retail index, money supply and fuel and material costs.

There are two main approaches for specifying factors in order to test the model: the statistical approach and the theoretical approach. The statistical approaches (i.e. factor analysis and principal components) involve building factors from a comprehensive set of asset returns and variables, while the theoretical approaches (i.e. macroeconomic variables or characteristics of firms) specify factors that are based on theoretical arguments and capture economy-wide systematic risks (Chen et al., 1986, Campbell et al., 1997). This model can be also tested both in the cross sectional context and in the time series context.

2.2.5 The Fama and French three factor model (FF3FM)

The Fama and French model is one of most popular multifactor models that dominate empirical research (Cochrane, 2005). The work of Fama and French (1992) analyzes the empirical evidence against the CAPM and confirms the results of Reinganum, (1981), Stambaugh, (1982) and Lakonishok and Sharpino, (1986) that the relation between average return and beta for common stocks is even flatter after the sample periods used in the early empirical work on the CAPM. Furthermore, the authors show that size, earnings-to-price, debt-to-equity and book-to-market ratios add to the explanation of expected stock returns. Fama and French (1993) and in the spirit of the arbitrage pricing theory (Fama and French, 2004) argue that size and book-to-market equity are not state variables but due to the fact that they produce undiversifiable risks in returns that are not captured by the market return and are priced separately from market betas can be regarded as state variables. The authors argue that the returns on the stocks of small firms covary more with one another than with returns on the stocks of large firms. As for the returns on high book-to-market (value) stocks, they covary more with one another than with returns on low book-to-market (growth) stocks. Based on these findings, Fama and French (1993, 1996) propose the following three-factor model:

$$E(R_i) = R_f + \beta_i((E(R_m) - R_f) + s_i E(SMB) + h_i E(HML) . \qquad 2.6$$

In equation 2.6, SMB (small minus big) is the difference between the returns on diversified portfolios of small and big stocks. HML (high minus low) is the difference between the returns on diversified portfolios of high and low book-to-market stocks, and the factor loadings β_i, s_i, h_i are the slopes that come from the Ordinary Least Squares (OLS) time series regression.

The main shortcoming of the FF3FM is its empirical motivation. The additional two independent variables (i.e. SMB and HML) are not motivated by predictions about state variables of concern to investors. Instead, they intend to capture the patterns uncovered by previous work on how average stock returns vary with size and the book-to-market equity. The most serious problem faced the model is the momentum effect of Jegadeesh and Titman (1993). The momentum effect relates to stocks that do well relative to the market over the last three to twelve months since they continue to do so for the next few months. The opposite is true for stocks that do poorly. This momentum effect is left unexplained by the FF3FM and the CAPM. According to Carhart (1997), one response is to add a momentum factor to the FF3FM. However, the momentum effect is a short-lived phenomenon and as such, it is irrelevant for estimates of the cost of capital.

2.2.6 Higher moment CAPM

An extension of the CAPM is the higher moment CAPM, which introduces the figures of skewness and kurtosis into the model. The systematic risk attempts to explain the variance of stock returns. However, the international literature also demonstrates that apart from the pricing of the first co-moment of stock returns with the market return, differences in average returns across assets are related to systematic third and fourth moments of the return distribution. Kraus and Litzenberger (1976) were the first to suggest that higher co-moments may also be significant in explaining stock returns. The authors argue that if the normality assumption of market returns is rejected, investors should also take into consideration portfolio skewness and kurtosis. If this is true then each stock's contribution to systematic skewness (coskewness) and systematic kurtosis (cokurtosis) may determine the attractiveness of a stock and consequently the required return (Hung et al., 2004). Harvey and Siddique (2000) show that coskewness along with a market portfolio proxy becomes a significant factor in explaining the cross-section of returns for stocks traded on the US market. The authors report that the systematic skewness requires an average annual risk premium of 3.6%. Fang and Lai (1997) depict evidence that the expected excess rate of returns are also related to both systematic skewness and systematic kurtosis. Dittmar (2002) presents a framework of a 4-moment CAPM in a conditional setting and shows that cokurtosis and coskewness factors are priced. Smith (2007) finds the price of coskewness risk to be large when market skewness is negative. More recently, Poti and Wang (2010) find that, while coskewness and cokurtosis risk help price different strategies and portfolios, momentum strategies and portfolios managed on the basis of available information neither CAPM nor its higher versions can give consistent results without generating high levels of SDF volatility. Hwang and

Satchell (1999) refer that both systematic risks are significant in emerging markets while similar results are reported by Messis et al. (2007) for the Greek market. Moreno and Rodriguez (2009) conclude that coskewness factor is economically and statistically meaningful in evaluating mutual fund performance. Coskewness has also been used in the pricing of real estate (Vines et al., 1994), in explaining the return generating process in futures markets (Christie-David and Chaudhry, 2001) or in the estimation of conditional VaR (Bali et al., 2008).

As previously reported, Kraus and Litzenberger (1976) and Harvey and Siddique (2000) developed asset pricing models incorporating coskewness term into CAPM. Loadings on market premium and premium squared can be estimated as follows:

$$R_{it} - R_{ft} = a_i + \beta_i (R_{mt} - R_{ft}) + \gamma_i (R_{mt} - R_{ft})^2 + e_{it} \qquad 2.7$$

where β_i is the systematic market risk similar to CAPM beta, while γ_i depicts systematic skewness.

Equation 2.8 except for systematic variance and systematic skewness incorporates systematic kurtosis. Thus, for the model's empirical estimation[4] the following time series regression is executed as in Fang and Lai (1997) and Hung et al. (2004):

$$R_{it} - R_{ft} = a_i + \beta_i (R_{mt} - R_{ft}) + \gamma_i (R_{mt} - R_{ft})^2 + \delta_i (R_{mt} - R_{ft})^3 + e_{it} \qquad 2.8$$

where δ_i is the loading of cokurtosis factor for asset i.

The measures of coskewness and cokurtosis are robust to portfolio (dis)aggregation because although non-linear in the market they are both linear in the stock component itself and consistent with asset pricing models (Hung et al., 2004). Investors tend to have negative preference to variance and kurtosis and positive preference to right-skewed securities (Arditti, 1967; Fang and Lai, 1997; Harvey and Siddique, 2000).

2.3 Theoretical background of dynamic models

[4] We use the models in equations 2.7 and 2.8 to test the effects of herding on the parameters coming from the higher moment CAPM. The detailed results are reported in Part III of this thesis.

This section refers to dynamic asset pricing models. The empirical contradictions of the CAPM point to the need for more complicated asset pricing models (Fama and French, 2004). It is not reasonable to assume that investors care only about the mean and variance of one-period portfolio returns. In the real world investors consider many periods in making their portfolio decisions, and in this intertemporal setting one must model consumption and portfolio choices simultaneously (Campbell et al., 1997).

2.3.1 The Intertemporal CAPM (ICAPM)

The intertemporal capital asset pricing model (ICAPM) of Merton (1973) is a natural extension of the CAPM. The ICAPM adopts a different assumption about investor objectives. In this model, investors are concerned not only with their end-of-period payoff, but also with the opportunities, they have to consume or invest the payoff. In period t-1, the model's investors consider how their wealth at time t might vary with future state variables such as labour income, the prices of consumption goods and the nature of portfolio opportunities at t, and expectations about the labour income, consumption and investment opportunities to be available after t. As a result, a second type of risk is included in the analysis. It may concern changes in the instantaneous investment opportunity set, as its variation alters the expected risk-return trade-off in the future. For example, investor with a given level of risk aversion, an increase in the volatility of market portfolio would force him to accept lower returns by lowering the amount of equity he holds. People generally dislike uncertainty and this fact makes them willingly pay an amount for hedging the portfolio. Hence, unexpected changes in any of the economic quantities that describe the investment opportunity set would constitute a source of risk to an average investor.

Merton's (1973) ICAPM results from the solution of an intertemporal utility-of-consumption maximization problem with continuously tradable assets. The solution of this dynamic problem can give the asset demand function and the equilibrium pricing equation. The following equation gives the testable[5] form of the model according to Bali and Engle (2010) in the context of time series regression:

[5] Bali and Engle (2010) use a Dynamic Conditional Correlation model as a first step for estimating the covariance of stock portfolio returns with market returns and state variables. As a second step the authors estimate the system of n portfolios using the Seemingly Unrelated Regressions (SUR) method.

$$R_{i,t+1} = C_i + ACov_t(R_{i,t+1}, R_{m,t+1}) + \sum_{j=1}^{k} B_j Cov_t(R_{i,t+1}, Z_{j,t+1}) + e_{i,t+1} \qquad 2.9$$

In the above equation, $R_{i,t+1}$ is the excess return of portfolio i at time t+1, and C_i is the constant term of portfolio i's returns. A is the average risk aversion coefficient common to all portfolios in the same regression system, $R_{m,t+1}$ is the excess market return, $Cov_t(\cdot)$ is the expected covariance at time t between the examined variables, $Z_{j,t+1}$ is the j-th state variable for j=1,2,…k, and $e_{i,t+1}$ is as usual the disturbance error.

The intuition behind this model is straightforward. Investors will always try to protect themselves against changes in the opportunity set. The Zj variable expresses such changes that could cause a fall in consumption. If the correlation between consumption and the state variable is negative, a positive change in Zj would result in a decrease in consumption. In relation to an asset whose return is positively correlated with changes in the Zj will have an increase in its return at a time of low consumption. Hence, because of a higher demand the expected return of this particular asset will be lower. The adverse holds for an asset whose return and the state variable Zj has negative correlation.

It is worth mentioning that the ICAPM does not explicitly identify the state variables that are included in the model. Brennan et al., (2004) argue that the opportunity set can be exhaustively described by the risk free rate, and the Sharpe ratio. Although there are not many empirical tests of the model in the literature, we have to report the studies of Faff and Chan (1998) using Australian data, Aquino (2006) using data from the Philippine market and Bali and Engle (2010) using US data. The findings show that the model fits quite well the data in the cases of the Australian market and the US market.

2.3.2 The Consumption CAPM (CCAPM)

Breeden (1979) developed a single beta asset pricing model in continuous time with uncertain consumption goods prices and uncertain investment opportunities. The CCAPM involves a single beta relative to a specific variable, rather than many betas measured to unspecified variables. This fact makes easier its empirical examination under stationarity assumptions on the joint distribution of rates of return and aggregate consumption. The expression of the CCAPM is:

$$E(R_i) = R_f + \beta_i^c((E(R_c) - R_f) \,. \qquad 2.10$$

In the above equation β_i^c is the consumption beta and Rc is the consumption growth. Although the strong theoretical foundation of this model (Lettau and Ludvigson, 2001), the empirical tests are not in favor. The model has been rejected on US data with time-separable utility function (Hansen and Singleton 1982, 1983). Furthermore, it has performed no better and in many cases worse than the simple static CAPM in explaining the cross section of average asset return in studies of Mankiw and Shapiro (1986), Campbell (1996) and Cochrane (1996). However, Lettau and Ludvigson (2001) state that the model's framework is a simple but powerful tool for addressing the criticisms of Merton (1973), that the static CAPM fails to account for the intertemporal hedging of asset demand, and Roll (1977), that the market return cannot be adequately proxied by an index of common stocks. The authors were wondering why the CCAPM performed poorly and applying it in a conditional setting found that the model did as well as the FF3FM on portfolios sorted by size and book-to-market ratio.

2.4 Models with time-varying systematic risk

The static version of the CAPM, or unconditional CAPM, assumes that the systematic risk (i.e. beta coefficient) is constant, since conditional information (i.e. available information up to time t-1) plays no role in determining excess returns. For being the beta coefficient constant means that the correlation between asset excess returns and market excess returns does not vary over time. However, beta measures the correlation between two expectations, which can vary over time and is therefore unlikely to be a static measure. This section presents two widely used models built on the time-varying nature of betas.

2.4.1 The conditional CAPM (or the Premium- Labour model)

The central idea behind the conditional version of CAPM is that assets' market betas vary through time. Chan and Chen (1988) and Ferson and Harvey (1991) show in their studies that market betas exhibit a significant amount of time variation. Jagannathan and Wang (1996) report that it is very important to take time variation in betas seriously since commercial firms like BARRA, which provide beta estimates for risk management and valuation purposes, use elaborate time-series models for the estimation of betas.

Jagannathan and Wang (1996) propose a model in which conditional beta is a function of risk premium. The conditional CAPM is of the following form

$$E(R_{i,t} \mid I_{t-1}) = \lambda_{0,t-1} + \lambda_{1,t-1}\beta_{i,t-1}, \qquad 2.11$$

where I_{t-1} denotes the common information set available to investors at the end of period t-1, $\beta_{i,t-1}$ is the conditional beta of asset i, $\lambda_{0,t-1}$ is the conditional expected return, and $\lambda_{1,t-1}$ is the conditional market risk premium. By taking unconditional expectations of both sides of equation 2.11, the authors get

$$E(R_{i,t}) = \lambda_0 + \lambda_1 \bar{\beta}_i + Cov(\lambda_{1,t-1}, \beta_{i,t-1}). \qquad 2.12$$

In equation 2.12, λ_1 is the expected risk premium and $\bar{\beta}_i$ is the expected beta. When the covariance between the conditional beta of asset i and the conditional market risk premium is zero, equation 2.12 resembles to the static CAPM. However, in general, the conditional risk premium on the market and conditional betas are correlated. For example, during bad economic conditions when the expected market risk premium is relatively high, more leveraged firms are more likely to face financial difficulties and thus have higher conditional betas.

However, the parameters in equation 2.9 are not directly observable and thus the empirical model's examination is difficult. Hence, Jagganathan and Wang (1996) after making some algebraic manipulations and adopting some certain assumptions propose the Premium-Labor model (PL-model) for the empirical study. Instead of using the conditional market risk premium (i.e. $\lambda_{1,t-1}$), the authors employ the spread between BAA- and AAA- rated bonds. This is because interest-rate variables are likely to be most helpful in predicting future business conditions as pointed out by Stock and Watson (1989). Hence, this variable (premium) captures the instability of the asset's beta over the business cycle. The second variable relates to the return on human capital. This variable is taken into consideration for measuring the aggregate wealth, since the empirical failure of the CAPM has been attributed to the bad proxy of the market index (Roll, 1977). The return on human capital is assumed to be a linear function of the growth rate per capita labor income. Thus, the PL-model[6] takes the following shape

$$r_i = \lambda_o + \lambda_1 \beta_i + \lambda_{prem} \beta_i^{prem} + \lambda_{labor} \beta_i^{labor} + v_i . \qquad 2.13$$

2.4.2 The Dual-Beta model (D-B model)

In view of the empirical evidence that the assumption of CAPM constant betas does not hold, while at the same time a number of studies depict the need of calculating separately beta coefficients for bull and bear markets (Levy, 1974), Fabozzi and Francis (hereafter FF) (1977) developed a dual-beta model that takes into consideration the market conditions. This way, the model allows investors to differentiate downside risk from upside risk. Contrary to the constant beta, the dual beta model does not assume that betas in up and down markets remain the same. Instead, the model calculates what the values are for the two betas, and thus permitting investors to make better-informed investing decisions. In equation 2.14, the D-B model of FF allows both alphas[7] and betas to vary according to market conditions:

$$R_{i,t} - R_f = A_{1,i} + A_{2,i} d_t + B_{1,i}(R_{m,t} - R_f) + B_{2,i} d_t (R_{m,t} - R_f) + e_{i,t} . \qquad 2.14$$

In the above equation, the d_t is a dummy (binary) variable which takes the value of unity in bull markets and zero otherwise. The coefficients $A_{2,i}$ and $B_{2,i} d_t$, measure the differential effects of bull market conditions on the alpha, $A_{1,i}$, and the beta, $B_{1,i}$, for

[6] The PL-model is empirically tested and compared with the new model proposed in this dissertation. For more details see Part II.

[7] The D-B model without assuming that alpha varies over bull and bear market conditions is:

$$R_{i,t} - R_f = A_{1,i} + B_{1,i} d_t (R_{m,t} - R_f) + B_{2,i}(1 - d_t)(R_{m,t} - R_f) + u_{i,t} .$$

the stock i. When conditions are adverse for the market then equation 2.14 resembles to the static CAPM. This happens because $A_{2,i}d_t = B_{2,i}d_t = 0$. If the alpha and beta for stock i differ over bull and bear markets then $A_{2,i}$ and $B_{2,i}$ will be significantly different from zero.

2.5 Summary

In this chapter we set the main models and approaches proposed in literature for modelling and pricing assets. The models are grouped into three basic categories: the static models, the dynamic models, and the models developed based on the unstable nature of betas. The section of static models starts with the CAPM, which marks the birth of asset pricing. We continue by introducing the reader to some alternative univariate models such as the Black Zero-beta CAPM and the International CAPM (ICAPM). The Arbitrage Pricing Theory (APT) along with the FF3FM and the higher moment CAPM constitute the category's multifactor models. Regarding dynamic asset pricing models that adopt more realistic assumptions about investors, the Intertemporal CAPM (ICPM) and the Consumption CAPM (CCAPM) are being considered. Finally, the models developed based on the time varying nature of betas, the conditional CAPM and the Dual-Beta model are presented.

CHAPTER 3

A NEW APPROACH OF ASSET PRICING

3.1 Introduction

As mentioned in the previous chapter, the measurement of expected returns and the risk calculation are the main issues in asset pricing (Campbell, 2000). The Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965) quantifies the risk return relationship, suggesting that the only relevant risk measure is the beta coefficient, which reflects the systematic risk. Due to the powerful and intuitively pleasing predictions (Fama and French, 2004) the model is still widely used by financial managers and investors to estimate the risk of the cash flow, the cost of capital and the performance of managed funds (Fletcher, 2000; Tang and Shum, 2003; Perold, 2004). However, the model has come under scrutiny since empirical findings indicate that asset returns cannot be explained by the market beta alone. For example, a number of studies show that average returns are also determined by the firm size, earnings yield, leverage, book-to-market and prior return (*inter alia*: Basu, 1977; Banz, 1981; Bhandari, 1988; Jegadeesh, 1990; Fama and French, 1992).

Another important consideration of the CAPM is the assumption of constant betas over 'bull' and 'bear' market conditions. However, if beta does in fact vary with market conditions then inferences based on its stable nature can be proved misleading. Woodward and Anderson (2009) note that the publication of separate alphas and betas over the 'bull' and 'bear' markets by investment houses signifies the importance of the beta/market condition relationship. In their study, the authors apply a logistic smooth transition market model (LSTM) for Australian industry portfolios and report that 'bull' and 'bear' betas are significantly different for most industries while the transition between 'bull' and 'bear' states is rather abrupt. Fabozzi and Francis (1977) first tested the stability of betas over the 'bull' and 'bear' markets. However, defining these specific conditions with three different ways, no evidence was found to support the hypothesis that stock market affects betas asymmetrically. On the contrary, Clinebell et. al. (1993) show that observed differences of beta coefficients between 'bull' and 'bear' market conditions are significant. Wiggins (1992) argues that the dual beta model of Fabozzi and Francis (1977) explains better the portfolio returns formed by size, past beta, and historic return performance. Bhardwaj and Brooks (1993) conclude that there is no size premium when beta varies in up and down markets as small firm stocks underperform large firm stocks. On the other hand, Howton and Peterson (1998) give evidence of a significant size effect with beta being capable of providing a significant explanation of the cross-sectional returns when the sample is segmented into 'bull' and 'bear' markets. Reyes (1999) examining the relationship between size and time-varying betas finds no statistical power for both small and large firm indexes of the UK market.

The existing evidence of nonlinearities in stock prices has been attributed to various behavioural dynamics of investors. In particular, Woodward and Anderson (2009) report that nonlinearities might be stemmed from investors' heterogeneity arising from different risk profiles and different risk horizons. Nonlinearities have also been attributed to investors' herding behavior (Lux, 1995). More recently and in the same line, Hwang and Salmon (2004) show that the estimated CAPM betas of individual assets will be biased and away from their equilibrium values when herding towards market portfolios exists.

In view of the strong evidence of betas' instability, we develop a novel approach for capturing their time variation by treating the pattern as a function of market return. We construct a new two factor model (TFM) which incorporates variables targeting to absorb the information conveyed by betas' instability. In the literature, there has been substantial divergence in the definition of 'bull' and 'bear' markets while the transition indicator of the logistic smooth transition autoregressive models (LSTAR) developed by Terasvirta (1994) is an important consideration, because this variable will reflect broad swings in the market. For example, Woodward and Anderson (1999) provide evidence that a different definition of the transition variable results in a substantially different number of cases with betas being statistically different in up and down market. In our approach, we are basically interested in a specific estimator which shows the beta's behaviour in different states and as such, it forms the basis of constructing the new variables. The model is free from subjective bias problems related to the selection of a critical threshold. The results are very promising both in the times series and in the cross-sectional contexts. In particular, it is indicated that this specification outperforms alternative models such as CAPM and Fama and FF3FM in explaining returns in time series regressions. Furthermore, we show that the particular portfolios used to model's construction are not being necessarily riskier. The new priced risk factors in time series analysis give valuable information of better understanding the characteristics of returns, targeting this way the reinforcement of stock market efficiency.

The next section develops analytically the necessary steps used to build our new two-factor model (TFM) and section 3.3 summarizes.

3.2 Methodology: A Two-Factor Model

Two steps constitute the new approach we use here for capturing any variations in beta coefficients. The first step contains the estimation of beta coefficients from the CAPM in time series regressions:

$$R_{it} - R_{ft} = a_i + \beta_i (R_{mt} - R_{ft}) + e_{it} \qquad 3.1$$

To remind here that $R_{it} - R_{ft}$ is the excess return of asset i, and $R_{mt} - R_{ft}$ is the market excess return. β_i is the systematic risk and α_i and e_{it} are assumed to be zero according to the model.

Using standard OLS method and daily returns data of three years time interval, since this particular period has been found to give the best daily beta predictions (Daves *et. al.*, 2000), we get the first estimated beta coefficient of period *t*.

Next, a rolling regression is applied. More precisely in order to obtain the second value of beta, the first observation is dropped and a new is added to the end of the sample. The procedure is followed for a five-year period estimating the respective betas of each day. Having around 1250 betas at hand, we rank them in ascending order relative to the market return on day t=1…1250.

Then, the averaged values of the estimated betas for each market return discrete interval for a given period are calculated. This way ensures the equality weights given at each observation catching up any differences in each and every market condition. At the same time, we avoid any subjective bias at the selected market interval. Being able to construct the used variables, a question arises regarding the form of beta coefficient as a function of R_{ms} (i.e. $\overline{\beta} = f(R_{ms})$, (Faff and Brooks, 1998)). Lin et al., (1992) suggest that beta mean fluctuates around an upward or downward parabolic trend pattern. Hence, we approach the functional form of $f(\cdot)$ by equation 3.2:

$$\overline{\beta} = \alpha * \exp^{(b*R_{ms} + c*R_{ms}{}^{2} + u)} \qquad 3.2$$

where α, b, c are the coefficients to be estimated, R_{ms} is the sorted market return, $\overline{\beta}$ are the average betas corresponding to each market return interval and u are the residuals. We do not make any assumption about the residuals distribution as we are interested in only for the magnitude of the estimated coefficients.

Through linearization and assuming that beta coefficients are nonnegative as usually happens in financial contexts (Andersen et al., 2006), equation 3.2 takes the following shape:

$$\ln(\overline{\beta}) = \ln(a) + b*R_{ms} + c*R_{ms}^{2} + u \qquad 3.3$$

If f is continuous in the interval $\left[R_{ms}^{-}, R_{ms}^{+}\right]$ and twice differentiable then $\frac{1}{\overline{\beta}}\frac{\partial\overline{\beta}}{\partial R_{m}} = (b + 2cR_{ms})$ or $\frac{\partial\overline{\beta}}{\partial R_{ms}} = \overline{\beta}(b + 2cR_{ms})$ and $\frac{\partial^{2}\overline{\beta}}{\partial R_{ms}^{2}} = 2c\overline{\beta}$. For $\overline{\beta}$>0 and c=0, f is linear. If c>0, f is convex as the second derivative is positive, while for c<0 f is concave with negative second derivative. Besides, $\frac{\partial\overline{\beta}}{\partial b} = \overline{\beta}R_{ms}^{2} > 0$, which shows that an increase in b will increase the β coefficient. Thus the function is increasing for b>0 and decreasing for b<0.

We proceed to the construction of a two-factor model (hereafter TFM) where the variables are formed based on the b_coefficients of equation 3.3. We expect that stocks with positive b_coefficients should give higher returns without an increase in the risk. The intuition behind this stems from the fact that at each state of market return nature, the expected return of security i is higher. Hence, we could say that 'Superior' stocks are the ones with increasing beta coefficient as market return increases and vice versa for the 'Inferior' stocks. A 'Superior' stock should contain all those characteristics that make it to appear higher returns than its competitors. For example, it could be a stock with relatively low leverage and in bad states of the world its beta coefficient to not increase as much as another stock with high leverage values (Jagannathan and Wang, 1996). Thus, the first variable named as 'SMISI' (i.e. Superior minus Inferior Stock Index) represents the difference in returns between the 30% of stocks with the highest b_coefficients and the 30% of stocks with the lowest b_coefficients. This variable aims at capturing the risk associated with 'Superior' and 'Inferior' stocks. The second explanatory variable, which we call it as 'Neutral' (Neutral Stock Index-NSI), is the remaining 40% of the stocks. The stocks constitute the index have on average zero b_coefficients. This index is supposed to be similar to the general index of S&P 500 if the assumption of constant betas coming from the CAPM holds. In Part III of this thesis, we examine whether 'Superior' and 'Inferior' portfolios correspond to different fundamental variables. Thus, the time series regression is given by the following equation:

$$R_{it} - R_{ft} = a_i + c_i SMISI_t + n_i NSI_t + e_{it}\,, \qquad 3.4$$

and the unconditional cross-section regression is:

$$r_i = \lambda_o + \lambda_{smisi}\hat{c}_i + \lambda_{nsi}\hat{n}_i + z_i\,. \qquad 3.5$$

The equations 3.4 and 3.5 are the ones, which will be tested and compared with other well-known models in the following two chapters.

3.3 Summary

In this chapter, we present the most empirical shortcomings of the CAPM reported in literature. The unstable nature of betas and the models developed to separate them into up and down markets betas motivated us to build a two-factor model (TFM) that takes into consideration this specific characteristic. This model constitutes two variables, which relate to the information obtained after running a nonlinear regression. From the total sample of selected stocks, we form three groups and separate them into ‘Superior’ and ‘Inferior’ stocks. Thus, the first variable aims at capturing the risk associated with ‘Superior’ and ‘Inferior’ stocks whereas the second variable contains the remaining stocks with invariant betas.

PART II: EMPIRICAL EVIDENCE

This part constitutes Chapter 4, 5 and 6. In this part, the main empirical findings regarding the performance of the TFM are presented. Tests of the CAPM are conducted both in time series and/or cross section regressions. Thus, the purpose of this part is to use both approaches for testing our model in order to have a better understanding of the TFM's performance. Furthermore, in chapter 6, we demonstrate the results associated with the accuracy of beta predictions by employing the TFM and other well-known models that treat systematic risk as time varying.

CHAPTER 4

TIME-SERIES EMPIRICAL RESULTS

4.1 Introduction

The Sharpe-Lintner CAPM is a direct implication of mean-variance efficiency, under the assumption of homogenous expectations and the existence of a risk-free rate. (Cuthbertson and Nitzsche, 2004). Thus, the expected value of an asset's excess return (the asset's return in excess of the risk free rate) is completely explained by the asset's beta times the expected value of market excess return. This implies that the intercept term in the time series regression is zero for each asset. The evidence that the relation between beta and average return is too flat is confirmed in time-series tests, such as Friend and Blume (1970), Black et al., (1972), Gibbons (1982) and Stambaugh (1982). The intercepts in time-series regressions of excess asset returns on the excess market return are positive for assets with low betas and negative for assets with high betas. If there are more than one factors such as in the APT, the same idea works. We should estimate again the alphas and betas and test the hypothesis of zero constants. Thus, to test the hypothesis that market betas or the betas of additional factors suffice to explain expected returns, one estimates the time series regression for a set of assets or portfolios and then jointly tests the vector of regression intercepts against zero (Fama and French, 2004). Cochrane (2005) reports that for pricing assets we have to choose portfolios that appear some spread in average returns, otherwise there will be nothing for the asset pricing model to test.

In early applications, researches use a variety of tests to determine whether the intercepts in a set of time-series regressions are all zero. Although the tests have the same asymptotic properties, there is controversy about which has the best small sample properties. Gibbons, Ross and Sanken (hereafter GRS) (1989) provide an F-test on the intercepts that has exact small-sample properties. This test has been also used by Fama and French (1996) for testing the three factor model in time series regressions, and this test we are going to use for testing the zero alpha's hypothesis of our employed models. The GRS test is explained in detail later in this chapter.

4.2 Methodological issues

This section briefly describes the CAPM and the Fama and French (1996) three factor model that will be compared against our proposed methodology in the context of time series regressions.

The CAPM

The capital asset pricing model is a set of predictions concerning equilibrium of expected return on risky assets (Bodie et al., 2002). In time series regressions the CAPM has the following form:

$$R_{it} - R_{ft} = a_i + \beta_i (R_{mt} - R_{ft}) + e_{it} \; . \qquad 4.1$$

To remind here that, $R_{it} - R_{ft}$ is the excess return of asset i, $R_{mt} - R_{ft}$ is the market excess return, β_i the systematic risk and α_i and e_{it} are assumed to be zero according to the model.

The Fama and French Three-Factor Model

The three-factor model suggested by Fama and French (1996) relates the expected return on a portfolio in excess of the risk-free rate $E(R_i) - R_f$ to three factors. The first one is the excess return on a broad market portfolio (i.e. $R_m - R_f$). The second is the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks (i.e. Small Minus Big, SMB). Finally, the third factor is the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks (i.e. High Minus Low, HML). Thus, the time series equation of the FF3FM is:

$$R_{it} - R_{ft} = a_i + \beta_i (R_{mt} - R_{ft}) + s_i SMB_t + h_i HML_t + e_{it} \qquad 4.2$$

The factor loadings, β_i, s_i, h_i, are the slopes that come from the OLS time series regression (equation 4.2) (Hussain and Toms, 2002). The assumptions regarding α_i and e_i are also hold here. It is important to refer at this point that Fama and French (1996) noted that the three-factor model has no foundation in finance theory, but it is merely a statistical model that summarises the empirical regularities that have been observed in US stock return (Gregory et al., 2001). However, estimates of α_i from the time series regression above are used to measure the special information of portfolio managers (Carhart, 1997) or to measure the speed with which prices respond to new information (Loughran and Ritter, 1995; Mitchell and Stafford, 2000). In addition, the model is offered as an alternative to the CAPM for estimating the cost of capital.

The Two Factor Model

The Two Factor Model (TFM) constitutes two variables. The first variable named as 'SMISI' (i.e. Superior minus Inferior Stock Index) represents the difference in returns between the 30% of stocks with the highest b_coefficients (see Chapter 3, equation 3.3) and the 30% of stocks with the lowest b_coefficients. This variable aims at capturing the risk associated with 'Superior' and 'Inferior' stocks. The second explanatory variable, which we call it as 'Neutral' (Neutral Stock Index-NSI), is the remaining 40% of the stocks. The stocks constitute the index have on average zero b_coefficients. This index is supposed to be similar to the general index of S&P 500 if the assumption of constant betas coming from the CAPM holds. The time series regression of the TFM is given by the following equation:

$$R_{it} - R_{ft} = a_i + c_i SMISI_t + n_i NSI_t + e_{it} \qquad 4.3$$

Regarding α_i and e_i, the same assumptions as above also hold here.

4.3 Data description

The dataset used concerns securities traded on the S&P 500. The rate of return of each security, r_i, at time t is calculated as $r_{i,t} = P_{i,t} / P_{i,t-1} - 1$. The choice to form portfolios at the start of each year ensures that we will not face the look-ahead bias problem (Banz and Breen, 1986). The risk free rate is a 3-month Treasury bill for the US market. For the construction of the variables used in the TFM we firstly employ daily observations for the estimation of the b_coefficients as mentioned above. To be included in one of the 'Superior' or 'Inferior' portfolio for a given year a stock must have statistically significant beta coefficients at least at the 10% level (i.e. t-stat $|1.70|$) for all previous 5 years. This way, we ensure that each beta coefficient has explanatory power and that it can be used for estimation purposes. After forming the portfolios, monthly returns are employed.

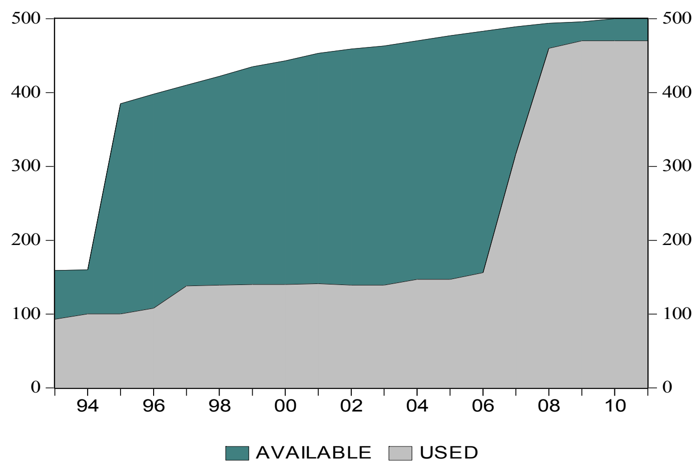
The models are tested on five different portfolios sorted on the estimated coefficients of equation 3.3 as well as on momentum portfolios. The latter category is mainly selected because the FF3FM failed to explain their abnormal returns (Jegadeesh and Titman, 1993). The data of the FF3FM, momentum, size, Earnings to Price (E/P) and book value to market equity (BV/ME) portfolios are retrieved from the authors' internet homepage[8]. To begin with the description of the rest of our portfolios, the first kind of them contains stocks sorted on their corresponding estimated a_coefficients (equation 3.3). (henceforth aP). These stocks are supposed to have similar betas to the regular CAPM betas if the market return is zero. Thus, the first portfolio consisted of stocks with the lowest betas, while portfolio 10 consisted of stocks with the highest betas. The second category refers to stocks sorted on the estimated b_coefficients (henceforth cP). As mentioned earlier, these coefficients are also used to construct the TFM's variables. The next kind of portfolios are formed on the basis of c_coefficients (henceforth cP) whereas the last category contains stocks sorted using the rate of beta change (henceforth RoBC) (i.e. $\partial\overline{\beta} / \partial R_{ms}$ with $\overline{\beta}$ being equal to ln(α)). In this latter category, we expect stocks with higher rate of beta change to earn higher returns. All portfolios are rebalanced each year following the

[8] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

same procedure. This gives a time series of monthly returns from January 1993 to August 2011 for all selected portfolios.

Figure 4.1 illustrates the available total number of stocks of each year and the surviving stocks after filtration. The used stocks start with almost one hundred at the very early stage of portfolio formation year and reach at 480 stocks at the last year covering the 95% of all traded stocks on S&P 500. The relatively low number of shares at the very early stage of the sample could cause survivorship bias. To examine possible effects related to survivorship bias, we split the sample after 2007 into two subsamples. In particular, we retained the same stocks as they were in 2006 and recalculated the returns. The survivorship bias results are presented in section 4.5 of this chapter.

Figure 4.1: Shares in analysis



4.4 Portfolio returns

4.4.1 One-way classification

Table 4.1 provides summary statistics of time series averages of portfolio returns. For each portfolio, the table shows the mean monthly returns in excess of the 3-month treasury bill, the standard deviation of the monthly excess returns and the t-statistics associated with the hypothesis of zero portfolio returns. The table exhibits the positive differences in returns between the highest and lowest aP, bP and RoBC portfolios. More concretely, the aP portfolios exhibit an almost linear and increasing return pattern when we move from the lowest to highest decile. The evidence is consistent with the theory stating that returns have a positive relation with systematic risk. The 1st decile portfolio gains 0.71% with the 10th reaching as high as 1.37% per month. To note here that higher returns are also associated with higher standard deviations, which seem to follow the same line pattern. As far as the bP portfolios are concerned, the increasing return pattern, though non linear, is not necessarily associated with higher standard deviation. For example, we observe a decreasing pattern in standard deviations as we move from the lowest bP portfolio to the highest one. The difference in returns per unit risk between the highest and lowest bP portfolios is 0.187%. Regarding the extreme decile portfolios sorted on the basis of c_coefficients, there are not observed differences in returns but for the middle one that is supposed to be linear with c coefficient being nearly zero.

Table 4.1: Summary statistics for Simple Monthly Excess Returns (in Percent) for the portfolios formed using the estimated coefficients of equation 3.3: 01/93-08/11, 224 Months.

	Deciles									
Portfolios	1	2	3	4	5	6	7	8	9	10
Coef_a	**Low beta**									**High beta**
Mean	0.71	1.03	0.84	0.93	1.00	0.90	1.00	1.00	1.22	1.37
Std. Dev.	3.89	3.94	4.26	4.48	5.13	5.18	5.36	5.63	6.61	9.51
t-statistics	2.72	3.89	2.93	3.10	2.91	2.60	2.78	2.65	2.75	2.15
Coef_b	**Decreasing**									**Increasing**
Mean	0.45	0.77	1.28	1.11	0.92	1.04	1.12	1.05	0.96	1.29
Std. Dev.	6.39	5.85	5.40	5.60	4.85	4.93	4.69	4.99	4.73	5.00
t-statistics	1.06	1.96	3.54	2.96	2.83	3.16	3.56	3.15	3.03	3.84
Coef_c	**Concave**									**Convex**
Mean	0.89	0.89	1.17	1.06	1.39	0.95	1.08	0.92	0.80	0.84
Std. Dev.	5.44	5.35	5.06	5.10	4.91	4.78	5.19	5.12	5.43	5.52
t-statistics	2.46	2.49	3.44	3.10	4.23	2.96	3.12	2.67	2.21	2.27
ROBC	**Low**									**High**
Mean	0.87	0.86	1.06	0.85	1.28	0.99	0.98	0.79	1.09	1.24
Std. Dev.	6.67	5.54	5.22	4.86	4.84	4.47	4.72	4.98	4.89	6.08
t-statistics	1.94	2.32	3.02	2.61	3.95	3.30	3.10	2.36	3.33	3.05

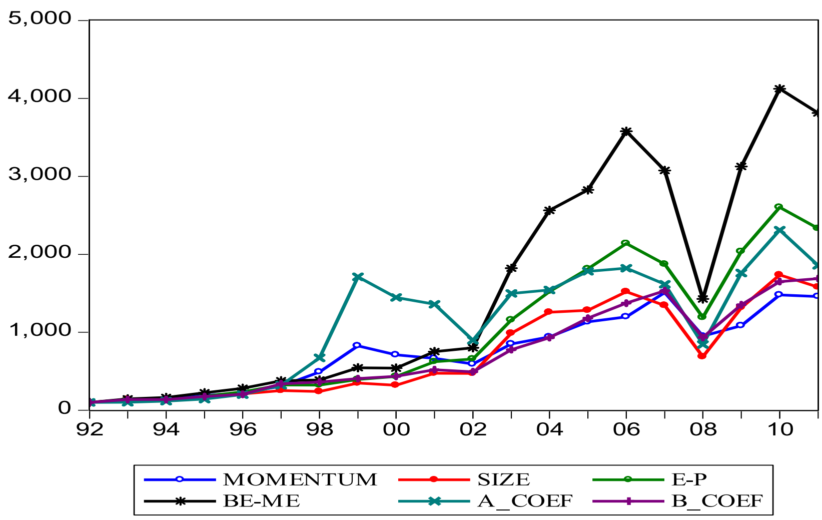
Table 4.2 makes a comparison among the aforementioned portfolios and that of momentum, size, E/P and BV/ME. The compared deciles are the best in terms of returns for each category. The table depicts not only the mean and standard deviation but also the return per unit risk. This measure constitutes a very crucial factor in determination of the attractiveness of an investment. The results establish the superiority of the 10th bcP decile. It appears to have the highest return per unit risk for both periods. The second higher performance possesses the E/P portfolio although at

the second period it did not well enough. Figure 4.2 shows the $100 investment at each one of them since 1993. The BV/ME reaches its highest value at almost $4000 while the bcP, the Size and the momentum portfolios move together during the examined period with the first one to end higher.

Table 4.2: Average Yearly returns for different periods and portfolios.

	Period:1993-2011				Period:2007-2011		
Portfolio	Mean	Std.Dev.	Ret./Risk	Portfolio	Mean	Std.Dev.	Ret./Risk
Momentum	15.7%	26.3%	59.7%	Momentum	5.30%	28.2%	18.8%
Size	18.4%	36.2%	50.8%	Size	8.07%	51.1%	15.8%
E-P	19.2%	26.9%	71.4%	E-P	4.46%	39.3%	11.3%
BV-ME	24.8%	39.9%	62.2%	BV-ME	9.95%	59.3%	16.8%
A coef	20.6%	50.2%	41.0%	A coef	7.49%	56.3%	13.3%
B coef	17.0%	23.5%	72.3%	B coef	6.86%	31.3%	21.9%

Figure 4.2: Cumulative return on $100 investment.



4.4.2 Portfolio returns formed on a two-way classification

For the 2 way classification, the method of Lakonishok, Shleifer and Vishny (1994) is applied. The portfolios are separated into 10 deciles. The results of the 2 way classification method are presented in table 4.3. We choose to report two portfolios sorted on the coefficient b and one from the a or c coefficients. The stocks are allocated to three equal groups. For example the 1-1 portfolio of panel A contains stocks with a and b_coefficients belonging to the lowest 30% group. Table 4.3 shows that the 3-3 portfolio of panel A relates to stocks with high and increasing beta. This particular portfolio gains higher returns from the low 1-1 portfolio that has the opposite characteristics. The return pattern increases almost monotonically as we move from the lowest to highest b coefficients and the portfolios appear statistically significant returns. To note here that a portfolio earns the yearly risk free rate if at the corresponding year no one stock meets the needs of this portfolio. Such cases we confronted four times for the c_b coefficient portfolios whose returns are depicted on Panel B.

Table 4.3: Summary statistics for Simple Monthly Excess Returns (in Percent) for the portfolios formed using two way classifications: 01/93-08/11, 224 Months.

Panel A: a and b coefficients									
Beta (a coef.)	1	1	1	2	2	2	3	3	3
Decr./Incr. (b coef.)	1	2	3	1	2	3	1	2	3
Mean	0.71	0.95	0.94	0.82	0.86	1.32	1.14	1.16	1.37
Std.Dev.	4.77	3.76	4.33	5.21	4.77	4.98	8.72	6.37	6.90
t-statistics	2.21	3.76	3.23	2.36	2.70	3.96	1.94	2.71	2.96
Panel B: c and b coefficients									
Conc./Conv. (c coef.)	1	1	1	2	2	2	3	3	3
Decr./Incr. (b coef.)	1	2	3	1	2	3	1	2	3
Mean	0.99	1.18	0.76	0.91	1.02	1.26	1.02	0.91	0.80
Std.Dev.	6.00	5.90	9.43	5.29	4.83	5.39	7.20	5.09	4.98
t-statistics	2.46	2.99	1.20	2.56	3.16	3.48	2.11	2.68	2.39

4.5 Testing for survivorship bias

Table 4.4 demonstrates the results of the two different in sample portfolios for testing the survivorship bias problem. Following the method of Banz and Breen (1986) we examine whether the returns over the 56 months (i.e. 1/2007-8/2011) for each portfolio are different. Let RTi(t) be the return vector to the ith portfolio (i=1,…,10) drawn from the total number of stocks that were available for estimation purposes since 2007 and forward and RSi(t) be the return to the corresponding portfolio drawn from the small sample that were used in 2006. Then the differences of portfolio returns are:

$$D_i(t) = RT_i(t) - RS_i(t)\,. \qquad 4.4$$

Running the regressions, $D_1(t) = a_1 + e_1, D_2(t) = a_2 + e_2, \ldots, D_{10}(t) = a_{10} + e_{10}$, we test zero a's of the Di(t) series with each e be a zero mean random variable. The Gibbons, Ross, Shanken (1989) test (hereafter GRS test[9]) is applied for testing the hypothesis. The table depicts that jointly a's are all zero and there are not statistically significant differences in returns between the total sample and the small sample. However, a more closely examination of the middle portfolios indicates an increase in their returns which in most of the cases is significant. This fact does not influence our decision to form variables that are based on the extreme deciles portfolios. It is rather strengthening our assumption of the existence of 'superior' and 'inferior' stocks since the differences are on average negative for the lowest deciles portfolios. In addition, the extreme deciles of ROBC appear an increase in their differences of almost 0.64% per month signalling another one category with statistically significant returns.

Table 4. 4: GRS test for testing the restriction that all ten alphas are jointly zero.

	Deciles										
Portfolio	1	2	3	4	5	6	7	8	9	10	GRS*
aP	0.11%	-0.17%	0.11%	0.03%	0.61%	0.00%	0.60%	0.25%	0.09%	-0.06%	1.14
bP	-0.21%	-0.57%	0.41%	0.44%	0.30%	0.66%	0.61%	0.13%	-0.37%	0.20%	1.41
cP	-0.22%	-0.33%	-0.20%	0.48%	0.59%	0.64%	0.81%	-0.04%	0.11%	-0.22%	1.38
RoBC	-0.54%	-0.63%	0.45%	0.25%	0.40%	0.38%	0.08%	0.65%	0.36%	0.18%	1.72

*The F critical values of the GRS test are 1.83 and 2.32 at the 5% and the 1% significant level respectively.

4.6 Time series regressions

In this section, we test if CAPM, FF3FM and TFM explain the returns of the aforementioned portfolios in the context of time series regressions. CAPM uses the market excess return as explanatory variable to capture the variation of portfolio returns. FF3FM employs the SMB (Small minus Big), the HML (High minus Low) along with market excess returns as factors. The SMB factor absorbs the size premium and the HML factor counts for the value premium. The new TFM uses the

---

[9] The GRS test follows the F distribution and it is defined as: $K_1 = \left(\frac{N-L-1}{L}\right) * \frac{K_0}{N}$, where $K_0 = \hat{a}\left[\operatorname{var}\left[\hat{a}\right]\right]^{-1}\hat{a}$, N the number of observations and L the number of regressions. The F distribution has L degrees of freedom in the numerator and N-L-1 degrees of freedom in the denominator. If $F_{v1,v2,\alpha} < \mathrm{K}_1$ we reject the null hypothesis and the alphas are not simultaneously zero continue: so there are significant abnormal returns. For 224 observations $F1_{10,213,5\%} = 1.83$, $F1_{10,213,1\%} = 2.32$ and $F2_{9,214,5\%} = 1.88$, $F2_{9,214,1\%} = 2.41$ for the 1 and 2 way classifications respectively and different level of significance.

SMISI and NSI factors as they were previously developed. Table 4.5 presents the descriptive statistics of the explanatory variables. The NSI factor gives the highest premium followed by SMISI, RM-RF and SMB. The high premium allows them to explain much of the returns variation. Despite the fact that the HML factor produces an average premium of just 0.184% per month, it appears high volatility implying its ability to capture substantial common return variation. It is worth mentioning the high correlation observed between the market risk premium and the NSI factor indicating their close relationship, though the latter one is free from the effects of betas' instability.

Table 4.5: Summary statistics for the monthly independent variables.

Total Sample: 1/93-8/11, 224 months										
Name	Mean	Std. Dev.	t-stat	p-value	ADF	Correlations				
RM-RF	0.284	4.353	0.978	0.329	-13.30	RM-RF	SMB	HML	SMISI	NSI
SMB	0.278	3.226	1.290	0.198	-15.40	0.139	1			
HML	0.184	4.162	0.660	0.509	-12.76	0.068	-0.194	1		
SMISI	0.336	3.410	1.474	0.141	-13.45	-0.131	-0.058	-0.187	1	
NSI	0.971	4.626	3.142	0.001	-13.34	0.930	0.199	0.167	-0.141	1
Subsample 1: 1/93-4/02, 112 months										
RM-RF	0.512	4.165	1.301	0.195	-10.88	RM-RF	SMB	HML	SMISI	NSI
SMB	0.201	3.789	0.562	0.574	-10.52	-0.015	1			
HML	0.171	4.692	0.386	0.700	-9.206	-0.283	-0.460	1		
SMISI	0.164	2.667	0.651	0.516	-12.03	0.156	-0.060	0.091	1	
NSI	1.229	4.243	3.064	0.002	-10.48	0.920	-0.029	-0.109	0.166	1
Subsample 2: 5/02-8/11, 112 months										
RM-RF	0.057	4.541	0.132	0.894	-8.284	RM-RF	SMB	HML	SMISI	NSI
SMB	0.355	2.557	1.468	0.144	-11.74	0.344	1			
HML	0.196	3.576	0.580	0.562	-8.593	0.495	0.321	1		
SMISI	0.508	4.023	1.335	0.184	-8.812	-0.305	-0.067	-0.451	1	
NSI	0.714	4.985	1.514	0.132	-8.643	0.940	0.509	0.485	-0.313	1

In tests of asset pricing in the time series context, the explanatory variables should capture common variation in stock returns. The empirical examination covers all the models and checks their power. The R^2 values and the zero alphas hypothesis constitute the two criteria for assessing the models. Table 4.6 demonstrates the results of the regressions on different portfolios using the market excess returns as independent variable. It is clear that alphas are not statistically different from zero. The GRS test shows that CAPM leaves unexplained a lot of returns variation and abnormal returns exist. The highest GRS value is observed for the concave portfolios. The R^2 ranges from a low of 0.341 to a high of 0.808 with an average of 0.695 for the 1 way classification portfolios. For the 2 way classification portfolios, the R^2's are smaller and the GRS test rejects the zero alphas hypothesis. The Durbin-Watson (DW) test statistic rejects the null hypothesis of zero autocorrelation in just 5 out of 68 cases. The bold letters indicate such events.

As one might expect, the slopes for the acP portfolios increase from a low of 0.522 to a high of 1.824. However, the slopes of the momentum portfolios follow an opposite pattern, indicating that low momentum portfolios are more sensitive than high momentum portfolios to the shifts of market excess returns. This evidence is a contradiction to theory that wants the highest returns to be accompanied by highest risk. The remained portfolios do not reveal a clear pattern although for the bcP the slopes are slightly downward. Panel A and panel B depict the regression results for the 2-way classification. It is worth to refer the opposite behaviour of the estimated betas relative to returns gaining the third group of a-b sorted portfolios.

Table 4. 6: Regressions of excess portfolio returns on the excess stock-market return, RM-RF: 01/1993-8/2011, 224 months.

$$R_p(t) - RF(t) = a + b[RM(t) - RF(t)] + e(t)$$

	Deciles										
	1	2	3	4	5	6	7	8	9	10	GRS*
Coef_a	**Low**									**High**	
a	0.561	0.863	0.617	0.689	0.730	0.606	0.685	0.686	0.831	0.850	
b	0.522	0.572	0.771	0.848	0.948	1.040	1.096	1.106	1.351	1.824	
t(a)	2.646	4.211	3.512	4.041	3.575	3.586	4.196	3.502	4.121	2.422	12.52
t(b)	10.73	12.16	19.11	21.65	20.19	26.77	29.23	24.57	29.15	22.63	
R^2	0.341	0.399	0.621	0.678	0.647	0.763	0.793	0.731	0.792	0.697	
DW	2.040	1.946	1.789	1.859	1.888	2.187	1.915	1.921	1.823	1.768	
Coef_b	**Decr.**									**Incr.**	
a	0.144	0.440	0.976	0.794	0.638	0.768	0.845	0.771	0.710	1.028	
b	1.080	1.154	1.062	1.105	0.982	0.965	0.954	0.992	0.875	0.901	
t(a)	0.497	2.193	5.228	4.132	4.169	4.442	5.806	4.597	3.775	4.953	17.13
t(b)	16.22	25.03	24.77	25.01	27.93	24.29	28.56	25.75	20.24	18.90	
R^2	0.542	0.738	0.734	0.738	0.778	0.726	0.786	0.749	0.648	0.616	
DW	2.008	1.812	1.736	2.011	1.867	1.851	2.193	2.105	1.888	1.916	
Coef_c	**Concave**									**Convex**	
a	0.630	0.592	0.881	0.757	1.111	0.676	0.783	0.625	0.508	0.561	
b	0.928	1.055	1.006	1.053	0.983	0.954	1.056	1.027	1.037	0.974	
t(a)	2.589	3.214	5.183	5.053	6.903	4.251	4.880	3.725	2.507	2.366	17.56
t(b)	16.52	24.90	25.78	30.58	26.59	26.10	28.64	26.63	22.28	17.87	
R^2	0.551	0.736	0.749	0.808	0.761	0.754	0.787	0.761	0.691	0.590	
DW	2.128	1.876	2.096	2.109	1.802	1.870	2.002	1.870	1.845	1.840	
ROBC	**Negative**									**Positive**	
a	0.525	0.566	0.765	0.577	1.002	0.740	0.709	0.498	0.818	0.930	
b	1.202	1.040	1.018	0.954	0.970	0.866	0.951	1.008	0.962	1.101	
t(a)	1.891	2.641	4.139	3.403	6.341	4.609	4.692	3.165	4.820	3.706	16.13
t(b)	18.85	21.12	23.96	24.45	26.73	23.48	27.38	27.90	24.68	19.10	
R^2	0.615	0.667	0.721	0.729	0.762	0.712	0.771	0.778	0.732	0.621	
DW	1.831	2.115	1.854	2.098	**1.595**	1.788	1.917	2.158	1.933	2.136	

Table 4.6 continued

Momentum (t-12 to t-2)										**High**	
a	-0.207	0.255	0.366	0.546	0.458	0.473	0.594	0.775	0.529	0.930	
b	1.733	1.335	1.099	0.978	0.885	0.870	0.819	0.834	0.899	1.028	
t(a)	-0.481	0.969	1.664	3.117	3.063	3.371	4.369	5.712	3.471	3.007	10.19
t(b)	17.54	22.10	21.72	24.40	25.74	27.25	26.22	26.76	25.64	14.56	
R^2	0.580	0.687	0.680	0.728	0.749	0.769	0.755	0.763	0.747	0.485	
DW	1.853	1.987	1.747	1.725	1.985	2.258	**2.432**	2.241	2.148	2.129	

Panel A: a and b coefficients

Beta (a coef.)	Low	1	1	2	2	2	High	3	3	
Decr./Incr. (b coef.)	Dec.	2	Inc.	1	2	3	1	2	3	GRS
a	0.518	0.758	0.744	0.541	0.584	1.036	0.676	0.780	1.001	
b	0.664	0.660	0.671	0.988	0.970	0.991	1.612	1.320	1.284	
t(a)	2.032	4.664	3.479	2.751	3.933	6.230	1.947	4.225	3.683	10.73
t(b)	11.34	17.67	13.65	21.87	28.46	25.94	20.19	31.13	20.56	
R^2	0.367	0.584	0.456	0.680	0.784	0.752	0.647	0.813	0.655	
DW	2.042	2.039	1.815	**1.618**	1.838	2.017	1.769	**1.615**	2.224	

Panel B: c and b coefficients

C coefficient	Conc.	1	1	2	2	2	Conv.	3	3	
Decr./Incr. (b coef.)	Dec.	2	Inc.	1	2	3	1	2	3	GRS
a	0.677	0.876	0.442	0.644	0.725	0.967	0.722	0.677	0.543	
b	1.086	1.072	1.111	0.923	1.037	1.016	1.031	0.829	0.895	
t(a)	2.733	3.620	0.813	2.792	6.339	4.678	1.912	2.809	2.610	9.630
t(b)	19.08	19.28	8.907	17.40	39.47	21.37	11.88	14.96	18.72	
R^2	0.621	0.626	0.263	0.577	0.875	0.673	0.388	0.502	0.612	
DW	1.874	2.042	2.157	1.935	1.805	**1.613**	1.782	2.003	1.755	

*The F critical values of the GRS test are 1.83 and 2.32 at the 5% and the 1% significant level respectively.

Table 4.7 presents the regressions on the FF3FM. The model cannot describe the returns of any portfolio. Alphas are all statistically different from zero, whereas the GRS values reject the null hypothesis. The intercepts of the FF3FM are on average 60 basis points per month and they are lower of almost 7% from the CAPM (67 basis points for CAPM). However, only in the case of the first bcP the intercept collapses to zero. The HML factor, the mimicking return for the book-to-market factor, absorbs a lot of variation and appears to be significant in every case while this does not happen for the SMB as 20 cases have zero explanatory power as indicated by their associated t-statistics. Given the strong slopes on HML and some of the SMB factors, it is not surprising that adding them on the regressions results in an increase of almost 10% in R^2. The lowest and highest R^2 values are observed for the acP. The hypothesis of autocorrelation according to DW test is rejected only two times. The results of the regressions using only SMB and HML factors are disappointing. The R^2s were too small and never reached more than 0.25. This evident is consistent with the results of Fama and French (1993) when the two factors were used alone for pricing different portfolios.

Table 4.7: Regressions of excess portfolio returns on the three-factor model: 01/1993-8/2011, 224 months.

$$R_p(t) - RF(t) = a + b[RM(t) - RF(t)] + s(t)SMB + h(t)HML + e(t)$$

	Deciles										
	1	2	3	4	5	6	7	8	9	10	GRS*
Coef_a	**Low**										**High**
a	0.506	0.826	0.574	0.652	0.652	0.504	0.606	0.594	0.692	0.730	
b	0.500	0.557	0.754	0.833	0.917	0.999	1.065	1.069	1.296	1.778	
s	0.040	-0.035	-0.009	0.009	0.078	0.246	0.169	0.143	0.419	0.615	
h	0.271	0.276	0.271	0.206	0.355	0.247	0.222	0.339	0.206	-0.211	
t(a)	2.526	4.328	3.595	4.024	3.594	3.326	4.010	3.415	3.871	2.301	12.00
t(b)	10.791	12.60	20.36	22.18	21.79	28.46	30.41	26.53	31.28	24.16	
t(s)	0.628	-0.583	-0.182	0.192	1.356	5.105	3.515	2.601	7.380	6.079	
t(h)	5.540	5.906	6.929	5.209	7.991	6.671	6.015	7.955	4.722	-2.725	
R^2	0.422	0.488	0.692	0.714	0.726	0.813	0.826	0.791	0.840	0.756	
DW	2.151	2.072	2.015	2.027	2.147	2.377	2.041	1.955	1.947	1.704	
Coef_b	**Decreasing**										**Increasing**
a	0.014	0.345	0.891	0.706	0.547	0.741	0.809	0.713	0.627	0.943	
b	1.028	1.117	1.029	1.070	0.946	0.954	0.940	0.969	0.842	0.868	
s	0.228	0.144	0.210	0.186	0.272	0.002	0.127	0.119	0.227	0.149	
h	0.440	0.358	0.192	0.252	0.134	0.158	0.022	0.173	0.161	0.287	
t(a)	0.053	1.952	5.023	3.938	3.887	4.394	5.606	4.409	3.477	4.880	15.75
t(b)	16.74	27.28	25.01	23.75	28.98	24.40	28.12	25.87	20.15	19.37	
t(s)	2.714	2.577	3.719	3.262	6.081	0.039	2.787	2.329	3.965	2.424	
t(h)	6.786	8.286	4.423	5.751	3.893	3.839	0.639	4.392	3.647	6.074	
R^2	0.624	0.801	0.764	0.776	0.815	0.744	0.793	0.771	0.683	0.673	
DW	2.220	1.933	1.841	2.060	1.816	1.999	2.224	2.086	1.933	1.945	
Coef_c	**Concave**										**Convex**
a	0.527	0.509	0.750	0.706	1.044	0.636	0.721	0.574	0.444	0.433	
b	0.887	1.022	0.955	1.033	0.957	0.938	1.032	1.007	1.012	0.923	
s	0.227	0.209	0.409	0.132	0.170	0.098	0.095	0.075	0.057	0.200	
h	0.279	0.184	0.172	0.112	0.143	0.089	0.235	0.194	0.297	0.470	
t(a)	2.274	2.902	5.178	4.820	6.743	4.035	4.859	3.575	2.373	2.160	16.36
t(b)	16.50	25.12	28.45	30.43	26.66	25.65	30.00	27.04	23.31	19.85	
t(s)	3.085	3.755	8.879	2.835	3.466	1.971	2.027	1.468	0.963	3.139	
t(h)	4.913	4.292	4.860	3.122	3.778	2.307	6.478	4.940	6.483	9.562	
R^2	0.603	0.765	0.821	0.820	0.782	0.762	0.821	0.785	0.740	0.711	
DW	2.259	1.964	2.077	2.095	1.836	1.911	2.002	2.008	1.967	2.139	
ROBC	**Negative**										**Positive**
a	0.438	0.479	0.678	0.508	0.949	0.678	0.661	0.420	0.752	0.791	
b	1.168	1.006	0.983	0.926	0.949	0.841	0.932	0.978	0.936	1.047	
s	0.185	0.190	0.168	0.144	0.008	0.064	0.055	0.190	0.184	0.405	
h	0.244	0.236	0.277	0.203	0.200	0.279	0.209	0.184	0.118	0.226	
t(a)	1.619	2.345	4.007	3.161	6.345	4.753	4.678	2.850	4.563	3.384	15.14
t(b)	18.61	21.23	25.08	24.86	27.39	25.45	28.46	28.64	24.50	19.32	
t(s)	2.152	2.926	3.122	2.815	1.699	1.410	1.230	4.071	3.516	5.455	
t(h)	3.684	4.724	6.683	5.169	5.475	7.995	6.052	5.123	2.929	3.948	
R^2	0.641	0.703	0.771	0.761	0.791	0.777	0.804	0.809	0.752	0.677	
DW	1.915	2.277	1.983	2.196	1.648	1.914	1.987	2.203	2.018	2.161	

Table 4.7 continued

Momentum	**Portfolios t-12 to t-2**									
a	-0.547	0.045	0.220	0.450	0.398	0.434	0.588	0.777	0.553	0.920	
b	1.600	1.252	1.042	0.940	0.862	0.855	0.816	0.835	0.908	1.025	
s	0.896	0.475	0.252	0.125	0.088	0.050	-0.022	0.009	0.003	0.479	
h	0.702	0.548	0.498	0.387	0.227	0.157	0.070	-0.025	-0.149	-0.672	
t(a)	-1.531	0.220	1.278	3.196	2.903	3.223	4.337	5.683	3.736	4.449	11.21
t(b)	19.32	26.13	26.06	28.82	27.09	27.38	25.98	26.35	26.46	21.38	
t(s)	7.887	7.250	4.600	2.801	2.029	1.178	-0.511	0.211	0.081	7.289	
t(h)	8.024	10.84	11.78	11.20	6.756	4.781	2.127	-0.755	-4.121	-13.25	
R^2	0.716	0.811	0.807	0.826	0.792	0.788	0.761	0.764	0.766	0.773	
DW	1.946	2.070	1.730	1.986	2.323	2.253	2.408	2.229	2.064	2.068	

Panel A: a and b coefficients

Beta (a coef.)	Low	1	1	2	2	2	High	3	3	
Decr./Incr. (b coef.)	Dec.	2	Inc.	1	2	3	1	2	3	GRS
a	0.388	0.734	0.711	0.478	0.509	0.958	0.546	0.714	0.883	
b	0.613	0.650	0.657	0.963	0.941	0.960	1.561	1.294	1.237	
s	0.178	-0.016	-0.045	0.008	0.136	0.198	0.649	0.228	0.346	
h	0.512	0.169	0.268	0.367	0.246	0.168	-0.196	0.053	0.193	
t(a)	1.810	4.685	3.534	2.818	3.837	6.072	1.755	3.970	3.376	8.03
t(b)	12.31	17.90	14.09	24.48	30.59	26.26	21.64	31.05	20.42	
t(s)	2.607	-0.321	-0.707	0.157	3.224	3.959	6.562	3.987	4.163	
t(h)	9.745	4.414	5.450	8.827	7.582	4.346	-2.580	1.211	3.022	
R^2	0.558	0.620	0.527	0.768	0.831	0.780	0.722	0.826	0.687	
DW	2.285	2.122	1.899	1.924	2.110	2.073	1.767	1.631	2.164	

Panel B: c and b coefficients

C coefficient	Conc.	1	1	2	2	2	Conv.	3	3	
Decr./Incr. (b coef.)	Dec.	2	Inc.	1	2	3	1	2	3	GRS
a	0.551	0.723	0.266	0.549	0.686	0.902	0.589	0.657	0.498	
b	1.037	1.012	1.043	0.885	1.022	0.990	0.979	0.820	0.877	
s	0.301	0.463	0.729	0.163	0.082	0.196	0.367	-0.024	0.041	
h	0.308	0.223	-0.042	0.332	0.112	0.095	0.247	0.160	0.212	
t(a)	2.392	3.293	0.508	2.568	6.200	4.430	1.596	2.750	2.467	8.630
t(b)	19.41	19.88	8.586	17.87	39.84	20.97	11.43	14.82	18.75	
t(s)	4.108	6.629	4.376	2.404	2.335	3.029	3.128	-0.321	0.650	
t(h)	5.456	4.150	-0.331	6.343	4.150	1.920	2.733	2.746	4.290	
R^2	0.678	0.697	0.327	0.644	0.885	0.688	0.426	0.520	0.642	
DW	2.020	1.963	2.140	2.071	1.843	**1.577**	1.850	2.072	1.735	

*The F critical values of the GRS test are 1.83 and 2.32 at the 5% and the 1% significant level respectively.

In table 4.8, we present the outcomes of the TFM regressions. They are much better than what has been reported until now. The GRS test is smaller in all cases than the F critical value without leaving abnormal returns. Alphas are smaller reaching an average of 0.163 percent per month. The n coefficients which represent the new beta coefficients do not change dramatically from those estimated using CAPM. The difference between the two was just 4.5% on average. A worthwhile increase is observed on the slope of the highest bP portfolio and a significant decrease on the slope of the lowest bP portfolio. This happens because SMISI absorbs more variation of returns. The finding is along the same line with the results of RoBC portfolios. The slopes of SMISI factor in the cases of bP and momentum portfolios follow an almost identical pattern. They increase monotonically from the lowest to highest deciles signalling the higher risk inherited by the former ones since they operate as ‘inferior’ stocks. The extreme positive deciles of momentum portfolios behave like ‘superior’ stocks and earn highest returns. The abnormal returns of momentum portfolios that failed to be captured by the FF3FM seem to be zero using the TFM if we look at the GRS test’s critical value. The magnitude of R^2 is not high enough as those reported by Fama and French (1996) in explaining portfolios based on fundamental variables. However, Cochrane (2005) argues that high R^2 values in time series regressions might be bad news because these extra sorts have not identified other sources of priced variation in stock returns. This happened on ‘momentum’ portfolios and the new ones. To note here, that different kinds of regressions have been also executed. For example, dropping the NSI variable from the TFM and adding the market excess return the results were not satisfactory. The intuition behind this stems from the fact that the market index contains similar information to that SMISI factor tries to price resulting in its power to being cancelled. The TFM also explains the return variation of portfolios formed on size, BE/ME and E/P. We also run regressions on the last 5 years of the sample where the number of used stocks approaches the 95% of the total sample. The TFM continues to better explain the returns without leaving abnormal returns while the R^2 values increase in magnitude reaching at 91%.

Table 4.8: Regressions of excess portfolio returns on the TFM: 01/1993-8/2011, 224 months.

$$R_{it} - R_{ft} = a_i + c_i SMISI_t + n_i NSI_t + e_{it}$$

	Deciles										
	1	2	3	4	5	6	7	8	9	10	GRS*
aP	**low**									**High**	
a	0.177	0.453	0.101	0.160	0.149	-0.028	-0.010	-0.019	0.004	-0.221	
c	0.082	0.038	-0.011	-0.062	-0.141	-0.099	-0.055	-0.101	-0.104	-0.062	
n	0.520	0.576	0.761	0.815	0.925	0.992	1.035	1.085	1.284	1.659	
t(a)	0.829	2.246	0.611	0.977	0.806	-0.177	0.060	-0.111	0.023	-0.574	0.76
t(c)	1.345	0.667	-0.233	-1.335	-2.665	-2.176	-1.191	-2.107	-1.899	-0.558	
t(n)	11.51	13.44	21.75	23.46	23.58	29.54	30.17	30.42	31.60	20.28	
R^2	0.375	0.452	0.686	0.721	0.728	0.805	0.809	0.814	0.824	0.657	
DW	2.015	1.949	1.730	1.951	1.943	2.073	2.030	2.039	1.906	1.815	
bP	**Decr.**									**Increas.**	
a	-0.129	-0.109	0.467	0.117	-0.014	0.061	0.166	0.043	-0.044	0.236	
c	-0.827	-0.436	-0.373	-0.152	0.045	0.089	0.127	0.246	0.360	0.387	
n	0.884	1.054	0.964	1.074	0.943	0.980	0.935	0.955	0.909	0.946	
t(a)	-0.521	-0.633	2.763	0.712	-0.094	0.439	1.261	0.260	-0.297	1.427	1.21

Table 4.8 continued

t(c)	-11.60	-8.821	-7.669	-3.219	1.061	2.231	3.359	5.161	8.386	8.137	
t(n)	16.82	28.93	26.84	30.73	29.95	33.21	33.53	27.16	28.68	26.92	
R^2	0.686	0.820	0.794	0.819	0.804	0.833	0.836	0.769	0.792	0.771	
DW	1.885	1.963	1.854	2.082	1.945	1.996	2.088	2.180	1.950	1.931	
cP	**Concave**									**Convex**	
a	0.141	-0.008	0.261	0.060	0.443	0.016	0.073	-0.063	-0.173	0.047	
c	-0.292	-0.086	-0.030	0.047	0.057	0.049	0.028	0.021	-0.042	-0.277	
n	0.877	0.957	0.943	1.010	0.955	0.942	1.032	1.002	1.019	0.911	
t(a)	0.616	-0.038	1.490	0.416	2.947	0.116	0.511	-0.414	-0.940	0.207	1.22
t(c)	-4.436	-1.484	-0.607	1.139	1.316	1.231	0.685	0.493	-0.806	-4.251	
t(n)	18.03	22.25	25.34	32.93	29.90	31.87	34.22	31.01	26.14	18.96	
R^2	0.629	0.700	0.749	0.832	0.803	0.822	0.843	0.815	0.761	0.649	
DW	2.033	2.008	2.005	2.265	1.987	1.887	1.748	1.957	1.805	1.972	
RoBC	**Negative**									**Positive**	
a	0.109	0.112	0.231	0.042	0.339	0.154	0.051	-0.253	0.062	-0.042	
c	-0.737	-0.491	-0.302	-0.213	0.019	-0.002	0.101	0.261	0.327	0.511	
n	1.036	0.942	0.953	0.904	0.960	0.858	0.922	0.978	0.948	1.147	
t(a)	0.458	0.620	1.433	0.280	2.538	1.088	0.352	-1.699	0.403	-0.211	1.29
t(c)	-10.77	-9.414	-6.502	-4.912	0.496	-0.049	2.433	6.099	7.439	8.860	
t(n)	20.53	24.50	27.80	28.28	33.84	28.56	30.13	30.91	29.26	26.93	
R^2	0.734	0.777	0.800	0.799	0.840	0.790	0.804	0.812	0.796	0.772	
DW	1.847	1.973	1.954	2.057	1.742	1.717	2.092	2.069	1.697	2.074	
Momentum (t-12 to t-2)										**Positive**	
a	-1.073	-0.527	-0.259	-0.029	-0.021	-0.052	0.072	0.272	-0.056	0.356	
c	-0.455	-0.141	-0.191	-0.118	-0.129	-0.033	0.039	-0.000	0.126	0.035	
n	1.558	1.244	1.032	0.920	0.798	0.807	0.764	0.762	0.823	0.879	
t(a)	-2.439	-1.967	-1.217	-0.172	-0.131	-0.350	0.494	1.791	-0.324	1.033	1.53
t(c)	-3.592	-1.831	-3.116	-2.383	-2.764	-0.769	0.933	-0.022	2.536	0.361	
t(n)	16.65	21.89	22.78	25.21	23.07	25.49	24.69	23.57	22.34	0.879	
R^2	0.586	0.695	0.717	0.752	0.720	0.751	0.736	0.719	0.693	0.398	
DW	1.973	2.078	1.803	1.828	2.228	1.914	2.095	1.984	1.922	1.991	

*The F critical values of the GRS test are 1.83 and 2.32 at the 5% and the 1% significant level respectively.

4.7 Residual tests for the explanatory variables

In this section, we compare the power of the explanatory variables using the residuals that come from the time series regressions of the excess market return and the NSI factor. We follow a slightly different approach to that used by Chen (1983) when comparing CAPM with APT. In particular, we run four different regressions. At the first regression the excess market return is regressed on the SMISI factor. If the model is not misspecified, the return of RM-Rf would be captured by its beta coefficients and the residuals would behave like white noise with zero mean. However, if the model is misspecified and b does not capture all the information then the respective residuals will contain the non-captured information as we expect. If the other two explanatory variables of the FF3FM are capable of explaining this information then we could say that they have more explanatory power than the SMISI factor and vice versa. Table 4.9 exhibits the results.

Table 4. 9: Residual based tests for the power of explanatory variables.

Panel A		A	b			Rsq	DW
1. R_{mt}-R_{ft}	=	0.290	-0.199 SMISI		+resSMISI	0.024	1.812
		(1.00)	(-1.905)*				
1.a. ResSMISI	=	-0.06	0.186 SMB	0.066 HML		0.020	1.890
			(-0.21)	(1.650)		(0.787)	
2. R_{mt}-R_{ft}	=	0.209	0.203 SMB	0.102 HML	+resFFM	0.026	1.869
		(0.695)	(1.839)*	(1.176)			
2.a. ResFFM	=	-0.000	-0.166 SMISI			0.017	1.896
		(0.017)	(-1.716)*				
Panel B							
3. NSI	=	0.976	-0.172 SMISI		+resSMISI	0.015	1.825
		(3.17)**	(-1.274)				
3.a. ResSMISI	=	-0.130	0.330 SMB	0.206 HML		0.020	1.890
			(-0.419)	(2.670)**		(2.329)*	
4. NSI	=	0.831	0.345 SMB	0.237 HML	+resFFM	0.083	1.948
		(2.686)**	(2.796)**	(2.542)**			
4.a ResFFM	=	-0.000	-0.099 SMISI			0.044	1.965
		(0.010)	(-0.961)				

Notes: t-statistics in parentheses. (*),(**) indicate statistically significance at 10% and 5% level respectively.

Panel A shows that the SMISI factor is statistically significant and the constant does not differ from zero. The information contained in residuals cannot be priced by the two FF factors as their coefficients are not significant. On the contrary, SMISI seems to explain the information on the residuals left from the regression 2. From this point of view, SMISI factor conveys more valuable information in explaining stock returns. In panel B, NSI factor is used as dependent variable. To remind here that it is highly correlated with S&P 500, though its transferring information is different in essence. The SMISI factor does not have any influence on NSI as expected since it tracks nonstationary betas. As for the FF factors, both of them appear to be statistically significant since the effects of time varying betas have been removed from the index.

4.8 The risk associated with some selected portfolios

Having found evidence that portfolios formed with different estimated coefficients earn higher returns, we then examine if they are fundamentally riskier. According to LSV a portfolio would be fundamentally riskier if it underperforms the competitive one in some states of the world and second the underperformance would coincide with 'bad' states, in which the marginal utility of wealth is high, making the portfolio unattractive to risk-averse investors. Table 4.10 shows the year-by-year performance of portfolios formed according to different criteria. The increasing portfolios consistently outperformed decreasing portfolios in 5 out of 19 years for the two extreme deciles. Statistically significant difference is also observed for the portfolio having as characteristic medium a and high b_coefficient compared with that of low a and b_coefficient. Based on the fact that almost zero ROBC portfolio performs well enough, the results show the significant difference in returns between this one and the lowest one, while the average returns of the 9th and 10th portfolios with the two lowest only marginally rejected the hypothesis of zero difference of returns.

Table 4.11 depicts portfolios' performance in four different states of the world. The first state contains the 10% of the sample, corresponding to 22 worst stock monthly returns of S&P 500. The next state is the 66 remaining negative months other than the 22 worst. The third state absorbs 114 positive months with the last one to contain the 22 best months in the sample. Panel 1A of the table presents the results of the aP portfolios. The highest beta portfolios did worst than the first two lowest beta portfolios in bad states, showing that they are fundamentally riskier. As for the bP portfolios, the 10th highest decile portfolio lost 6.6 percent of its value in the worst 22 months, whereas the lowest retreated by 9.1 percent. For the next 66 worst months the highest portfolio lost 1% and the lowest 2.1%. The highest portfolio did worst only for the 22 best months as it increased by 6.4% and the lowest by 8.2%. Since the fundamentally riskiness of the portfolios is depicted basically at bad states of the world we could conclude that strategies of portfolio formation based on the b_coefficients did not expose investors to greater downside risk. In the same line are the findings of portfolios formed on the rate of beta change.

Panel 2 of table 4.11 presents numbers similar to those in Panel 1 except that in this case the states of the world are formulated using the quarterly GDP growth. The total sample is consisted of 74 quarterly US GDP data. Quarters are classified again into 4 states of the world. The first state contains the 10 worst quarterly GDP data. The next state corresponds to the 27 next worst quarters with the third state being consisted of the 27 best quarters other than the 10 best quarters belonged to the fourth state.

Table 4.10: Year by Year Returns for portfolios formed with different coefficients.

	Panel 1		Panel 2		Panel 3		Panel 4			Panel 5		Panel 6
	Low-High beta		Decreasing-Increasing		Concave-Convex		Rate of Beta change			L.H.beta/D.I.		Cv.Cx/D.I.
	(10-1)	(9,10-1,2)	(10-1)	(9,10-1,2)	(5,6-1,2)	(5,6-9,10)	(10-1)	(9,10-1,2)	(5,6-1,2)	(3.3-1.1)	(2.3-1.1)	(2.3-1.1)
1993	-0.084	-0.096	0.185	0.108	-0.089	0.002	0.008	0.067	0.090	-0.355	-0.052	-0.241
1994	0.279	0.223	-0.027	-0.023	0.103	0.101	-0.172	-0.037	-0.061	0.122	0.100	0.081
1995	-0.135	-0.077	0.144	0.039	0.047	-0.009	0.066	0.065	0.048	-0.073	0.052	0.118
1996	0.311	0.148	-0.022	-0.063	0.054	-0.036	0.052	-0.013	-0.084	0.151	0.100	-0.159
1997	0.338	0.140	0.393	0.188	0.285	0.333	-0.058	0.082	0.205	0.150	0.169	0.490
1998	0.959	0.714	0.017	0.044	0.052	0.192	-0.158	-0.225	-0.121	0.457	0.058	0.264
1999	1.493	0.969	0.313	0.093	0.115	0.028	0.007	0.126	0.060	0.490	0.267	0.010
2000	-0.558	-0.609	-0.118	-0.010	-0.270	-0.229	0.089	0.065	-0.045	-0.290	-0.063	0.185
2001	-0.221	-0.024	0.262	0.080	0.008	-0.012	0.155	0.115	0.152	0.099	-0.169	-0.091
2002	-0.394	-0.296	0.186	0.226	0.216	-0.012	0.026	0.080	0.147	-0.125	-0.092	0.175
2003	0.349	0.319	0.360	0.431	0.145	-0.005	0.686	0.431	0.083	0.459	0.197	0.422
2004	-0.154	-0.117	0.137	0.079	-0.050	0.040	0.104	0.075	0.116	-0.107	0.098	0.018
2005	0.129	-0.047	0.233	0.101	-0.011	-0.051	0.159	0.127	0.020	0.101	-0.046	-0.043
2006	-0.180	-0.093	0.087	0.064	-0.095	0.077	0.056	0.025	-0.046	0.228	0.114	0.278
2007	-0.162	-0.177	0.160	0.211	0.172	0.029	-0.040	-0.059	0.169	0.267	0.132	0.161
2008	-0.294	-0.214	-0.059	-0.064	0.098	0.275	0.051	0.017	0.083	-0.164	-0.030	-0.035
2009	0.747	0.658	0.010	-0.040	-0.173	0.163	0.040	-0.050	0.007	0.319	0.172	-0.841
2010	0.116	0.158	-0.064	-0.067	0.013	-0.063	-0.075	-0.081	-0.068	0.121	0.061	-0.126
2011	-0.282	-0.200	0.123	0.086	0.018	-0.006	0.107	0.053	0.024	-0.072	-0.057	0.017
Average	0.118	0.072	0.122	0.123	0.033	0.046	0.058	0.045	0.041	0.093	0.053	0.035
t-statistics	1.016	0.831	3.564	2.758	1.095	1.575	1.425	1.553	1.891	1.659	2.030	0.543
p-value	0.322	0.417	0.002	0.012	0.287	0.132	0.170	0.137	0.074	0.114	0.057	0.593

Notes: At the end of each year, 6 different kind in nature portfolios are formed. Each one of them is divided into 10 deciles. Panel 1 depicts the differences in returns of the one and two highest and lowest deciles portfolios. The portfolios formed using as characteristics the estimated constant coefficient of equation 3. At panel 2, 3 and 4 there are the differences in returns among the portfolios having as characteristics the b_coefficient, the c_coefficient and the rate of beta change of equation 3. Those portfolios constructed using one way classification. Panel 5 and Panel 6 report the results of portfolios formed using a 2 way classification. The Low beta and Decreasing portfolio (L. beta/D.) is that with an estimated constant belonging at the lowest decile and at the same time its b_coefficient is from the smallest one. The Concave and decreasing portfolio (Cv./D.) is that with negative c_coefficient and lowest b_coefficient.

Table 4.11: Portfolios' performance in different states of the world.

Panel 1: Portfolio Returns across Best and Worst Stock Market Months																
P./1A: aP	1	2	3	4	5	6	7	8	9	10	(10-1)	(t-stat)	(9,10-1,2)	(t-stat)		
W_{22}	-0.038	-0.039	-0.052	-0.061	-0.062	-0.079	-0.085	-0.080	-0.102	-0.141	-0.103	-6.566*	-0.081	-6.784*		
N_{64}	-0.010	-0.003	-0.014	-0.014	-0.017	-0.018	-0.018	-0.017	-0.023	-0.041	-0.031	-3.766*	-0.026	-4.429*		
P_{114}	0.019	0.020	0.022	0.026	0.026	0.026	0.030	0.028	0.036	0.046	0.027	3.844*	0.0216	4.085*		
B_{22}	0.039	0.048	0.058	0.063	0.075	0.082	0.081	0.084	0.105	0.154	0.115	8.031*	0.0859	6.493*		
P./1B: bP	1	2	3	4	5	6	7	8	9	10	(10-1)	(t-stat)	(9,10-1,2)	(t-stat)		
W_{22}	-0.091	-0.087	-0.079	-0.074	-0.078	-0.066	-0.065	-0.068	-0.065	-0.066	0.025	1.554	0.023	1.929*		
N_{64}	-0.021	-0.022	-0.015	-0.020	-0.016	-0.018	-0.018	-0.019	-0.017	-0.010	0.012	1.948*	0.008	2.142*		
P_{116}	0.022	0.027	0.031	0.027	0.027	0.029	0.028	0.029	0.027	0.031	0.009	2.042*	0.005	1.375		
B_{22}	0.082	0.087	0.088	0.095	0.075	0.073	0.080	0.078	0.068	0.064	-0.018	-1.037	-0.018	-1.323		
P./1C: RoBC	1	2	3	4	5	6	7	8	9	10	(10-1)	(t-stat)	(9,10-1,2)	(t-stat)	(5,6-1,2)	(t-stat)
W_{22}	-0.094	-0.073	-0.071	-0.074	-0.065	-0.063	-0.066	-0.074	-0.072	-0.085	0.009	0.469	0.005	0.356	0.020	1.902*
N_{64}	-0.018	-0.023	-0.017	-0.018	-0.014	-0.012	-0.018	-0.022	-0.015	-0.018	0.000	0.141	0.004	1.199	0.007	1.926*
P_{114}	0.026	0.027	0.026	0.026	0.029	0.024	0.028	0.027	0.029	0.034	0.009	1.731*	0.006	1.688*	0.001	0.471
B_{22}	0.097	0.086	0.084	0.075	0.080	0.070	0.070	0.074	0.071	0.083	-0.013	-0.742	-0.015	-0.981	-0.016	-1.764*
Panel 2: Portfolio Returns across Best and Worst GDP Growth Quarters (74 quarters)																
P./2A: aP	1	2	3	4	5	6	7	8	9	10	(10-1)	(t-stat)	(9,10-1,2)	(t-stat)	GDP	
W. 10	0.024	0.016	0.022	0.013	0.032	0.032	0.023	0.010	0.051	0.044	0.019	0.277	0.027	0.512	-0.016	
N.W. 27	0.024	0.028	0.031	0.028	0.032	0.013	0.036	0.033	0.027	-0.010	-0.034	-1.413	-0.017	-0.910	0.020	
N.B. 27	0.020	0.037	0.021	0.022	0.023	0.032	0.029	0.024	0.023	0.036	0.016	0.626	0.000	0.042	0.037	
B.10	0.019	0.047	0.029	0.074	0.056	0.068	0.038	0.070	0.115	0.242	0.223	2.889*	0.145	2.179*	0.047	
P./2B: bP	1	2	3	4	5	6	7	8	9	10	(10-1)	(t-stat)	(9,10-1,2)	(t-stat)		
W. 10	0.018	0.030	0.052	0.027	0.024	0.028	0.034	0.021	0.006	0.023	0.005	0.104	-0.009	-0.249		
N.W. 27	0.005	0.0137	0.029	0.019	0.022	0.031	0.035	0.021	0.030	0.037	0.032	2.081*	0.024	1.614		
N.B. 27	0.021	0.017	0.030	0.029	0.015	0.026	0.025	0.032	0.028	0.043	0.022	1.653	0.046	1.854*		
B. 27	0.024	0.078	0.091	0.107	0.095	0.066	0.065	0.086	0.069	0.062	0.037	1.246	0.014	0.747		
P./2C: RoBC	1	2	3	4	5	6	7	8	9	10	(10-1)	(t-stat)	(9,10-1,2)	(t-stat)	(5,6-1,2)	(t-stat)
W. 10	-0.004	0.032	0.040	0.015	0.034	0.046	0.029	0.034	0.019	0.026	0.029	0.488	0.008	0.177	0.026	0.743
N.W. 27	0.024	0.016	0.024	0.021	0.043	0.028	0.022	0.013	0.023	0.033	0.009	0.507	0.008	0.631	0.015	1.310
N.B. 27	0.026	0.019	0.020	0.029	0.021	0.027	0.032	0.023	0.035	0.040	0.013	0.904	0.014	1.704*	0.001	0.151
B. 27	0.095	0.080	0.097	0.056	0.099	0.044	0.059	0.057	0.087	0.075	-0.020	-0.564	-0.006	-0.221	-0.016	-0.669

* indicates statistically significant level 10%. Notes: The table presents the portfolio performance for four different states of the world. The first state of the world contains the 10% of the total sample, corresponding to 22 worst stock monthly returns based on the S&P 500. The next state is the 66 remaining negative months other than the 22 worst, the 114 positive months other than the 10% of the best of the sample and the 22 best months in the sample. The portfolios formed on the basis of the estimated coefficients of equation 3 and the rate of beta change. Panel 2 has the same meaning but in this case the states are defined using the GDP growth. The GDP quarters are also classified into 4 states of the world. The first state contains the 10 worst quarterly GDP data, the next state has the 27 next worst quarters, the third state is consisted of the 27 best quarters other than the best 10 quarters which belong to the fourth state.

Having established the four states of the world, average quarterly returns for each portfolio are matched up with each state. The results do not differ significantly from Panel 1. bP portfolios continue to gain higher returns even at the best states of the world. The same happens to RoBC portfolios. The evidence is slightly different for the aP portfolios. A positive difference is currently observed at one of the two worst states. The findings of this section indicate that that the selected portfolios earn higher returns without posing investors to higher downside risk. The results are consistent with those of LSV who showed that value strategies are not accompanied by higher systematic risk as the theory of asset pricing equilibrium states.

4.9 Fundamental characteristics of the new variables

In this last part, we present what fundamentals correspond to portfolios used in the construction of the TFM. As mentioned earlier, 'Superior' stocks should accommodate better fundamentals than 'Inferior' stocks in order to justify their higher returns. To investigate this we make use of Z-scores. The selected variables are the P/E ratio (P/E), the year-over-year Book value per share growth (BVG), the Debt to total Capitalization ratio (D/C) and the year over year sales growth (SG). Z-scores have been calculated for a five years period before and after the portfolio formation year. Following Chincarini and Kim (2006) we consider low P/E and D/C ratios and high BVG and SG ratios as evidence of better fundamental characteristics of a given portfolio. The Book value per share growth and Sales growth from year t-2 to year t-1 are calculated as $(BV_{-1}-BV_{-2})/BV_{-2}$. The procedure is similar to that used by LSV. Table 4.12 presents the results. P/E ratio for the 'Superior' portfolio is on average lower than 'Inferior' and 'Neutral' portfolios just before the formation period and remains lower for the subsequent years. The 'Neutral' portfolio appears positive P/E values for 9 out of 11 years. The 'Inferior' portfolio exhibits lower P/E ratios before the formation period, however, its values are increased two years after the year zero. Z-scores related to D/C ratio are depicted in panel B. The values are low enough for the 'Superior' portfolio even though the 'Inferior' one appears the lowest. At panel B, 'Superior' and 'Neutral' portfolios consistently overcome 'Inferior' portfolio when BVG is taken into consideration. Finally, panel D shows the one year growth of sales.

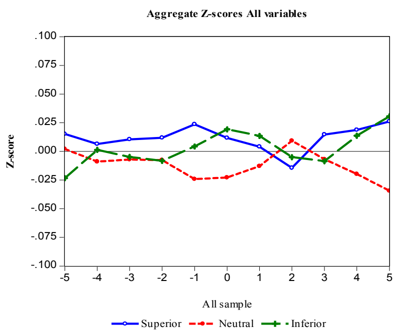
‘Superior’ portfolio overwhelms the rest ones having before and after formation year positive values but for one case.

Table 4. 12:: Z-scores corresponding to four fundamental ratios.

	-5	*-4*	*-3*	*-2*	*-1*	*0*	*1*	*2*	*3*	*4*	*5*
Panel A: P/E ratio											
Superior	0.039	-0.015	0.017	0.048	-0.039	-0.010	-0.003	-0.040	-0.050	-0.030	-0.012
Neutral	-0.032	0.014	0.013	-0.039	0.040	0.020	0.036	0.002	0.020	0.010	0.039
Inferior	0.009	-0.006	-0.027	-0.004	-0.009	-0.026	-0.047	0.035	0.025	0.014	-0.047
Panel B: Debt to Total Capitalization (D/C)											
Superior	0.042	0.003	-0.007	-0.014	-0.005	0.012	0.029	0.018	-0.019	-0.018	-0.031
Neutral	-0.010	0.011	0.019	0.019	0.015	0.009	0.004	0.013	0.024	0.041	0.036
Inferior	-0.041	-0.034	-0.032	-0.023	-0.022	-0.028	-0.040	-0.040	-0.014	-0.039	-0.017
Panel C: YoY_Book Value per share Growth (BVG)											
Superior	0.075	-0.029	0.022	0.016	0.007	0.012	0.015	-0.019	-0.040	0.001	0.000
Neutral	-0.020	0.026	-0.001	0.004	0.013	0.002	0.012	0.031	0.024	-0.023	-0.032
Inferior	-0.050	-0.018	-0.023	-0.058	-0.044	-0.029	-0.040	-0.048	-0.006	0.014	0.043
Panel D: YoYSG (SG)											
Superior	0.066	0.044	0.031	0.065	0.043	0.037	0.027	-0.061	0.030	0.026	0.062
Neutral	-0.014	-0.036	0.004	-0.056	-0.054	-0.065	-0.024	0.021	-0.008	-0.005	-0.032
Inferior	-0.076	-0.017	-0.056	-0.003	0.031	0.051	0.007	0.023	-0.016	0.015	0.016

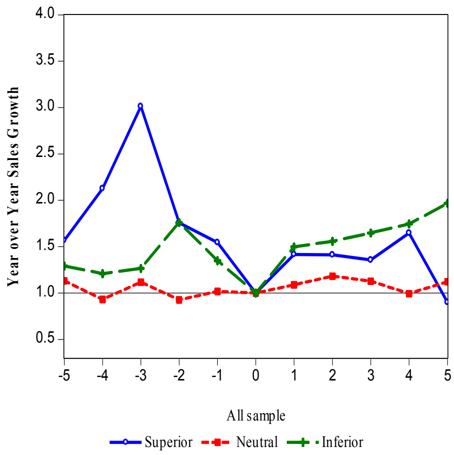
In figure 4.3 we also present the aggregate Z-scores. All variables take the sign reported above with weights being equal to all of them. We are able to observe that ‘Superior’ portfolio has on average higher aggregate Z-score values than its competitors at least up to one year before the formation period. ‘Inferior’ portfolio performs well enough relative to the ‘Superior’ one to two years after the portfolio formation but both of them appear decreasing values up to the second year after year zero. As for the ‘Neutral’ portfolio, it does not exhibit much variation at least before the formation period though negative, but it starts rebalancing just after the formation period.

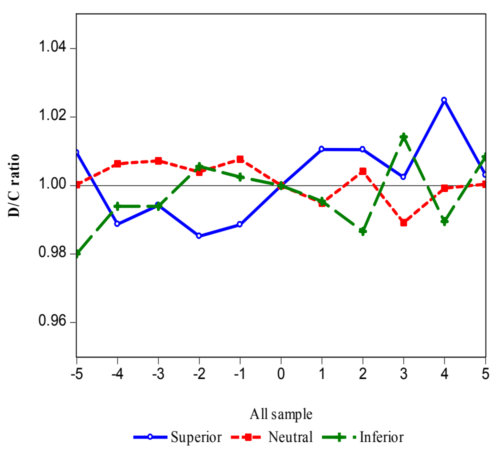
Figure 4.3: Aggregate Z-scores.



We have also examined the aggregate z-scores at two different sub-samples. Even though the general conclusions do not change dramatically, we found some inconsistencies regarding SG and D/C z-scores for the 2002-2011 sub-period. More concretely, 'Inferior' portfolio exhibits higher SG and lower D/C values than 'Superior' portfolio. In light of this fact, we follow Fama and French (1995) and investigate not the z-scores per se but how these specific portfolios' variables behave before and after the formation period. Thus, at each portfolio formation year t=1993 to 2011, the ratios are calculated for t+i with i= -5,…5. The ratio for t+i is standardized being equal to 1.0 in the portfolio formation year. Then the ratios are averaged across portfolio formation year t. Figure 4.4 depicts the results. SG increases in the case of 'Superior' portfolio for four consecutive years after the formation period. Hence, the observed lower values of z-score after the formation period for the given sub-period are due to the higher increase of SG for the competitive portfolios. As far as the D/C ratio is concerned, it is significantly lower before the year zero for the 'Superior' portfolio in contrast to 'Neutral' and 'Inferior' portfolios. To sum up, the evidence shows that 'Superior' portfolio exhibits better fundamental characteristics than 'Inferior' portfolio according to z-scores not only before the formation period but also after this. From this point of view, 'Superior' portfolio justifies its higher observed returns in relation to 'Inferior' portfolio.

Figure 4.4: The 11-year evolution of Sales Growth and D/C ratio relative to the formation period.





4.10 Conclusions

This chapter presents the empirical findings and the performance of our new TFM in the context of time series. Our new TFM consists of two variables. The first one is the 'SMISI' and captures the risk associated with the difference between 'Superior' and 'Ineferior' stocks whose betas are increasing and decreasing in market return respectively. The second variable, the 'NSI', is constituted from invariant betas and operates as the market factor.

The model is tested and compared against CAPM and FF3FM in the context of time series regressions on five different kinds of portfolios. These portfolios are formed using the estimated coefficients of a nonlinear regression each one of which accommodates different properties. Momentum portfolios are also included into analysis. The findings show that neither CAPM nor FF3FM explain the variation of portfolio returns. The GRS tests reject the hypothesis of no abnormal returns with the intercepts being high enough. The superiority of the TFM is apparent. In particular, the model displays lower GRS test values for all examined portfolios, lower mispricing errors and R^2s similar to those of FF3FM. The SMISI factor is priced in several cases. As for the 'NSI' factor, the high t-statistic values indicate its importance in explaining portfolio returns.

In this chapter, we have also argued that 'Superior' stocks should accommodate better fundamentals for justifying positive b_coefficients and higher returns. With the use of z-scores, the results indicate that 'Superior' stocks have lower P/E, D/C ratios and higher BVG and SG. Although the picture changes for the D/C and SG ratios during the 2002-2011 sub-period, it seems to be due to the fact that 'Inferior' portfolio increases more than average its values. The aggregate z-scores, which help to combine all variables and give more consistent explanations, show that 'Superior' portfolio dominates 'Inferior' at least for the years preceding the formation period. The observed differences in returns between extreme deciles of the estimated portfolios are not associated with higher risk when different states of the world are considered.

Our empirical findings mentioned in this chapter have significant implications. They provide insights into the behaviour of securities and their returns resulting from beta nonstationarity. The new risk factors give valuable information of better understanding the characteristics of returns, targeting the reinforcement of stock market efficiency. Investors, banks, fund managers and other interested parties would be able to make their portfolio choices and form their investment strategies according to the amount of risk they can or wish to undertake. The new constructed portfolios could possibly supply their arsenal with more tools and choices.

CHAPTER 5

CROSS-SECTIONAL TESTS

5.1 Introduction

Fama and MacBeth (FMcB) (1973) conducted the first empirical examination regarding the validity of the CAPM. They found that on average a positive trade off exists between return and risk, leading to a conclusion in favour of the CAPM. However, empirical evidence in 1990s (e.g. Jegadeesh, 1992; Davis, 1994; Fama and French, 1996, Groenewold and Fraser, 1997) expresses doubts with regard to the validity of betas as risk measures, since their findings suggest that betas are not always significantly related to returns.

The limited empirical support found for the CAPM is interpreted in the literature either as evidence against the CAPM itself or as evidence that the testing methodology is not suitable. As far as the former case is concerned, the literature presents alternative tests of measures to the market premium factor suggested by the CAPM. For example, Banz (1981) finds that the size effect has a strong impact on stock returns, indicating that smaller firms have higher returns and thus higher betas. Similar findings are obtained by Zarowin (1990), Fama and French (1992) and Daniel and Titman (1997). Measures, such as book to market value and earnings to price ratio, appear to significantly influence the stock returns (Berk, 1995; Fama and French, 1996). Stocks with high such ratios tend to have higher returns than stocks with low such ratios. Similar results have been found by Chan et al. (1991) for the Japanese market and Levis and Liodakis (2001) for the UK market. Liquidity also appears to influence the expected stock returns as explained by Jacoby et al. (2000)

while Chen (1983) and more recently Groenewold and Fraser (1997) conclude that the Arbitrage Pricing Theory (APT) of Ross (1976) outperforms the CAPM.

The FMcB testing methodology has been criticized for a number of reasons. Roll (1977) argued that the CAPM cannot be tested because the composition of the real market portfolio is not observed. Isakov (1999) reported that this particular methodology does not leave beta to appear as a useful measure of risk as the model is expressed in terms of expected returns but tests can only be performed on realized returns. In addition, the realized market excess return does not behave as expressed since it is too volatile and is often negative. Pettengill et al. (1995) proposed an alternative approach with which the excess market returns are separated into positive and negative, concerning that investors perceive the possibility of the risky assets' return being below the risk-free rate. However, the FMcB procedure is still used in most empirical studies (Fraser et al., 2004) for testing models in the cross- sectional framework.

5.2 Methodological issues

In this section, three models previously presented in Chapter 2 will be compared against our proposed methodology. The three models are the Capital Asset Pricing Model, the three-factor model suggested by Fama and French (1996) and the Premium-Labor model (PL-model) developed by Jagannathan and Wang (JW) (1996). The selected models will be tested both conditionally and unconditionally in the cross sectional context. Below, we provide a review of the models and the empirical cross sectional equations.

The CAPM

In the cross sectional context, the CAPM states that differences in average returns depend linearly and solely on asset betas (Cuthbertson and Nitzsche, 2004). Cross-section tests are based on a two-stage procedure of FMcB. At the first step, we run the following time series regression of each security or portfolio i:

$$R_{it} - R_{ft} = a_i + \beta_i (R_{mt} - R_{ft}) + e_{it} \qquad 5.1$$

with $R_{it} - R_{ft}$ being the excess return of asset i, $R_{mt} - R_{ft}$ the market excess return, β_i the systematic risk and α_i and e_{it} are assumed to be zero according to the model. In a second step cross-section regression the sample average monthly returns (r_i) are regressed on the β_i's estimates from the first step regression as in equation 5.2:

$$E[r_i] = \lambda_o + \lambda_1 \hat{\beta}_i + \eta_i \qquad 5.2$$

In 5.2, the λ_0 and λ_1 are constant across all assets. In addition, from equation 5.2 we expect that $\lambda_0 = 0$ and $\lambda_1 = \overline{R_m} - \overline{R_f}$ where the bars indicate the sample mean values. This is the unconditional CAPM, since conditional information plays no role in determining excess returns.

The conditional cross-section version of CAPM is as follows:

$$E[r_{it} \mid I_{t-1}] = \lambda_{0t-1} + \lambda_{1t-1} \hat{\beta}_{it-1} + \eta_i . \qquad 5.3$$

In 5.3, I_{t-1} is the information set available at time t and λ_{1t-1} the conditional market risk premium. The same assumptions for the conditional cross-section regressions hold for the rest models. All models are tested both unconditionally and conditionally.

Fama and French three factor model

As mentioned earlier, the three-factor model suggested by Fama and French (1996) relates the expected return on a portfolio in excess of the risk-free rate $E(R_i) - R_f$ to three factors. The first one is the excess return on a broad market portfolio (i.e. $R_m - R_f$). The second is the SMB (i.e. Small Minus Big, SMB) and the third is the HML (i.e. High Minus Low, HML). In the time series regression, the model has the following form:

$$R_{it} - R_{ft} = a_i + \beta_i (R_{mt} - R_{ft}) + s_i SMB_t + h_i HML_t + e_{it} \qquad 5.4$$

The factor loadings, β_i, s_i, h_i, are the slopes that come from the OLS time series regression (equation 5.4) which constitutes the first step of FMcB procedure as above.

The cross-section regression is given by:

$$r_i = \lambda_o + \lambda_1 \hat{\beta}_i + \lambda_{SMB} \hat{s}_i + \lambda_{HML} \hat{h}_i + u_i . \qquad 5.5$$

The intercept λ_o in the above equation should not be statistically different from zero while the factor risk premiums should be priced.

The Premium-Labour model

The Premium-Labour model (PL-model) developed by Jagannathan and Wang (JW) (1996) introduces two additional variables (For more details see in Chapter 2). The first variable (premium) tries to capture the instability of the asset's beta over the business cycle. For this purpose, the authors use the spread between BAA- and AAA-rated bonds, since interest-rate variables are likely to be most helpful in predicting future business conditions as pointed out by Stock and Watson (1989). The second variable relates to the return on human capital. This variable is taken into consideration for measuring the aggregate wealth, since the empirical failure of the CAPM has been attributed to the bad proxy of the market index (Roll, 1977). The return on human capital is assumed to be a linear function of the growth rate per capita labor income, the time series of which is used in the analysis. After estimating the betas (being orthogonal to one another) of the aforementioned variables in the time series context, the second step cross- section regression is as follows:

$$r_i = \lambda_o + \lambda_1 \hat{\beta}_i + \lambda_{prem} \hat{\beta}_i^{prem} + \lambda_{labor} \hat{\beta}_i^{labor} + v_i \,. \qquad 5.6$$

This is the PL-model of JW, which is going to be used for empirical examination in the rest of this chapter.

The Two Factor Model

In chapter 3, the TFM was analytically developed and presented in the context of time series analysis. However, we have to remind the two variables used to build the model. The first variable named as 'SMISI' (i.e. Superior minus Inferior Stock Index) represents the difference in returns between the 30% of stocks with the highest b_coefficients and the 30% of stocks with the lowest b_coefficients. This variable aims at capturing the risk associated with 'Superior' and 'Inferior' stocks. The b_coefficients are estimates of the nonlinear equation 3.3. These specific coefficients aim at capturing the time variability of betas. The second explanatory variable, which we call it as 'Neutral' (Neutral Stock Index-NSI), is the remaining 40% of the stocks.

The stocks constitute the index have on average zero b_coefficients. This index is supposed to be similar to the general index of S&P 500 if the assumption of constant betas coming from the CAPM holds. Thus, the time series regression is given by the following equation:

$$R_{it} - R_{ft} = a_i + c_i SMISI_t + n_i NSI_t + e_{it}\,, \qquad 5.7$$

and the unconditional cross-section regression is:

$$r_i = \lambda_o + \lambda_{smisi} \hat{c}_i + \lambda_{nsi} \hat{n}_i + z_i\,. \qquad 5.8$$

5.3 Data description

The dataset used concerns securities traded on the S&P 500. The rate of return of each security, R_i, at time t is calculated as $R_{it} = P_{it} / P_{it-1} - 1$. The testing period spans from July 2001 to June 2011. The risk free rate is a 3-month Treasury bill for the US market. For the construction of the variables used in the TFM we firstly employ daily observations for the estimation of the b_coefficients as mentioned above. To be included in one of the 'Superior' or 'Inferior' portfolio for a given year a stock must have statistically significant beta coefficients at least at 10% level (i.e. t-stat $|1.70|$) for all previous 5 years. This way, we ensure that each beta coefficient has explanatory power and that it can be used for estimation purposes. After forming the portfolios, monthly returns are employed. The monthly return observations of the FF3FM are retrieved from the authors' internet homepage[10]. For the PL_model the same variables used by JW are also employed here. The bond yields of BAA and AAA used as the premium in the PL-model. Similarly the per capita monthly income series was obtained from the Federal Reserve Bulletin published by the Board of Governors of the Federal Reserve System and was used as the labor variable. Following JW, the growth rate in labor income is computed as:

$$R_t^{labor} = [L_{t-1} + L_{t-2}] / [L_{t-2} + L_{t-2}]\,,$$

where L_{t-1} is the per capita labor income for month t-1, which becomes known at the end of month t.

[10] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

The models are tested on two different portfolios sorted on the historical beta coefficients and the Book Value per share. The beta based portfolios are formed following the standard FMcB methodology. The first five years of monthly observations (i.e. t-120,…,t-61) are used to estimate the betas for each security. Stocks with statistically significant betas higher than the 10% level were excluded from the sample. After estimating the stocks' βi coefficients from equation 5.1, the stocks were ranked on the basis of estimated betas and were assigned to one of the ten portfolios. The first portfolio consisted of stocks with the lowest betas, while portfolio 10 consisted of stocks with the highest betas. This process was then completed for each subsequent year in our data set. This gives a time series of monthly returns from July 1996 to June 2011 for each of the ten portfolios. After forming the portfolios, the beta of each portfolio is then estimated over the second period of 5 years (i.e. t-60,…,t-1) regressing now the realized portfolio returns on the market index. This is done in order to reduce the 'errors in variables' problem. The second kind portfolios are formed every calendar year, starting in 2001, where we first sort firms into deciles based on their Book Value per share at the end of June. For consistency purposes, the beta portfolios have the same starting point every year. The Book-Value per share data were taken from Compustat.

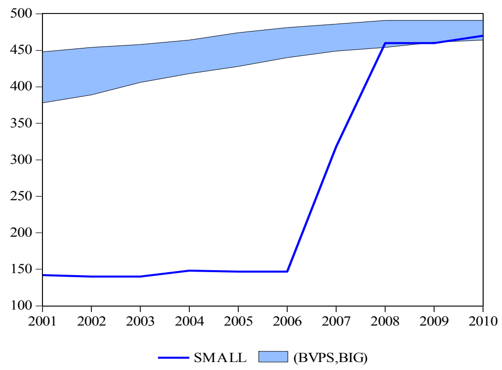
Following Fraser et al. (2004), we repeat this procedure by updating the beta estimates on a monthly basis. Thus, time series of risk premiums of the models are generated. The test of significance of the risk-premia is done as follows (Fama and MacBeth, 1973; Clare and Thomas, 1994):

$$t_{\lambda} = \frac{\hat{\lambda}}{s(\hat{\lambda})/\sqrt{n}} . \qquad 5.9$$

In the above equation, $\hat{\lambda}$ is the mean value of the estimated risk premium, $s(\hat{\lambda})$ is the standard deviation and n shows the number of observations. The variables are priced over the estimation period at the 10 per cent level, when $|t|$ is greater than 1.30.

To note here that the relatively low number of stocks at the very early stage of the sample compared to the number of shares constitute the S&P 500 can cause survivorship bias problems. To examine possible effects related to survivorship bias, we also form big and small sample portfolios. The small sample portfolios contain stocks that were used in the construction of the TFM. This is due to the fact that during the construction of the variables, the asked number of observations is higher (i.e. 8 years). The big sample portfolios contain stocks with statistically significant betas at least at the 10% level. Although the higher number of data availability the BVps portfolios are also formed from those stocks. For compatibility reasons between the two different kinds of portfolios, we chose to reduce the number of stocks by 10% on average. Figure 5.1 depicts the number of shares contained in the two samples as well as the available data of the BVps.

Figure 5.1: Number of shares in analysis



Tables 5.1 and 5.2 provide summary statistics of time series averages of portfolio returns for the two samples. For each portfolio, the tables show the mean monthly returns in excess of the 3-month treasury bill, the standard deviation of the monthly excess returns and the t-statistics associated with the hypothesis of zero portfolio returns. Both tables exhibit the positive differences in returns between the lowest and highest BVps portfolios and highest and lowest beta based portfolios. The pattern of portfolio returns between the big and small samples looks similar. A deviation is observed between the 9^{th} and 10^{th} decile of small sample beta sorted portfolios.

Table 5.1: Summary statistics for Simple Monthly Excess Returns (in Percent) for the portfolios formed using Book value per share and beta coefficients: 07/01-06/11, 120 Months, Big sample (429 shares on average per year).

	Deciles									
	1	2	3	4	5	6	7	8	9	10
BV per share	**Low**									**High**
Mean	1.91	1.42	0.99	0.95	1.06	0.97	0.92	0.63	0.79	0.34
Std. Dev.	6.20	5.37	5.03	5.44	5.86	4.87	5.41	5.56	5.31	6.25
t-statistics	3.38	2.89	2.15	1.92	1.98	2.18	1.87	1.24	1.64	0.60
Beta	**Low**									**High**
Mean	0.56	0.81	0.60	0.98	0.85	0.97	0.97	1.08	1.25	1.30
Std. Dev.	3.30	3.83	4.04	4.32	5.00	5.20	5.99	6.50	7.11	9.85
t-statistics	1.85	2.31	1.63	2.48	1.87	2.05	1.78	1.81	1.92	1.44

Table 5.2: Summary statistics for Simple Monthly Excess Returns (in Percent) for the portfolios formed using Book value per share and beta coefficients: 07/01-06/11, 120 Months, Small sample (257 shares on average per year).

	Deciles									
	1	2	3	4	5	6	7	8	9	10
BV per share	**Low**									**High**
Mean	1.26	0.95	0.77	0.72	0.68	0.91	0.59	0.58	0.83	0.16
Std. Dev.	5.79	5.16	4.91	5.60	5.64	4.79	6.27	5.34	4.99	6.53
t-statistics	2.39	2.02	1.71	1.40	1.32	2.08	1.03	1.19	1.83	0.27
Beta	**Low**									**High**
Mean	0.42	0.61	0.49	1.01	0.66	0.83	0.79	0.77	1.13	0.73
Std. Dev.	3.58	3.72	4.04	4.30	4.78	5.46	6.40	6.84	7.41	9.76
t-statistics	1.27	1.80	1.34	2.57	1.50	1.66	1.36	1.24	1.67	0.82

The estimated average betas produced by CAPM are depicted in table 5.3. We do not find significant differences in betas within portfolios formed on BVps. However, this is not the case of beta-sorted portfolios as they range from a low of 0.47 to a high of 1.65. In addition, at both samples the slopes seem to follow identical pattern.

Table 5.3: The estimated average slopes for the portfolios formed using Book value per share and beta coefficients. Both samples are included.

	Deciles									
	1	2	3	4	5	6	7	8	9	10
BV ps Big	1.21	1.00	0.96	0.99	1.04	0.90	0.95	0.94	0.85	0.98
Beta Big	0.47	0.64	0.73	0.79	0.89	0.91	1.02	1.15	1.26	1.65
BVps Small	1.17	0.94	0.87	1.05	0.97	0.91	1.18	0.91	0.79	1.07
Beta small	0.48	0.57	0.68	0.69	0.79	0.95	1.17	1.30	1.40	1.82

In table 5.4, we present the findings of the existence of survivorship bias. Following the method of Banz and Breen (1986) we examine whether the returns over the 120 months for each portfolio are different. For brevity reasons[11], we report only the results of the Gibbons, Ross, Shanken (1989) test (hereafter GRS test) of the zero a's hypothesis. The table depicts that jointly a's are different from zero and statistically significant differences in returns between the big and the small sample exist. However, a more closely examination of portfolios indicates that only three out of ten and one out of ten cases are different from zero for the BVps and beta portfolios respectively.

[11] For more details of the GRS test see in Chapter 4.

Table 5.4: GRS test for testing the restriction that all ten alphas are jointly zero (constants in percent, std. errors in parentheses).

	Deciles										
	1	2	3	4	5	6	7	8	9	10	GRS test
BV per share	0.65	0.47	0.22	0.23	0.38	0.06	0.33	0.05	-0.04	0.18	3.37
	(0.23)	(0.15)	(0.15)	(0.16)	(0.16)	(0.14)	(0.19)	(0.11)	(0.14)	(0.11)	
Beta	0.14	0.20	0.11	-0.03	0.20	0.14	0.18	0.30	0.12	0.57	2.71
	(0.13)	(0.16)	(0.16)	(0.13)	(0.15)	(0.12)	(0.17)	(0.19)	(0.18)	(0.14)	

5.4 Unconditional and Conditional cross-section regressions

Panel A of table 5.5 depicts the evidence of the unconditional cross-sectional regressions from July 2001 to August 2011. It tries to identify risk premiums associated with factors other than market risk. As we can see, the coefficients λ_0 are not statistically different from zero for the BVps portfolios. This is consistent with the Sharpe-Lintner hypothesis (SLH). The R^2 of the regression is only 0.7% for the case of CAPM while it goes up to 70% and 90% for the TFM and FF3FM respectively. The SMISI factor is priced and the market risk premium has the expected positive sign apart from the case of FF3FM though not significant at any level. As for the PL-model, it has relatively low R^2 while neither labor factor nor premium factor influence the returns. The results of the portfolios formed on beta coefficients are rather different. The R^2's increase and reach as high as 84.9% for the PL-model with the rest models to follow closely. Two intercepts appear to be significant violating the SLH while the FF3FM appears high R^2 value although none of its factors are priced. Panel B of Table 5 depicts the results for the period from July 2006 to August 2011. The TFM continues to have relatively high R^2 values with the FF3FM to lose power relatively to its previously observed R^2 values. CAPM still retains the poor performance consistent with the results of Jagannathan and Wang (1996) with PL-model to perform better in terms of R^2. The same tests have been also carried out using the small sample. The findings differ significantly with regard to R^2 values that appear to be lower.

Table 5.5: Unconditional Cross-sectional regressions of the selected models.

Panel A: 2001-2011 (BS)	λ_0	λ_1	λ_{SMISI}	λ_{NSI}	λ_{SMB}	λ_{HML}	λ_{labor}	λ_{prem}	R^2
BV per share	0.014	-0.004							0.007
	(0.75)	(-0.24)							
	-0.009		0.042	0.018					0.701
	(-0.75)		(3.74)*	(1.54)					
	0.009	-0.008			0.023	-0.002			0.914
	(0.78)	(-0.57)			(2.53)*	(-0.30)			
	0.009	0.004					-0.006	1.305	0.244
	(0.03)	(0.11)					(-0.99)	(0.93)	
Beta portfolios	0.003	0.005							0.825
	(2.98)*	(6.15)*							
	0.004		-0.002	0.005					0.828
	(2.10)**		(-0.34)	(3.11)*					
	0.002	0.008			-0.002	0.001			0.833
	(0.95)	(1.80)			(-0.36)	(0.48)			
	0.006	0.006					0.001	0.201	0.849
	(1.36)	(2.37)**					(0.91)	(0.85)	
Panel B: 2006-2011 (BS)	c_o	c_{mar}	c_{SMISI}	c_{NSI}	c_{SMB}	c_{HML}	c_{labor}	c_{prem}	R^2
BV per share	0.030	-0.019							0.456
	(3.52)*	(-2.59)*							
	0.014		0.022	-0.006					0.762
	(1.87)		(4.45)*	(-0.78)					
	0.003	0.003			0.003	-0.012			0.879
	(0.47)	(0.45)			(0.73)	(-2.83)*			
	0.028	-0.013					0.000	0.355	0.496
	(2.32)**	(-0.96)					(0.64)	(0.21)	
Beta portfolios	-0.001	0.018							0.006
	(-0.01)	(0.22)							
	-0.192		0.526	0.221					0.559
	(-2.13)**		(2.92)*	(2.47)*					
	-0.055	0.135			-0.069	-0.318			0.323
	(-0.17)	(0.33)			(-0.23)	(-1.05)			
	-0.209	0.363					0.144	-3.06	0.642
	(-1.19)	(3.01)*					(2.59)*	(-0.37)	

*,** depict significance at 5% and 10% respectively.

The results of the conditional cross-sectional regressions are presented in table 5.6. The risk premia are demonstrated in the first column, the second column shows the t-ratio with the third and fourth columns to depict the normality test and the average GRS test coming from the time series first step regression respectively. We firstly note that in the case of BVps portfolios the variables of the TFM are priced though a proportion of portfolio returns left unexplained. This also happens with CAPM, while the market risk and the HML factor in the FF3FM appear to be significant with the constant not being statistically different from zero. Related to PL-model no factor is significant. The t statistics should be cared with caution, since in some cases the distribution of the estimated risk premia are clearly not normal, a result consistent with Clare and Thomas (1994) when macro-economic variables were used. For the beta based portfolios we have to refer that almost no risk premia are priced apart from the case of PL-model. The GRS test depict that TFM clearly outperforms CAPM and FF3FM models in the first step time series regressions. The test is not available in PL-model since the regressions have been conducted separately for each one of the variables. The same tests have been also carried out using this time the estimated betas constant for one year as exactly FMB done in their study. Once again the variables of the TFM are priced with this model along with the PL-model to be the better ones when the period from July 2006 to June 2011 is considered.

Table 5.6: Estimated risk premia in conditional cross-section regression.

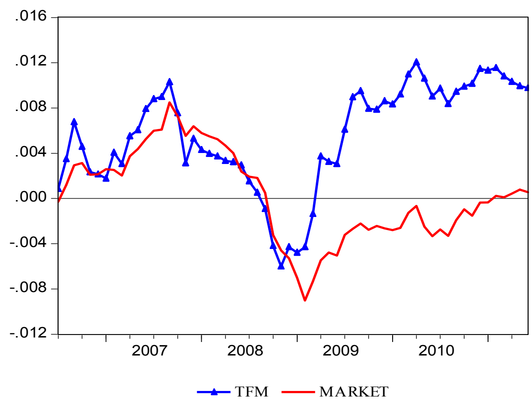
Panel A: 2001-2011 (BS)			λ_k	t	JB	GRS test
BVps	CAPM	λ_0	-0.011	-2.06*	8.73	
		λ_1	0.024	4.18*	5.83*	16.4
	TFM	λ_0	-0.018	-2.77*	35.8	
		λ_{SMISI}	0.019	2.56*	22.7	
		λ_{NSI}	0.032	3.97*	53.7	2.97*
	FF3FM	λ_0	-0.004	-0.53	739.4	
		λ_1	0.017	1.61*	627.4	
		λ_{SMB}	0.007	1.13	35.1	
		λ_{HML}	-0.012	-2.07*	4.80*	10.36
	PLM	λ_0	0.004	1.03	651.2	
		λ_1	-0.001	-0.11	67.4	
		λ_{prem}	0.000	-0.11	17.1	
		λ_{labor}	0.012	0.08	0.27*	N/A
Panel B: 2001-2011 (BS)			λ_k	t	JB	GRS test
Beta port.	CAPM	λ_0	0.003	0.88	26.0	
		λ_1	0.006	1.03	50.5	11.9
	TFM	λ_0	0.004	0.80	28.1	
		λ_{SMISI}	0.001	0.08	33.5	
		λ_{NSI}	0.005	0.62	47.8	1.39*
	FF3FM	λ_0	0.006	1.64*	16.6	
		λ_1	0.002	0.47	20.9	
		λ_{SMB}	0.001	0.12	1733.1	
		λ_{HML}	-0.003	-0.60	68.9	5.52
	PLM	λ_0	-0.008	-1.46*	0.30*	
		λ_1	0.025	3.49*	11.9	
		λ_{prem}	0.002	1.35*	90.7	
		λ_{labor}	0.041	0.27	466.2	N/A

* depicts significance at 10% level

5.5 Portfolio and models' performance in extreme market conditions

Before presenting the results associated with the portfolio and models' performance in extreme market conditions, we show in figure 5.2 the five-year moving averages of estimated slope and excess market return. All models accommodate the market risk. However, the TFM gave the most accurate results in estimating market risk premium when beta sorted portfolio returns were used as dependent variables in the conditional-cross sectional regressions. From the figure there seems to be a close relation between the two series up to the last quarter of 2008. Since then and up to the end of the sample, the estimated market risk premium diverges significantly. However, at this point we have to refer two significant observations. Having conducted cointegration test of the two series the results of which found significant, we expect them to converge again in the near future. In addition, we could say that the estimated premium seems to work as a short term moving average where once above the market excess returns signals buying opportunities. Of course, it needs further consideration and left for future research.

Figure 5.2: Five year moving averages of TFM estimated slope and excess market return (8/2006-6/2011).



Having found evidence that portfolios formed with different criteria gains higher returns, we then examine if they are fundamentally riskier. According to Lakonishok et al. (1994) a portfolio would be fundamentally riskier if it underperforms the competitive one in some states of the world and second the underperformance would coincide with 'bad' states, in which the marginal utility of wealth is high, making the portfolio unattractive to risk-averse investors. In addition, Chan and Lakonishok (1993) state that downside risk is a major concern of money managers. Due to the fact that beta represents a stock's return sensitivity to market ups and downs, it is expected to be a good measure of downside risk. For this point of view, low beta portfolios should face lower downside risk than high beta portfolios. The opposite should happen when market rises. To examine this, tables 5.7 and 5.8 present the results of the ten largest down and up-market months of both portfolios. We are able to distinguish between the two examined portfolios some very interesting characteristics. Firstly, in down markets, the lowest decile BVps portfolio appears to have lower returns with respect to the highest one. However, this fact could be explained in the case of beta based portfolios due to the lower beta coefficient as presented previously in table 5.3. Instead, BVps portfolios do not exhibit such differences in the estimated betas that could explain those return divergences. Thus, there might be some other reasons associated with this better performance. In up markets, the lowest BVps portfolio does not differentiate from the highest one though this is the case between the two extreme beta based portfolios.

Table 5.7: Ten largest down market months: Simple Monthly Excess market Return (in Percent) and returns on portfolios formed using Book value per share and beta coefficients.

			Deciles									
	Month	Market	1	2	3	4	5	6	7	8	9	10
BV per share			**Low**									**High**
1	10/08	-17.0	-20.8	-18.4	-16.0	-18.0	-21.3	-15.6	-20.6	-23.1	-22.3	-25.7
2	9/02	-11.1	-5.5	-6.1	-6.9	-7.7	-8.8	-10.6	-8.7	-11.7	-10.1	-11.0
3	2/09	-11.0	-6.0	-5.6	-7.3	-13.0	-12.7	-10.6	-8.1	-12.4	-14.1	-20.2
4	9/08	-9.2	-8.8	-11.5	-10.5	-10.6	-10.1	-9.6	-11.4	-10.2	-11.0	-5.6
5	6/08	-8.8	-9.2	-6.9	-8.4	-6.1	-9.9	-9.6	-10.1	-8.8	-6.5	-8.7
6	1/09	-8.6	-5.1	-3.9	-2.9	-5.9	-8.0	-9.2	-8.8	-6.5	-8.7	-15.0
7	9/01	-8.4	-14.6	-10.3	-13.4	-12.9	-14.9	-11.8	-13.9	-12.5	-8	-9.2
8	5/10	-8.2	-8.0	-5.3	-6.3	-6.6	-7.8	-7.3	-7.8	-8.1	-7.8	-8.3
9	7/02	-8.0	-7.6	-6.0	-7.7	-9.2	-11.4	-8.3	-13.6	-10.4	-12.7	-9.9
10	11/08	-7.5	-11.5	-7.8	-11.7	-11.8	-9.7	-4.1	-7.0	-10.0	-8.7	-12.0
Average		-9.8	-9.7	-8.2	-9.1	-10.2	-11.5	-9.7	-11.0	-11.4	-11.2	-13.1
Beta based			**Low**									**High**
1	10/08	-17.0	-14.1	-13.4	-17.7	-16.6	-18.5	-19.1	-22.3	-25.0	-27.0	-25.8
2	9/02	-11.1	-5.8	-4.0	-6.3	-8.5	-8.6	-7.3	-8.4	-10.8	-10.3	-14.7
3	2/09	-11.0	-10.9	-11.8	-10.3	-9.3	-12.2	-13.7	-14.1	-8.9	-9.6	-10.8
4	9/08	-9.2	-6.7	-6.2	-6.0	-6.6	-9.2	-6.9	-8.1	-13.1	-15.6	-18.0
5	6/08	-8.8	-7.8	-7.8	-9.1	-6.9	-11.3	-7.7	-10.3	-8.5	-11.4	-10.3
6	1/09	-8.6	-2.8	-4.6	-4.1	-9.6	-9.4	-9.0	-13.5	-10.0	-6.0	-4.1
7	9/01	-8.4	-5.0	-8.6	-7.7	-9.7	-8.2	-10.5	-8.1	-14.4	-17.8	-25.8
8	5/10	-8.2	-5.0	-5.4	-6.8	-6.9	-6.9	-7.4	-9.0	-9.4	-6.9	-9.9
9	7/02	-8.0	-6.8	-11.2	-6.3	-5.6	-10.2	-9.5	-11.1	-14.3	-8.7	-12.8
10	11/08	-7.5	-4.0	-5.1	-6.6	-4.8	-7.8	-12.9	-11.2	-12.2	-10.6	-17.0
Average		-9.8	-6.9	-7.8	-8.1	-8.4	-10.2	-10.4	-11.6	-12.7	-12.4	-14.9

Table 5.8: Ten largest up market months: Simple Monthly Excess market Return (in Percent) and returns on portfolios formed using Book value per share and beta coefficients.

			Deciles									
	Month	Market	1	2	3	4	5	6	7	8	9	10
BV per share			**Low**									**High**
1	4/09	9.4	19.4	14.5	15.4	18.4	18.9	15.5	17.1	20.3	18.1	23.3
2	9/10	8.7	11.7	13.3	10.2	10.7	11.9	9.4	9.3	9.6	9.6	7.9
3	3/09	8.5	11.0	11.3	9.3	9.2	11.7	7.0	9.6	9.4	9.9	14.7
4	10/02	8.5	11.6	7.8	3.6	9.0	6.4	5.7	3.3	4.7	2.3	4.3
5	4/03	8.0	8.8	5.8	9.5	8.5	8.4	9.1	9.7	7.8	7.3	10.9
6	7/09	7.4	8.7	10.6	9.1	10.2	11.2	9.2	9.2	10.0	9.7	8.4
7	11/01	7.4	11.3	11.0	8.3	9.3	9.2	6.7	8.6	7.0	4.6	8.0
8	7/10	6.9	7.5	6.4	8.1	6.6	8.6	6.3	8.0	5.9	8.5	7.7
9	12/10	6.5	6.0	7.0	7.3	6.1	6.9	6.1	6.6	9.3	7.5	8.6
10	3/10	5.9	7.7	7.3	6.7	7.3	7.0	7.7	6.7	6.5	6.6	7.2
Average		7.7	10.4	9.5	8.7	9.5	10.0	8.3	8.8	9.1	8.4	10.1
Beta based			**Low**									**High**
1	4/09	9.4	3.2	8.6	10.4	14.2	17.1	21.4	26.9	23.0	18.9	31.9
2	9/10	8.7	6.0	6.6	8.1	8.8	10.9	10.9	12.2	12.9	13.3	13.3
3	3/09	8.5	2.7	6.4	7.2	10.2	10.0	9.0	11.0	10.7	17.0	17.9
4	10/02	8.5	-0.8	-0.2	1.1	4.1	7.5	5.9	4.1	6.5	9.8	20.1
5	4/03	8.0	4.4	5.3	7.0	7.0	5.8	5.1	8.1	12.6	10.5	16.4
6	7/09	7.4	5.5	6.1	7.8	7.6	7.9	8.1	9.1	8.7	17.6	19.2
7	11/01	7.4	0.9	5.0	3.3	7.8	8.6	7.8	6.8	8.8	12.1	19.6
8	7/10	6.9	2.9	4.7	5.5	5.3	6.0	7.2	9.7	12.1	8.9	10.7
9	12/10	6.5	4.6	4.6	5.9	7.0	6.2	7.8	7.4	7.5	7.4	15.0
10	3/10	5.9	3.6	3.3	4.7	6.4	6.6	6.9	8.0	7.2	10.7	13.0
Average		7.7	3.3	5.0	6.1	7.8	8.7	9.0	10.3	11.0	12.6	17.7

Following Chan and Lakonishok (1993), we also conduct cross-sectional regression exploring the models' performance during extreme market conditions. This time, a large down (up) market is defined as a month where the market excess return is larger in magnitude than the median of those observations that are negative (positive). The median of negative markets was found to be -2.43% with the observations to sum up in 26, while the median of positive markets was 2.22% including 34 observations. The panel data method is employed in this case primarily on due to the low number of observations that could be possibly distort the results, which are displayed in table 5.9. The evidence shows that all models in worst cases leave unexplained returns but they do better in up markets. Furthermore, the CAPM seems to work reasonable well compared to the findings reported previously. The R^2 values are high enough while the SMISI factor of the TFM depicts the expected negative (in the case of beta sorted portfolios) and positive sign in down and up markets respectively.

Table 5.9: Cross-sectional regression results classified by down and up market months.

Panel A: Worst months	λ_0	λ_1	λ_{SMISI}	λ_{NSI}	λ_{SMB}	λ_{HML}	λ_{labor}	λ_{prem}	R^2
BV per share	-0.067	0.004							0.829
	(-6.75)*	(0.46)							
	-0.070		0.013	0.008					0.831
	(-6.26)*		(1.41)	(0.69)					
	-0.033	-0.029			0.011	-0.019			0.840
	(-3.16)*	(-2.50)*			(1.94**	(1.95)**			
	-0.067	0.005					-0.062	0.001	0.829
	(-6.92)*	(0.54)					(-0.40)	(1.08)	
Beta portfolios	-0.010	-0.051							0.794
	(-7.09)*	(-57.4)*							
	-0.013		-0.036	-0.051					0.796
	(-5.19)*		(-2.00)*	(-24.1)*					
	-0.019	-0.041			-0.027	0.002			0.792
	(-4.27)*	(-9.12)*			(-2.84)*	(0.31)			
	-0.005	-0.055					0.182	-0.001	0.799
	(-2.21)*	(-20.1)*					(2.65)*	(-1.09)	
Panel B: Best months	c_o	c_{mar}	c_{SMISI}	c_{NSI}	c_{SMB}	c_{HML}	c_{labor}	c_{prem}	R^2
BV per share	0.013	0.049							0.820
	(1.10)	(4.08)*							
	0.006		0.001	0.058					0.817
	(0.69)		(0.11)	(5.46)*					
	-0.000	0.061			0.015	0.007			0.821
	(-0.01)	(4.42)*			(2.32)*	(1.12)			
	0.013	0.049					0.075	-0.000	0.821
	(1.28)	(5.34)*					(0.69)	(-0.16)	
Beta portfolios	0.008	0.052							0.646
	(6.63)*	(53.6)*							
	0.005		0.053	0.058					0.666
	(-2.01)*		(1.89)**	(20.3)*					
	0.031	0.034			0.035	-0.041			0.667
	(2.95)*	(3.89)*			(4.54)*	(-2.11)*			
	-0.005	0.061					-0.618	0.001	0.675
	(-1.03)	(11.9)*					(-8.25)*	(1.06)	

*,** depict significance at 5% and 10% respectively.

5.6 Conclusions

In this chapter we examine the efficacy of different models to explain the relationship between expected return and risk in the cross-sectional context. Three different well-known models (i.e. CAPM, FF3FM and P-L model) are tested against our TFM. The findings show that in the cross-sectional analysis both conditionally and unconditionally, the stock market prices different risk factors. Related to the BVps portfolios, the SMISI factor is priced and the market risk premium has the expected positive sign apart from the case of FF3FM though not significant at any level. As for the PL-model, it has relatively low R^2 while neither labor nor premium factors influence the returns. The results of the portfolios formed on beta coefficients depict that PL-model increases its R^2 with the rest models to follow closely. In addition, two intercepts violate the SLH as they appear to be statistically different from zero.

The conditional cross-sectional regressions in the case of BVps portfolios identify the power of the TFM variables in explaining asset returns even though a proportion of them left unexplained. This also happens with CAPM, while the market and the HML factors in the FF3FM appear to be significant with the constant not being statistically different from zero. Related to PL-model no factor is priced. For the beta sorted portfolios, we should refer that almost no risk premia are priced apart from the case of PL-model. In addition, the GRS test calculated in the first step time series regressions depict the outperformance of TFM in relation to CAPM and FF3FM models.

In extreme market conditions, the selected portfolios appear to have a different reaction. For example, the lowest portfolios are less influenced than the highest ones in downward movement of the markets. However, in upward movement of the markets the lowest BVps portfolio does not differentiate from the highest one though this is the case between the two extreme beta sorted portfolios. The findings of the models' performance in extreme conditions present that all models in down moths leave unexplained returns but they do better in up months. Due to the fact that all models accommodate the market risk, we have proceeded with the estimation of risk premium when beta sorted portfolio returns were used as dependent variables in the conditional-cross sectional regressions. The TFM gave the most accurately results. Moreover, our findings suggest that a close relation between the estimated and realized risk premium exists at least up to the last quarter of 2008. The cointegration test between these time series found to be significant expecting them to converge again in the near future.

The implications of this study show that there are additional factors other than the market risk that affect stock returns. The new risk factors which found to be significant both in time series and cross section analyses, give valuable information of better understanding the characteristics of returns, targeting the reinforcement of stock market efficiency.

CHAPTER 6

BETA PREDICTION

6.1 Introduction

The beta coefficient coming from the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965) plays a central role in modern finance. Among others, it is used by academics, portfolio managers and investors, to model and control systematic risk. This enables the accurate estimation of betas an important task (Brenner and Smidt, 1977). As mentioned earlier in this thesis, an implicit assumption that is done in tests of the CAPM is the time-invariant nature of the beta coefficient. This implies that returns are stationary and their distribution has time-invariant parameters. However, different studies have shown its instability over time leading to important practical problems (Faff et al., 1992; Groenewold and Fraser, 1999; Huang, 2001). The stationarity assumption holds even in 'bull' and 'bear' market conditions. However, Levy (1974) showed that beta may differ under different market conditions and the inferences based on the stable nature of beta will be rather misleading.

The variation on asset returns (Rosenberg and Guy, 1976a, 1976b; Bos and Newbold, 1984) may arise due to the influence of microeconomic factors such as operational changes in the company or macroeconomic factors such as the rate of inflation and expectations about relevant future events. More recently, there is evidence that inefficiencies of CAPM stem from behavioural characteristics such as herding (Hwang and Salmon, 2004). The betas of individual assets in the presence of herding will be biased and away from their equilibrium values. Herding comes out from the investors' decision to imitate the observed decisions of others rather than follow their own beliefs and information. This fact may lead to a situation in which the market price fails as a sufficient statistic to reflect all relevant fundamental information (Banerjee, 1992; Bikhchandani et al., 1992).

The significant role of the estimation of betas triggered the development of techniques that allow the modelling and estimation of time varying betas. In the literature, there are conceptually two different modelling approaches (Eisenbeiss et al., 2007). The first one is based on econometric models where the systematic risk is modelled and estimated as a function of economic variables. The most widely used variables in the literature are the interest rates, budget deficit, inflation and oil prices (Abel and Kreuger, 1989; Shanken, 1990; Faff and Brooks, 1998).

The second and most prominent modelling technique is based on time series regressions. The different versions of the GARCH models and the Kalman filter algorithm are two of the most documented methods. Bollerslev et al. (1988) applied a Multivariate GARCH model (MGARCH) with US data and found evidence that conditional covariances and the implied betas are time varying. Other studies employed the MGARCH model are those of Braun et al. (1995) and McClain et al. (1996). Gonzales-Rivera (1996) conclude that a bivariate GARCH-M model is superior to its counterpart GARCH model in explaining time varying systematic risk for the US computer industry stock returns using weekly data for a period of 25 years. Pagan and Schwert (1990) compare GARCH, EGARCH, Markov switching regime model and three non-parametric models for forecasting US monthly stock return volatility. They argue that nonlinearities play an important role in stock market returns and conventional ARCH or GARCH models failed to capture. Faff et al. (2000) with daily data at hand from 32 different UK industry sectors evidenced the superiority of Kalman filter algorithm. The univariate GARCH type models such as GARCH(1,1), Threshold ARCH (TARCH) and Exponential GARCH (EGARCH) as well as the Schwert and Seguin (1990) model do not support strong performance ability even though they can capture time variation of systematic risk. However, Brooks et al. (2002) support that international betas are time varying and the GARCH models were able to identify this variation. Choudhry and Wu (2008, 2009) investigated the forecasting ability of GARCH models and the Kalman filter method with daily and weekly data for stocks traded on UK market. The results showed that the Kalman filter approach did better in most of the cases. Among the examined GARCH models, the asymmetric GJR-GARCH model (Glosten et al., 1993) performed better than BEKK-GARCH (Engle and Kroner, 1995) and bivariate GARCH. Univariate and bivariate GARCH models have also been used for detecting the effects of terrorism and war on oil prices as well as for gauging spillover effects (McMillan et al., 2010; Kollias et al., 2012, 2013). Koutmos et al. (1994) found evidence of significant time varying parameters of betas in Japan and US market implementing the Schwert and Seguin (1990) model.

Our objectives of this part of the thesis are fourfold. Firstly, we aim at testing the accuracy prediction of time varying betas of three different in kind models and compare them with the betas coming from our TFM. From the GARCH family, the univariate GARCH(1,1) model, the TARCH model and the EGARCH model are employed. In addition, the GARCH and TARCH models are also tested in a bivariate form by dropping the assumption of constant covariances. As far as the Kalman filter algorithm is concerned, we accept that the stochastic form of beta coefficient follows a random walk process. The random walk and the AR(1) processes have been found to be the most common forms used in the literature (Faff et al., 2000). Furthermore, the Schwert and Seguin (1990) model is applied. The authors extend the market model incorporating an additional term that captures the varying part of volatility that is present in market returns.

Our second goal is the estimation of various out of sample beta forecasts using nine consecutive years and three different samples. By estimating out of sample forecasts for many years, we ensure the results' consistency in that they will be independent of the particularities of a given period. The different samples will allow us to understand better the appropriate interval needed for beta predictions.

Third, we hope from a more closely examination of the models' parameters, which accommodate the best and worst results according to MAE criterion, to give us some early signs about the candidate models with the smallest forecasting errors. Finally, the fact that the CAPM model is firmly based on the assumption that asset returns are iid normal (i.e. identically, independently and normally distributed) motivates us to apply a few diagnostic tests for finding out if the existence of iid normal returns is accompanied by better performance. This chapter proceeds as follows. In the next section, we present the theoretical background. Section 3 shows the data, section 4 includes the empirical results and section 5 concludes.

6.2 Theoretical Background

6.2.1 The CAPM

The estimation of beta comes from the CAPM, which is:

$$R_{i,t} - r_f = a_{i,t} + b_{i,t}(R_{m,t} - r_f) + e_{i,t}\,. \qquad 6.1$$

Again, $R_{i,t} - r_f$ is the excess return of asset I (r_i), $R_{m,t} - r_f$ is the excess return of market (r_m) and $b_{i,t} = Cov(r_i, r_m) / \mathrm{var}(r_m)$ is the beta coefficient or else the systematic risk of asset i. The random shock, $e_{i,t}$, is assumed to have zero mean and a serially independent and homoscedastic variance-covariance matrix.

6.2.2 Univariate and bivariate GARCH models

6.2.2.1 The univariate GARCH (1,1) model

Betas are typically constructed using OLS regression from a set of historical data. However, this backward-looking method is not suitable for investors who are concerned about the future value of betas. GARCH models provide a simple method for computing time varying beta. It is succeeded using the conditional covariances between the asset i and market return as well as the time varying conditional market variance. To obtain the conditional covariance equation and following Faff et al (2000), we adopt the assumption of constant correlation for the period under consideration between the returns of asset i and the market returns. In this way, the beta coefficient of asset i on time t is estimated as:

$$\beta_{it}^{UG} = \frac{\mathrm{cov}(r_{it}, r_{mt})}{\sigma_{mt}^2} = \frac{\rho_{im}\sigma_{it}\sigma_{mt}}{\sigma_{mt}^2} = \frac{\rho_{im}\sigma_{it}}{\sigma_{mt}}\,. \qquad 6.2$$

The GARCH model that was developed independently by Bollerslev (1986) and Taylor (1986) allows the conditional variance to be dependent upon previous own lags (Brooks, 2002). Equation 6.3 is used for estimating the conditional variance of asset i:

$$y_{i,t} = \mu + u_{i,t} \qquad 6.3$$

with the conditional variance being $\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2$. For the conditional variance, σ_t^2, to be nonnegative and positive, the following conditions must be met: $a_0 > 0; a_1 \geq 0; \beta \geq 0 and a_1 + \beta < 1$.

In equation 6.3 , y_i is the daily excess stock return of asset i, μ is a constant and u is the error term which follows N~ $(0,\sigma^2)$. In this equation we could add a lagged value of y_i for capturing time dependence of the return series and smoothing them of possible structural shifts over the sample period (Zhang and Wirjanto, 2006). We could also use a MA term such as a lagged value of the error term taking into account the effect of non-synchronous trading (Choudhry, 2005). However, we assume that asset returns are uncorrelated and the consequences of non-synchronous trading of the selected stocks on the final results would be trivial.

6.2.2.2 The Threshold ARCH model

The Threshold ARCH (TARCH) model is an extension of GARCH adding a new term to count for possible asymmetries. The TARCH model which was proposed by Zakoian (1994) has the following form:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1} \qquad 6.4$$

where $I_{t-1}=1$ if $u_{t-1}<0$ or zero otherwise. If $\gamma>0$ there will be leverage effect while for non-negativity of the variance should:
$a_0 > 0; a_1 \geq 0; \beta \geq 0 and a_1 + \gamma \geq 0$.

6.2.2.3 The exponential GARCH model

The EGARCH model that was developed by Nelson (1991) is defined as:

$$\ln(\sigma_t^2) = \alpha_0 + \beta\ln(\sigma_{t-1}^2) + \delta\left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}}\right] + \gamma\frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}}. \qquad 6.5$$

For the EGARCH model, there is no need for non-negativity constraints on the parameters. The leverage effect is accounted for in the case where the relationship between volatility and returns is negative such that, γ, will be negative. Thus, positive shocks (good news) generate less volatility than negative shocks (bad news).

6.2.2.4 Bivariate (VECH) GARCH (1,1)

The bivariate GARCH models are similar to univariate ones in that they normally converge rapidly. The problems may arise in cases where the variables are not jointly stationary (Alexander, 2001). For multivariate GARCH models the most popular are the VECH, the diagonal VECH and the BEKK model. The BEKK model of Engle and Kroner (1995) ensures positive definiteness of the covariance matrix Ht (Hafner and Herwartz, 2008), a major weakness of the VECH model. However for major systems the estimated parameters increase significantly. For example for N=20 the BEKK model has 1010 parameters while the VECH 630 (Kroner and Ng, 1998). Equation 6.6 represents the bivariate GARCH(1,1) model (Choudhry, 2005):

$$Y_t = M + E_t, E_t \sim N(0, H_t) \qquad 6.6$$

where $Y_t = \begin{bmatrix} r_{i,t} \\ r_{m,t} \end{bmatrix}$ is a (2x1) vector containing returns from asset i and the market index m. M is a 2x1 vector of intercepts in the conditional mean ($M = \begin{bmatrix} \mu_{r_i} \\ \mu_{r_m} \end{bmatrix}$), Ht is a 2x2 conditional covariance matrix and the conditional variance-covariance equations of a diagonal VECH bivariate GARCH(1,1) model may be written:

$$VECH(H_t) = C + AVECH(\mathrm{E}_{t-1}E_{t-1}^{'}) + BVECH(H_{t-1}H_{t-1}^{'}) \qquad 6.7$$

where C is 3x1 vector containing the intercepts in the conditional variance-covariance equations, A and B are 3x3 diagonal matrices containing the parameters on the lagged disturbance squares and on the lagged variances or covariances respectively. More illustrative the diagonal bivariate VECH model is simply:

$$h_{11,t} = c_{01} + a_{11}e_{1,t-1}^2 + b_{11}h_{11,t-1} \qquad (6.7a)$$

$$h_{12,t} = c_{02} + a_{22}e_{1,t-1}e_{2,t-1} + b_{22}h_{12,t-1} \qquad (6.7b)$$

$$h_{22,t} = c_{03} + a_{33}e_{2,t-1}^2 + b_{33}h_{22,t-1} \qquad (6.7c)$$

The coefficient α_{11} depicts the ARCH process in the residuals from asset i. The α_{33} coefficient presents the ARCH process in the market index (m) equation residuals. The parameters α_{22} and b_{22} show the covariance GARCH parameters between asset i and market index. A positive conditional variance is ensured, if the values of C, α_{11},

α_{33}, b_{11} and b_{33} are restricted to zero or greater. The calculation of time-varying beta coefficient is done as:

$$\beta_{it}^{BG} = \hat{h}_{12,t} / \hat{h}_{22,t} \qquad 6.8$$

where the symbol $\wedge$ indicates the estimated value of conditional variance and covariance.

6.2.2.5 Bivariate (VECH) TARCH (1,1)

The conditional variance covariance equation of a bivariate TARCH model has the following form:

$$VECH(H_t) = C + AVECH(\mathrm{E}_{t-1}E_{t-1}^{'}) + BVECH(H_{t-1}H_{t-1}^{'}) + DVECH(\mathrm{E}_{t-1}E_{t-1}^{'})(I_{t-1}) \; 6.9$$

where the last term on the RHS of equation 6.9 depicts the asymmetries.

6.2.3 Kalman Filter

For the state space model the observation equation is similar to CAPM (i.e. eq.6.1). However, accepting that b is not constant we have to hypothesize a model for it. The same assumption holds for the alpha coefficient. Thus, the coefficients a_t and b_t are treated as time varying processes and the following matrix equation represents the model coefficients (Wells, 1994):

$$\begin{bmatrix} \alpha_{i,t} \\ \beta_{i,t} \end{bmatrix} = \begin{bmatrix} \varphi_{11} & 0 \\ 0 & \varphi_{22} \end{bmatrix} \cdot \begin{bmatrix} \alpha_{i,t-1} \\ \beta_{i,t-1} \end{bmatrix} + \begin{bmatrix} \xi_t \\ v_t \end{bmatrix}.$$

The vector $\left[a_{i,t} \; \beta_{i,t} \right]^{'}$ is the state vector at time t. The coefficient matrix Φ is the transition matrix, and the vector $\left[\xi_t \; v_t \right]^{'}$ is the noise vector which is assumed to be normally distributed with zero mean and constant variance covariance matrix Ξ. Setting the diagonal elements of Φ equal to unity then equation 6.10 is the random walk model. According to Faff et al. (2000) this model gives the best characterization of the time varying beta. Consequently, the estimated beta i used in the analysis is:

$$\beta_{it}^{KFRW} = \beta_{it-1} + v_t \, . \qquad 6.10$$

6.2.4 Schwert and Seguin model

The Schwert and Seguin (1990) (S&S) model adds a term to the market model which equals to R_{mt} / σ_{mt}^2. This new term is the market excess return divided by the conditional variance of a given period, obtained from a GARCH(1,1) process. The Schwert and Seguin model takes the form:

$$R_{i,t} - r_f = a_{i,t} + b1_{i,t}(R_{m,t} - r_f) + b2_{i,t}\left(\frac{R_{m,t} - r_f}{\sigma_{m,t}^2}\right) + e_{i,t}\,. \qquad 6.11$$

where again $e_{i,t} \sim N(0, \sigma_t^2)$.

6.2.5 The Two Factor Model

The aforementioned models are compared with our new approach. Following the procedure described in detail in Chapter 3 in this thesis, our basic nonlinear equation is 6.12:

$$\overline{\beta} = \alpha * \exp^{(b*R_{ms} + c*R_{ms}{}^2 + u)} \qquad 6.12$$

where α, b, c are constants to be estimated, R_{ms} the shorted market return, $\overline{\beta}$ the average betas corresponding to each market return interval and u the residuals with $u \sim iid(0, \sigma^2)$. Through linearization of the above equation we get:

$$\ln(\overline{\beta}) = \ln(a) + b * R_{ms} + c * R_{ms}^2 + u\,. \qquad 6.13$$

As we have shown the function is increasing for b>0 and decreasing for b<0. The exponential constant term of equation 6.13 is the first beta coefficient of our approach and we symbolize it as NM. This beta is going to be used for comparisons in the rest of this section with the aforementioned models. We also make use the coefficient of the NSI of the TFM, which has the following form:

$$R_{it} - R_{ft} = a_i + c_i SMISI_t + n_i NSI_t + e_{it}\,. \qquad 6.14$$

The NSI consists from stocks with average zero b_coefficient. Hence, this index is assumed to be free from stocks with variant betas, and thus it is similar to the general index of S&P 500 if the assumption of constant betas coming from the CAPM holds.

The estimated coefficient of this index will be compared with our first beta (i.e. NM) as well as with the estimated beta of the CAPM for some selected stocks.

6.3 Data description

The dataset used concerns 135 securities traded on the S&P 500. In principle, the selection of stocks is random but all of them should have the appropriate number of observations for estimating the parameters of our new model. The only common characteristic with the study of Lin et al. (1992) is the arbitrarily selection of stocks. We do not set the restrictions imposed by them since our purpose is to test different hypotheses regarding the coefficients of the models and the normality of returns. However, we have to refer that the average revenue of the selected securities earned in 2011 was almost \$40 millions according to Compustat data with the average value of all companies participated in S&P 500 was \$20 millions. The median of the revenue for the selected stocks was \$16 millions and for the S&P companies was \$8.3 millions. Hence, we could say that our sample is constituted from relatively 'rich' companies as they managed to have revenues above average. The daily rate of return of each security, r_i at time t, is calculated as $r_{i,t} = (P_t / P_{t-1}) - 1$. The period under analysis is from 1/1/1993 to 30/08/2011. The risk free rate is a 3-month Treasury bill for the US market. The first year of out of sample prediction is 2003.

As mentioned earlier, we use three different samples for testing the accuracy of prediction of time varying betas. The first one is fixed and starts from 1/1/1993 with a ten year window but adding each year the new daily return observations. This way the first year of estimation (i.e. 2003) contains observations of 10 years and the last year (i.e. 2011) contains observations of 19 years. This specific sample has been selected since for the estimation of GARCH and Kalman filter models a relatively large number of observations are used (Faff and Brooks, 1998; Faff et al., 2000). The second and third samples concern windows of 10 and 5 years respectively. This variation allows us to see the existence of any discrepancies between longer and shorter testing periods and accordingly to form predictions. Each year we drop the stocks failed to meet the non-negativity variance assumption that poses the GARCH models or to converge according to KFRW model and make the comparisons on the survived securities. As for the estimation and data selection of the TFM we follow the same procedure reported in chapters 4 and 5.

6.4 Empirical Results

6.4.1 MSE and MAE as measures of forecast accuracy.

The tests of beta forecast accuracy, which follow, make use of the mean square error (hereafter MSE) and the mean absolute error (hereafter MAE). Following Faff et al. (2000), MSE and MAE are defined as:

$$MSE_i = \sum (R_{it}^* - R_{it})^2 / T \text{ and } MAE_i = \sum | R_{it}^* - R_{it} | / T \qquad 6.15$$

where R_{it}^* and R_{it} are the realized next year returns of security i and the predicted returns for the same security respectively. The lower the forecast error measure is, the better the forecasting performance. Table 6.1 provides information about the MSE. The mean values show that the NM performs well enough especially when the two biggest samples are employed. The KFRW model dominates in the smallest sample (i.e. 5 years). As expected, in 2008 the models appeared too poorly in predictions mostly because the high volatility of this specific year. On the other side, the year 2010 appears the highest accuracy followed by 2006. The results of the MAE are presented in table 6.2. They do not differ significantly from the previous ones. The new model continues to predict better in biggest samples and the KFRW model in the smallest one. The GARCH(1,1) model and the S&S model do better in the 5 years period.

Table 6.1: Mean square error per model for each year (In percent).

Year	UGAR	UTAR	UEGAR	BGAR	BTAR	KFRW	S&S	NM	NoS
2003	0.0257	0.0333	0.0675	0.0262	0.0286	0.0243	0.0244	0.0245	116
2004	0.0196	0.0212	0.0344	0.0200	0.0207	0.0191	0.0191	0.0192	106
2005	0.0185	0.0194	0.0329	0.0188	0.0193	0.0181	0.0183	0.0184	90
2006	0.0186	0.0202	0.0296	0.0189	0.0192	0.0183	0.0185	0.0185	102
2007	0.0215	0.0244	0.0392	0.0217	0.0238	0.0210	0.0216	0.0211	100
2008	0.0985	0.1173	0.1662	0.0995	0.1119	0.0986	0.1000	0.0937	107

Table 6.1 continued

Year	UGAR	UTAR	UEGAR	BGAR	BTAR	KFRW	S&S	NM	NoS
2009	0.0405	0.0541	0.1133	0.0431	0.0486	0.0396	0.0390	0.0385	82
2010	0.0169	0.0228	0.0583	0.0180	0.0198	0.0163	0.0161	0.0159	103
2011	0.0178	0.0270	0.0571	0.0188	0.0206	0.0173	0.0170	0.0169	105
Mean	0.0308	0.0377	0.0665	0.0317	0.0347	0.0303	0.0304	0.0296	101
Std. Dev.	0.0264	0.0317	0.0455	0.0266	0.0304	0.0266	0.0270	0.0250	10
Min.	0.0169	0.0194	0.0296	0.0180	0.0192	0.0163	0.0161	0.0159	82
Max.	0.0985	0.1173	0.1662	0.0995	0.1119	0.0986	0.1000	0.0937	116
Panel B: 10 YEARS									
Year	UGAR	UTAR	UEGAR	BGAR	BTAR	KFRW	S&S	NM	NoS
2003	0.0257	0.0333	0.0675	0.0262	0.0286	0.0243	0.0244	0.0245	116
2004	0.0199	0.0208	0.0246	0.0199	0.0205	0.0191	0.0191	0.0192	106
2005	0.0186	0.0197	0.0211	0.0188	0.0197	0.0181	0.0183	0.0184	90
2006	0.0192	0.0191	0.0241	0.0187	0.0195	0.0183	0.0186	0.0185	102
2007	0.0221	0.0266	0.0440	0.0221	0.0312	0.0211	0.0218	0.0211	100
2008	0.1184	0.1438	0.1489	0.0972	0.1557	0.0973	0.1018	0.0937	107
2009	0.0469	0.0662	0.0712	0.0416	0.0589	0.0393	0.0387	0.0385	82
2010	0.0174	0.0256	0.0478	0.0170	0.0219	0.0161	0.0160	0.0159	103
2011	0.0177	0.0356	0.0697	0.0174	0.0216	0.0170	0.0168	0.0169	105
Mean	0.0340	0.0434	0.0577	0.0310	0.0420	0.0301	0.0306	0.0296	101
Std. Dev.	0.0330	0.0403	0.0397	0.0260	0.0440	0.0262	0.0276	0.0250	10
Min.	0.0174	0.0191	0.0211	0.0170	0.0195	0.0161	0.0160	0.0159	82
Max.	0.1184	0.1438	0.1489	0.0972	0.1557	0.0973	0.1018	0.0937	116
Panel C: 5 YEARS									
Year	UGAR	UTAR	UEGAR	BGAR	BTAR	KFRW	S&S	NM	NoS
2003	0.0244	0.0282	0.0274	0.0246	0.0267	0.0242	0.0242	0.0245	116
2004	0.0192	0.0199	0.0215	0.0192	0.0236	0.0191	0.0191	0.0192	106
2005	0.0185	0.0192	0.0246	0.0184	0.0218	0.0182	0.0183	0.0184	90
2006	0.0187	0.0211	0.0587	0.0182	0.0205	0.0183	0.0185	0.0185	102
2007	0.0207	0.0399	0.0482	0.0204	0.0359	0.0206	0.0211	0.0211	100
2008	0.0916	0.5117	1.2469	0.1312	0.1955	0.0903	0.0921	0.0937	107
2009	0.0394	0.1645	0.0980	0.0392	0.0536	0.0378	0.0379	0.0385	82
2010	0.0168	0.0497	0.1082	0.0166	0.0242	0.0158	0.0159	0.0159	103
2011	0.0173	0.0838	0.0738	0.0174	0.0319	0.0167	0.0168	0.0169	103
Mean	0.0296	0.1042	0.1897	0.0339	0.0482	0.0290	0.0293	0.0296	101
Std. Dev.	0.0243	0.1598	0.3977	0.0371	0.0562	0.0239	0.0245	0.0250	10
Min.	0.0168	0.0192	0.0215	0.0166	0.0205	0.0158	0.0159	0.0159	82
Max.	0.0916	0.5117	1.2469	0.1312	0.1955	0.0903	0.0921	0.0937	116

Note: the minimum values are underlined. NoS stands for the number of shares used each year.

Table 6.2: Mean absolute error per model for each year (In percent).

Year	UGAR	UTAR	UEGAR	BGAR	BTAR	KFRW	S&S	NM	NoS
Panel A: ALL YEARS									
2003	1.0861	1.2396	1.6066	1.0994	1.1509	1.0437	1.0464	1.0513	116
2004	0.9273	0.9794	1.2009	0.9373	0.9621	0.9114	0.9135	0.9166	106
2005	0.9155	0.9479	1.1887	0.9257	0.9434	0.9050	0.9109	0.9138	90
2006	0.9249	0.9711	1.1324	0.9332	0.9522	0.9168	0.9229	0.9216	102
2007	0.9955	1.0683	1.2952	1.0003	1.0618	0.9832	0.9996	0.9875	100
2008	1.9048	2.1116	2.4334	1.9022	2.0934	1.8880	1.9211	1.8467	107
2009	1.3330	1.5819	1.9484	1.3670	1.4898	1.3144	1.3009	1.2928	82
2010	0.8870	1.0436	1.3781	0.9134	0.9747	0.8680	0.8615	0.8534	103
2011	0.8874	1.0727	1.3339	0.9102	0.9589	0.8718	0.8658	0.8636	105
Mean	1.0957	1.2240	1.5020	1.1099	1.1764	1.0780	1.0825	1.0719	101
Std. Dev.	0.3350	0.3866	0.4315	0.3315	0.3859	0.3340	0.3425	0.3201	10
Min.	0.8870	0.9479	1.1324	0.9102	0.9434	0.8680	0.8615	0.8534	82
Max.	1.9048	2.1116	2.4334	1.9022	2.0934	1.8880	1.9211	1.8467	116

Table 6.2 continued

Year	UGAR	UTAR	UEGAR	BGAR	BTAR	KFRW	S&S	NM	NoS
Panel B: 10 YEARS									
Year	UGAR	UTAR	UEGAR	BGAR	BTAR	KFRW	S&S	NM	NoS
2003	1.0861	1.2396	1.6066	1.0994	1.1509	1.0437	1.0464	1.0513	116
2004	0.9359	0.9648	1.0488	0.9345	0.9605	0.9106	0.9131	0.9166	106
2005	0.9196	0.9545	0.9979	0.9254	0.9588	0.9044	0.9103	0.9138	90
2006	0.9428	0.9422	1.0597	0.9287	0.9632	0.9162	0.9245	0.9216	102
2007	1.0151	1.0994	1.3127	1.0109	1.1960	0.9874	1.0067	0.9875	100
2008	2.0360	2.2773	2.3542	1.8822	2.4837	1.8857	1.9408	1.8467	107
2009	1.4076	1.7009	1.6841	1.3433	1.6740	1.3073	1.2953	1.2928	82
2010	0.8924	1.0957	1.2469	0.8835	1.0315	0.8609	0.8575	0.8534	103
2011	0.8760	1.2119	1.3722	0.8741	0.9832	0.8640	0.8600	0.8636	105
Mean	1.1235	1.2763	1.4092	1.0980	1.2669	1.0756	1.0838	1.0719	101
Std. Dev.	0.3792	0.4421	0.4280	0.3286	0.5101	0.3338	0.3486	0.3201	10
Min.	0.8760	0.9422	0.9979	0.8741	0.9588	0.8609	0.8575	0.8534	82
Max.	2.0360	2.2773	2.3542	1.8822	2.4837	1.8857	1.9408	1.8467	116
Panel C: 5 YEARS									
Year	UGAR	UTAR	UEGAR	BGAR	BTAR	KFRW	S&S	NM	NoS
2003	1.0489	1.1299	1.1309	1.0526	1.1056	1.0443	1.0411	1.0513	116
2004	0.9170	0.9369	0.9894	0.9158	1.0285	0.9117	0.9110	0.9166	106
2005	0.9173	0.9435	1.0491	0.9127	1.0090	0.9061	0.9110	0.9138	90
2006	0.9288	0.9912	1.4963	0.9132	0.9921	0.9148	0.9230	0.9216	102
2007	0.9788	1.3745	3.3584	0.9654	1.2927	0.9705	0.9843	0.9875	100
2008	1.8276	3.2742	4.2384	1.9366	2.5506	1.8135	1.8384	1.8467	107
2009	1.3210	2.3906	1.9420	1.3021	1.5636	1.2813	1.2831	1.2928	82
2010	0.8810	1.5146	1.7909	0.8697	1.0709	0.8496	0.8526	0.8534	103
2011	0.8717	1.6160	1.3547	0.8727	1.1182	0.8590	0.8622	0.8636	105
Mean	1.0769	1.5746	1.9278	1.0823	1.3035	1.0612	1.0674	1.0719	101
Std. Dev.	0.3136	0.7860	1.1295	0.3477	0.5012	0.3115	0.3175	0.3201	10
Min.	0.8717	0.9369	0.9894	0.8697	0.9921	0.8496	0.8526	0.8534	82
Max.	1.8276	3.2742	4.2384	1.9366	2.5506	1.8135	1.8384	1.8467	116

Note: the minimum values are underlined. NoS stands for the number of shares used each year.

Because of the substantially differences in accuracy among the samples, table 6.3 tests the hypothesis of zero mean using the t-statistic. The table does not include the accuracy differences of the new model since they remain similar to all samples. The t-statistic is not different from zero when the MSE is employed apart from the cases of UTARCH and BGARCH at 10% level. However, as for the MAE the differences are statistically significant for most of the cases especially for the first two panels. The Kalman filter model predicts better in the smallest sample although the difference is statistically significant only for panel B, while for the rest two panels the zero hypothesis is marginally rejected at the 10% level. The UGARCH, the BGARCH and the S&S model do also better in the smallest sample although for the latter the differences are not significant at any level. The TARCH and EGARCH models exhibit better performance with longer time series data.

Table 6.3: Hypothesis testing of equal mean among the tested samples.

Panel A: All Sample-10 Years Sample						
		MSE			MAE	
Model	Mean	T-value	P-Value	Mean	T-Value	P-Value
UGARCH	-0.0031	-1.428	0.191	-0.0277	-1.819	0.106
UTARCH	-0.0056	-1.889	0.095*	-0.0522	-2.183	0.060*
UEGARCH	0.0088	1.710	0.125	0.0927	2.738	0.025**
BGARCH	0.0006	2.242	0.055*	0.0118	2.230	0.056*
BTARCH	-0.0072	-1.527	0.165	-0.0905	-2.092	0.069*
KFRW	0.0002	1.552	0.159	0.0024	1.815	0.106
S&S	-0.0001	-0.793	0.450	-0.0013	-0.502	0.628
Panel B: All Sample-5 Years Sample						
		MSE			MAE	
Model	Mean	T-value	P-Value	Mean	T-Value	P-Value
UGARCH	0.0012	1.679	0.131	0.0188	2.262	0.053*
UTARCH	-0.0664	-1.551	0.159	-0.3505	-2.409	0.042**
UEGARCH	-0.1232	-1.026	0.334	-0.4258	-1.419	0.193
BGARCH	-0.0022	-0.607	0.560	0.0275	2.939	0.018**
BTARCH	-0.0134	-1.514	0.168	-0.1271	-2.620	0.030**
KFRW	0.0012	1.436	0.188	0.0168	2.069	0.072*
S&S	0.0011	1.312	0.225	0.0151	1.733	0.121
Panel C: 10 Years Sample-5 Years Sample						
		MSE			MAE	
Model	Mean	T-value	P-Value	Mean	T-Value	P-Value
UGARCH	0.0043	1.502	0.171	0.0466	2.119	0.066*
UTARCH	-0.0608	-1.522	0.166	-0.2983	-2.415	0.042**
UEGARCH	-0.1320	-1.090	0.307	-0.5185	-1.781	0.112
BGARCH	-0.0029	-0.750	0.474	0.0156	1.522	0.166
BTARCH	-0.0062	-1.406	0.197	-0.0366	-1.484	0.176
KFRW	0.0010	1.405	0.197	0.0143	1.824	0.105
S&S	0.0012	1.220	0.257	0.0164	1.488	0.174

* indicates test statistic significance at the 10% level.

** indicates test statistic significance at the 5% level.

6.4.2 Diebold and Mariano test statistic.

As an additional measure for accessing the forecast accuracy of the models, the Diebold and Mariano (DM) (1995) test is applied. That was and still is the main objective of the test and not for comparing models in out of sample forecasts (Diebold, 2012). With the results of MAE at hands, the null hypothesis of equal forecast accuracy can be represented as $\mathrm{E}(d_{12t}) = 0$ where d_{12t} is the time-t quadratic loss differential between forecasts 1 and 2 (i.e. $d_{12t} = L(e_{1t}) - L(e_{2t})$, $L(e_t) = e_t^2$).

Under the DM assumptions the test is:

$$DM = \frac{\bar{d}_{12}}{\hat{\sigma}_{\bar{d}_{12}}} \rightarrow \mathrm{N}(0,1), \qquad 6.16$$

where $\bar{d}_{12} = \frac{1}{T}\sum_{t=1}^{T} d_{12t}$ is the sample mean loss differential and $\hat{\sigma}_{\bar{d}_{12}}$ is a consistent estimate of $\bar{d}_{12}$. The DM test can be implemented by regression of the loss differential on an intercept, using heteroscedasticity and autocorrelation robust standard errors (Diebold, 2012). The null hypothesis of equal predictive accuracy at the 5% level is rejected if the test is greater than 1.64 in absolute terms.

Table 6.4 presents the results of the DM test. The table is separated into three panels each one of which depicts the three different samples. The percentages, which are the mean values of all years, show the proportion of stocks that accept the three hypotheses (i.e. Best, Worst or Equal accuracy). From panel A, among the GARCH models the UGARCH and the UEGARCH models exhibit the best (i.e. hypothesis B) and worst (i.e. hypothesis W) results respectively. The KFRW model once again shows the best performance. The remaining two models perform well enough as they present similar accuracy to the KFRW model. Examining the findings of panels B and C, the general conclusion does not change substantially though we can see a noteworthy improvement at the performance of the UGARCH and BGARCH models. In addition, the KFRW increases the proportion of stocks with most accurately results signifying its superiority. Table 6.5 supplements table 6.4 depicting the number of years for which each model exhibits its best and worst performance. For a given year, a best performance is considered if a model presents percentages higher than those of both equal and worse accuracy prediction hypotheses (i.e. B>E,W). The opposite is true for the worst performance (i.e. B<E,W).

Table 6.4: Diebold and Mariano test results.

Panel A: All sample								
	Hypothesis	UTARCH	UEGARCH	BGARCH	BTARCH	KFRW	S&S	NM
UGARCH	B	44.1%	72.5%	59.2%	47.4%	14.7%	22.9%	16.8%
	W	23.4%	11.9%	18.1%	24.9%	52.1%	47.5%	49.9%
	E	32.4%	15.6%	22.6%	27.7%	33.2%	29.6%	33.3%
UTARCH	B		58.4%	25.9%	35.4%	16.6%	19.3%	17.3%
	W		23.4%	41.0%	45.6%	52.9%	50.3%	53.7%
	E		18.2%	33.1%	18.9%	30.4%	30.4%	29.0%
UEGARCH	B			14.3%	21.8%	8.3%	8.2%	7.7%
	W			73.1%	59.0%	76.7%	76.3%	75.9%
	E			12.7%	19.2%	15.0%	15.5%	16.5%
BGARCH	B				41.0%	11.9%	17.2%	13.0%
	W				30.0%	59.5%	57.7%	58.3%
	E				29.0%	28.6%	25.1%	28.7%

Table 6.4 continued

BTARCH	B					17.0%	18.4%	14.4%
	W					54.2%	51.7%	55.2%
	E					28.8%	29.9%	30.4%
KFRW	B						34.7%	33.3%
	W						27.8%	28.0%
	E						37.6%	38.7%
S&S	B							27.9%
	W							36.8%
	E							35.3%

Panel B: 10 Years sample

	Hypothesis	UTARCH	UEGARCH	BGARCH	BTARCH	KFRW	S&S	NM
UGARCH	B	49.2%	70.6%	51.3%	53.6%	16.3%	24.9%	18.4%
	W	23.4%	13.4%	23.0%	19.8%	47.9%	42.8%	48.7%
	E	27.4%	16.0%	25.7%	26.5%	35.8%	32.2%	32.9%
UTARCH	B		52.2%	23.5%	41.2%	16.7%	19.3%	16.8%
	W		27.7%	45.3%	42.0%	58.2%	53.4%	57.3%
	E		20.1%	31.2%	16.8%	25.1%	27.2%	25.9%
UEGARCH	B			13.9%	29.5%	6.5%	8.6%	7.0%
	W			73.7%	47.4%	76.7%	75.1%	76.5%
	E			12.4%	23.1%	16.8%	16.4%	16.6%
BGARCH	B				49.6%	13.7%	19.9%	14.1%
	W				21.7%	55.8%	52.8%	55.2%
	E				28.7%	30.5%	27.2%	30.7%
BTARCH	B					12.6%	13.1%	13.0%
	W					60.6%	58.4%	60.4%
	E					26.8%	28.5%	26.6%
KFRW	B						38.6%	34.8%
	W						22.7%	24.3%
	E						38.8%	40.9%
S&S	B							29.0%
	W							35.2%
	E							35.8%

Panel C: 5 Years sample

	Hypothesis	UTARCH	UEGARCH	BGARCH	BTARCH	KFRW	S&S	NM
UGARCH	B	69.09%	71.55%	31.67%	62.63%	26.21%	25.80%	34.18%
	W	13.11%	8.47%	28.81%	12.65%	34.03%	33.35%	28.81%
	E	17.80%	19.99%	39.52%	24.72%	39.76%	40.85%	37.01%
UTARCH	B		49.43%	16.30%	32.95%	14.15%	14.64%	13.70%
	W		34.45%	60.25%	51.59%	64.37%	63.48%	63.24%
	E		16.11%	23.46%	15.46%	21.48%	21.89%	23.05%
UEGARCH	B			7.68%	29.19%	5.78%	6.83%	7.71%
	W			76.02%	54.28%	73.82%	73.11%	73.37%
	E			16.30%	16.53%	20.40%	20.05%	18.92%
BGARCH	B				59.40%	21.86%	27.54%	32.83%
	W				14.64%	35.90%	30.72%	28.51%
	E				25.96%	42.24%	41.74%	38.67%
BTARCH	B					9.29%	10.78%	12.46%
	W					64.45%	63.01%	60.38%
	E					26.26%	26.21%	27.16%

Table 6.4 continued

KFRW	B	35.49%	40.98%
	W	20.36%	17.33%
	E	44.15%	41.69%
S&S	B		34.32%
	W		25.46%
	E		40.22%

6.4.3 The coefficients of the models

In this section, the estimated parameters of each model are evaluated. In table 6.6 the averaged values of the total number of stocks that were used in analysis and constitute the population sample are compared with those stocks of each model with the best or worst results according to MAE criterion across the whole tested period (i.e. 9 years). As stated earlier, one of our objectives is the investigation, if any, of the differences on the estimated parameters that could lead investors and portfolio managers at an early stage to form a better view about a model's accuracy reducing the chances of selecting the worst one. Starting with the UGARCH model it is obvious that all the conditions set up previously are met. The 5 years population sample depicts identical long run volatility with the all population sample. As for the 10 stocks with the best predictions, their long run volatility is reduced significantly compared with their corresponding population average values at least for the all and the 5 years sample. On the contrary, the 10 stocks with the worst performance increase their volatility relative to the population values. The highest difference in volatility is observed for the 5 years sample. Dealing with the TARCH model, large differences between best and worst stocks are observed for the coefficient γ. As we mentioned above this coefficient measures the asymmetries between 'good news' and 'bad news'. It is obvious that the γ coefficient tends to be equal to the population mean for the best stocks having a positive sign while it goes to zero or becomes negative for the worst stocks. More concretely, bad news has larger effects on the volatility of the best stocks than good news. The opposite is true for the volatility of the worst stocks.

Table 6.5: Number of years with best and worst performance.

Panel A: Number of years with best performance

All Sample	UTAR	UEGAR	BGAR	BTAR	KFRW	S&S	NM
UGARCH	**6**	**9**	**9**	**7**	**0**	**2**	**0**
UTARCH		**9**	**0**	**3**	**0**	**0**	**0**
UEGARCH			**0**	**0**	**0**	**0**	**0**
BGARCH				**6**	**0**	**1**	**0**
BTARCH					**0**	**0**	**0**
KFRW						**4**	**3**
S&S							**1**

10 Years	UTAR	UEGAR	BGAR	BTAR	KFRW	S&S	NM.
UGARCH	**5**	**9**	**8**	**8**	**0**	**2**	**0**
UTARCH		**7**	**2**	**6**	**0**	**1**	**0**
UEGARCH			**0**	**2**	**0**	**0**	**0**
BGARCH				**7**	**0**	**1**	**0**
BTARCH					**0**	**0**	**0**
KFRW						**4**	**3**
S&S							**2**

5 Years	UTAR	UEGAR	BGAR	BTAR	KFRW	S&S	NM
UGARCH	**7**	**9**	**2**	**9**	**0**	**1**	**4**
UTARCH		**6**	**1**	**4**	**0**	**0**	**0**
UEGARCH			**0**	**0**	**0**	**0**	**0**
BGARCH				**9**	**0**	**1**	**2**
BTARCH					**0**	**0**	**0**
KFRW						**3**	**4**
S&S							**4**

Panel B: Number of years with worst performance

All Sample	UTAR	UEGAR	BGAR	BTAR	KFRW	S&S	NM
UGARCH	**1**	**0**	**0**	**0**	**8**	**6**	**8**
UTARCH		**0**	**4**	**1**	**8**	**7**	**7**
UEGARCH			**4**	**3**	**7**	**8**	**9**
BGARCH				**0**	**9**	**7**	**9**
BTARCH					**7**	**6**	**9**
KFRW						**3**	**4**
S&S							**5**

10 Years	UTAR	UEGAR	BGAR	BTAR	KFRW	S&S	NM
UGARCH	**2**	**0**	**0**	**0**	**8**	**6**	**8**
UTGARCH		**0**	**6**	**0**	**7**	**6**	**6**
UEGARCH			**3**	**3**	**7**	**6**	**9**
BGARCH				**0**	**8**	**7**	**9**
BTGARCH					**9**	**9**	**9**
KFRW						**3**	**3**
S&S							**4**

5 Years	UTAR	UEGAR	BGAR	BTAR	KFRW	S&S	NM
UGARCH	**0**	**0**	**4**	**0**	**5**	**5**	**2**
UTARCH		**0**	**7**	**0**	**7**	**6**	**8**
UEGARCH			**7**	**2**	**9**	**9**	**9**
BGARCH				**0**	**6**	**4**	**4**
BTARCH					**9**	**9**	**8**
KFRW						**3**	**0**
S&S							**1**

The last univariate model of the GARCH family is the UEGARCH model. The model depicts similar γ coefficients for all groups of stocks. A significant difference we observe on the long run volatility regarding the worst 5 years period stocks where it is smaller than its population counterpart.

In relation to the BGARCH model the findings are rather identical with the univariate case. The ARCH coefficients (A_{11} and A_{33}) are all positive implying volatility clustering, while the sum of A's and B's coefficients is less than unity, indicating that shocks to volatility are not explosive. The coefficients of the covariance parameters are also positive and significant. The fact indicates a sign that a strong interaction between the two returns exists. Significant differences for the case of worst stocks relative to the population average are also detected for the c_{01} and c_{03} coefficients which appear to be higher. The analysis of the BTARCH model indicates the existence of positive d coefficients in all cases disclosing asymmetries in the arrival of good and bad news. Once again, the worst stocks on average present significant differentiation from the population mean particularly for the 5 years period.

The panel with the Kalman Filter random walk model (KFRW) exhibits not only the random beta coefficients but also the constants and their associated z-statistics. Although it is clear the strong variation of betas among the samples, a noteworthy difference is related to the statistical significance of the estimated α coefficients of the worst stocks. In the smallest sample, the overwhelming majority of the constants are significant at any level. The fact postulates the difficulty of predicting returns when the constant parameters are statistically significant.

The coefficients of the Schwert and Seguin model (S&S) are also presented in table 6.6. Generally speaking, the statistical significance of the b2 coefficient for the two different groups of stocks is strong enough since only the 23% of the cases appear high p-values. The absolute size of b2 is very small in magnitude compared with the b1 coefficient. However, the additional parameter may still impact upon the measurement of systematic risk as indicated by the worst group of stocks which shows large deviations from the population mean.

Table 6.6: Coefficients of the models.

Model: UGARCH		Population			Best (10)			Worst (10)	
Coefficients	All	10Y	5Y	All	10Y	5Y	All	10Y	5Y
$a_o x10^5$	1.73(0.84)	1.76(0.75)	2.69(1.79)	0.69(0.67)	4.08(10.3)	0.91(0.72)	0.72(1.15)	0.67(0.51)	1.88(1.52)
$\alpha 1$	0.07(0.00)	0.08(0.04)	0.09(0.01)	0.07(0.02)	0.13(0.14)	0.08(0.03)	0.08(0.03)	0.11(0.05)	0.16(0.11)
β	0.89(0.02)	0.89(0.01)	0.85(0.04)	0.90(0.04)	0.80(0.30)	0.89(0.04)	0.91(0.04)	0.88(0.05)	0.83(0.11)
Model: UTARCH		Population			Best (10)			Worst (10)	
Coefficients	All	10Y	5Y	All	10Y	5Y	All	10Y	5Y
$a_o x10^5$	1.57(0.71)	1.68(0.68)	2.56(1.97)	0.23(0.14)	0.19(0.13)	0.54(0.39)	4.55(10.6)	2.44(2.62)	1.93(2.90)
$\alpha 1$	0.04(0.00)	0.04(0.00)	0.04(0.00)	0.03(0.02)	0.03(0.02)	0.04(0.04)	0.06(0.09)	0.09(0.05)	0.11(0.10)
γ	0.06(0.00)	0.07(0.00)	0.08(0.01)	0.04(0.01)	0.05(0.02)	0.07(0.05)	0.00(0.06)	0.01(0.04)	-0.03(0.05)
β	0.90(0.01)	0.90(0.01)	0.87(0.04)	0.94(0.03)	0.94(0.03)	0.91(0.07)	0.90(0.14)	0.89(0.08)	0.88(0.12)
Model: UEGARCH		Population			Best (10)			Worst (10)	
Coefficients	All	10Y	5Y	All	10Y	5Y	All	10Y	5Y
a_o	-0.27(0.06)	-0.29(0.06)	-0.53(0.28)	-0.30(0.14)	-0.32(0.14)	-0.35(0.44)	-1.06(2.01)	-0.50(0.37)	-2.17(3.91)
δ	0.12(0.01)	0.13(0.01)	0.13(0.02)	0.14(0.05)	0.15(0.07)	0.12(0.07)	0.13(0.14)	0.09(0.08)	0.07(0.11)
γ	-0.05(0.00)	-0.05(0.00)	-0.06(0.01)	-0.05(0.02)	-0.05(0.02)	-0.04(0.03)	-0.05(0.06)	-0.07(0.01)	-0.06(0.05)
β	0.98(0.01)	0.97(0.01)	0.95(0.03)	0.98(0.01)	0.97(0.01)	0.97(0.05)	0.87(0.25)	0.94(0.04)	0.73(0.50)
Model: BGARCH		Population			Best (10)			Worst (10)	
Coefficients	All	10Y	5Y	All (10)	10Y (10)	5Y (10)	All (10)	10Y(10)	5Y(3)
c_{01} $x10^5$	0.07(0.01)	0.11(0.02)	0.24(0.21)	0.09(0.02)	0.10(0.03)	0.23(0.21)	0.07(0.01)	0.11(0.03)	0.57(0.40)
a_{11}	0.06(0.00)	0.06(0.00)	0.06(0.01)	0.06(0.00)	0.06(0.01)	0.06(0.01)	0.06(0.01)	0.06(0.01)	0.08(0.02)
b_{11}	0.94(0.00)	0.93(0.01)	0.92(0.02)	0.93(0.01)	0.94(0.01)	0.92(0.02)	0.94(0.01)	0.93(0.01)	0.89(0.04)
c_{02} $x10^5$	0.09(0.01)	0.15(0.03)	0.30(0.13)	0.10(0.07)	0.09(0.03)	0.22(0.18)	0.10(0.05)	0.19(0.11)	0.30(0.30)
a_{22}	0.04(0.00)	0.04(0.00)	0.05(0.01)	0.04(0.01)	0.04(0.01)	0.05(0.01)	0.04(0.01)	0.04(0.01)	0.04(0.01)
b_{22}	0.95(0.00)	0.94(0.01)	0.92(0.01)	0.94(0.02)	0.95(0.01)	0.93(0.02)	0.95(0.01)	0.94(0.02)	0.91(0.04)
c_{03} $x10^5$	1.37(0.64)	1.55(0.55)	2.60(1.45)	0.65(0.70)	0.34(0.22)	0.91(0.95)	1.26(0.99)	2.15(1.59)	4.55(4.73)
a_{33}	0.06(0.00)	0.07(0.00)	0.08(0.01)	0.07(0.04)	0.06(0.03)	0.09(0.05)	0.06(0.03)	0.07(0.03)	0.12(0.09)
b_{33}	0.91(0.01)	0.90(0.00)	0.86(0.03)	0.92(0.05)	0.93(0.03)	0.87(0.12)	0.92(0.04)	0.90(0.05)	0.65(0.39)
Model: BTARCH		Population			Best			Worst	
Coefficients	All	10Y	5Y	All (10)	10Y (10)	5Y (10)	All (10)	10Y (10)	5Y (10)
c_{01} $x10^5$	0.10(0.01)	0.12(0.02)	0.17(0.15)	0.09(0.02)	0.12(0.03)	0.12(0.07)	0.11(0.02)	0.10(0.02)	0.07(0.03)
a_{11}	0.01(0.00)	0.00(0.01)	-0.02(0.01)	0.01(0.00)	-0.01(0.01)	-0.02(0.02)	0.00(0.00)	-0.01(0.00)	-0.02(0.03)
b_{11}	0.93(0.00)	0.94(0.01)	0.94(0.01)	0.94(0.01)	0.94(0.01)	0.95(0.03)	0.93(0.01)	0.95(0.01)	0.97(0.02)
d_{11}	0.10(0.01)	0.11(0.00)	0.12(0.03)	0.09(0.01)	0.11(0.01)	0.09(0.03)	0.10(0.01)	0.11(0.02)	0.08(0.04)
c_{02} $x10^5$	0.09(0.01)	0.13(0.02)	0.24(0.13)	0.06(0.03)	0.09(0.05)	0.12(0.11)	0.15(0.16)	0.28(0.19)	0.42(0.44)
a_{22}	0.02(0.00)	0.02(0.00)	0.01(0.01)	0.02(0.01)	0.02(0.01)	-0.01(0.01)	0.02(0.01)	0.03(0.02)	0.02(0.02)
b_{22}	0.94(0.00)	0.93(0.00)	0.92(0.01)	0.95(0.01)	0.94(0.01)	0.94(0.03)	0.93(0.04)	0.92(0.05)	0.89(0.13)
d_{22}	0.05(0.00)	0.05(0.01)	0.07(0.02)	0.04(0.01)	0.04(0.02)	0.07(0.02)	0.04(0.02)	0.03(0.02)	0.04(0.03)
c_{03} $x10^5$	1.26(0.57)	1.43(0.53)	2.28(1.22)	0.35(0.39)	0.43(0.49)	1.34(1.54)	1.98(2.44)	3.09(4.03)	7.75(17.1)
a_{33}	0.04(0.00)	0.04(0.01)	0.04(0.01)	0.02(0.01)	0.03(0.02)	0.05(0.08)	0.06(0.08)	0.07(0.07)	0.05(0.06)
b_{33}	0.91(0.01)	0.90(0.01)	0.87(0.03)	0.95(0.03)	0.93(0.05)	0.86(0.16)	0.88(0.03)	0.84(0.16)	0.83(0.21)
d_{33}	0.05(0.00)	0.06(0.00)	0.08(0.01)	0.04(0.02)	0.04(0.02)	0.11(0.13)	0.05(0.04)	0.10(0.09)	0.13(0.16)
Model: KFRW		Population			Best			Worst	
Coefficients	All	10Y	5Y	All (10)	10Y (10)	5Y (10)	All (2)	10Y (1)	5Y (7)
$ax10^4$				0.40(1.46)	1.91(1.41)	2.54(2.49)	0.25(0.38)	0.25	9.21(3.24)
b	0.89(0.03)	0.86(0.05)	0.92(0.05)	0.60(0.19)	0.69(0.20)	1.01(0.40)	0.38(0.35)	1.36	0.59(0.39)
a_zstat				0.55(0/10)	0.83(0/10)	0.67(0/10)	0.99(1/2)	0.06(0/1)	2.04(6/7)
b_zstat				2.66(10/10)	2.98(7/10)	27.4(10/10)	1.53(1/2)	2.31(1/1)	15.0(7/7)
Model: S&S		Population			Best			Worst	
Coefficients	All	10Y	5Y	All (10)	10Y (10)	5Y (10)	All (10)	10Y (10)	5Y (10)
$ax10^5$				15.9(12.3)	18.4(17.0)	43.7(28.9)	30.6(10.3)	50.9(13.0)	61.4(77.2)
b1	0.84(0.05)	0.84(0.06)	0.90(0.05)	0.76(0.28)	0.76(0.34)	0.75(0.46)	0.41(0.20)	0.30(0.20)	0.92(0.47)
$b2x10^5$	0.30(0.15)	0.27(0.20)	-0.07(0.79)	0.32(0.99)	-0.08(0.98)	-0.37(0.15)	1.63(0.40)	2.56(0.52)	3.01(1.84)
a_pv				0.51(0/10)	0.53(0/10)	0.38(3/10)	0.28(2/10)	0.16(4/10)	0.30(4/10)
b1_pv				0.0(10/10)	0.0(10/10)	0.0(10/10)	0.0(10/10)	0.0(10/10)	0.0(10/10)
b2_pv				0.15(8/10)	0.34(2/10)	0.32(5/10)	0.0(10/10)	0.0(10/10)	0.11(6/10)
Rsq				0.22(0.09)	0.22(0.13)	0.27(0.18)	0.12(0.04)	0.14(0.05)	0.20(0.08)

Table 6.6: continued

Model: NM	Population			Best			Worst		
Coefficients	All	10Y	5Y	All (10)	10Y (10)	5Y (10)	All (0)	10Y (0)	5Y (2)
a	0.88(0.08)	0.88(0.08)	0.88(0.08)	0.71(0.33)	0.68(0.35)	0.79(0.34)			0.55(0.07)
$bx10^2$	0.11(0.54)	0.11(0.54)	0.11(0.54)	-0.17(1.02)	-0.52(1.12)	-0.29(1.32)			-1.08(0.99)
$cx10^2$	-0.26(0.31)	-0.26(0.31)	-0.26(0.31)	-0.16(0.42)	-0.12(0.45)	-0.31(0.34)			0.53(0.38)
a_pv				0.08(8/10)	0.17(6/10)	0.03(8/10)			0.00(2/2)
b_pv				0.30(3/10)	0.29(3/10)	0.36(2/10)			0.59(0/2)
c_pv				0.24(4/10)	0.21(4/10)	0.24(5/10)			0.51(0/2)
Rsq				0.34(0.20)	0.37(0.22)	0.35(0.22)			0.23(0.02)

Notes: the table presents the coefficients of the models. Most of the numbers in parentheses depict standard deviations while some of them show the number of stocks with statistically significant coefficients. For example 9/10 means that 9 out of 10 stocks have coefficients with t-statistics more than 1.7 in absolute terms. In addition, the number in parentheses beside the samples depicts the stocks used for estimating the presented values.

The last model of table 6.6 concerns the NM. To remind here, the beta of the NM is the exponential of ln(a) in equation 6.13. The results imply the increasing and concave function of population mean as indicated by the positive and negative b and c coefficients respectively. The best predictions have been achieved with decreasing and concave betas for the NM. As previously reported, decreasing b_coefficients have 'Inferior' stocks. Hence, the fact may indicate that investors may believe that those stocks will continue to have the same behavior. In other words, they will appear higher losses than the general index in down markets and lower gains than the general index in up markets.

6.4.4 The iid assumption of returns

In this part, we refer the findings about the hypothesis that asset returns are identically, independently and normally distributed (iid-normal). The CAPM used for asset pricing is based on these assumptions. More accurately, the results concern the two different in essence groups of stocks, the best and worst ones for the period of 5 years. Table 6.7 reports the results. The first three columns related to the normality of the variables. The Jarque-Bera test for normality exhibits very large values and the normality assumption is rejected at all cases. The non-normality of the underlying return series does not necessarily imply non-normality of the residuals coming from asset pricing models and the distribution of the residuals should be carefully examined (Graves and McDonald, 1989). However, Groenewold and Fraser (2001) using data from Australian industrial sectors showed that the residuals as well as the returns are typically not iid-normal, exactly as in our case. The autocorrelation coefficients and the Q(6) statistic depict that autocorrelation is present regarding the group with the best stocks. For the second group almost half of the models reject the hypothesis of the autocorrelation existence. The heteroskedasticity test results are similar to that of autocorrelation as most of the returns belonged to the worst stocks do not suffer from heteroskedasticity problems unlike to the returns of the best stocks where none of the models accept the null hypothesis.

Table 6.7: Diagnostic tests of returns for the two groups of stocks.

Model	Skew	Kurt	JB	ρ1	ρ2	ρ3	ρ4	ρ5	ρ6	Q (6)	ARCH6
Panel A: Best predictions											
UGAR	0.017	8.0	1904.0	-0.055	-0.032	-0.006	0.000	-0.024	-0.012	25.5	15.6
UTAR	-0.324	11.3	7952.9	-0.015	-0.020	-0.018	-0.019	-0.016	0.003	13.0	33.1
UEGAR	-0.316	16.2	25642.5	0.019	-0.015	-0.021	-0.022	0.000	0.002	17.2	24.0
BGAR	0.231	10.1	4087.9	-0.043	-0.011	0.002	-0.021	-0.008	-0.006	28.5	27.7
BTAR	-0.274	9.4	2854.0	-0.056	-0.039	0.035	-0.003	-0.027	0.004	17.4	28.1
KFRW	-0.257	11.8	6367.9	-0.018	-0.061	-0.005	0.003	-0.025	-0.006	15.4	25.1
S&S	-0.193	10.3	10765.0	-0.021	-0.040	0.001	-0.002	-0.018	-0.023	14.2	19.3
NM	-0.169	10.5	4222.4	-0.034	-0.035	0.015	-0.008	-0.011	-0.017	14.2	25.2
Mean	-0.160	10.9	7974.5	-0.027	-0.031	0.00	-0.009	-0.016	-0.007	18.1	24.7
Panel B: Worst predictions											
Model	Skew	Kurt	JB	ρ1	ρ2	ρ3	ρ4	ρ5	ρ6	Q (6)	ARCH6
UGAR	-0.859	18.0	17425.1	-0.024	-0.020	0.001	-0.009	-0.023	-0.010	8.6	14.4
UTAR	-0.509	13.5	15545.7	-0.034	-0.051	0.017	-0.028	-0.031	0.002	24.9	13.4
UEGAR	-0.343	14.4	14406.6	-0.010	-0.001	0.008	-0.033	-0.012	-0.017	8.3	4.8
BGAR	0.142	6.8	806.0	-0.048	-0.061	-0.001	0.004	-0.032	0.023	14.7	17.3
BTAR	-0.961	23.8	59147.0	-0.042	-0.028	0.017	-0.016	-0.028	-0.006	18.7	13.6
KFRW	-0.024	8.7	3030.8	0.027	-0.017	-0.017	-0.028	-0.021	-0.012	11.6	11.3
S&S	-0.379	8.6	3015.6	-0.039	-0.029	0.002	-0.007	-0.008	0.002	10.6	5.8
NM	-0.739	21.9	33297.2	0.038	-0.032	-0.035	0.017	0.095	0.004	36.0	32.7
Mean	-0.459	14.4	18334.1	-0.017	-0.030	-0.001	-0.013	-0.008	-0.002	16.6	14.1

Notes: JB is the Jarque-Bera test for normality following the χ^2 distribution. The 5% critical value for the χ^2 is 5.99. Q (6) is the Box-Pierce-Ljung statistic for first to sixth order autocorrelation. It also follows the χ^2 distribution which for 5% critical level and 6 degrees of freedom is 12.59. The ARCH (6) test is the Engle's test for sixth order ARCH and its critical value is again 12.59.

6.4.5 Spearman correlation and realized betas

In the last part of this chapter, we calculate and exhibit correlations between predicted time varying betas and realized betas. Realized betas are calculated using both daily and monthly returns. Following Andersen et al. (2006), the realized beta for stock i, in year t, is:

$$\hat{\beta}_{it} = \frac{\sum_{j=1}^{N_t} r_{ijt} r_{mjt}}{\sum_{j=1}^{N_t} r_{mjt}^2} \qquad 6.17$$

where r_{ijt} is the return of stock i on day j (or on month j) of year t, r_{mjt} is the return of the S&P 500 on day j (or on month j) of year t, and N_t is the number of days (or months) into which year t is partitioned. This time, we use 25 out of 30 stocks that constitute the DJIA index and belong to the S&P 500. The models for estimating betas concern the values of the NM (i.e. exp(a) of equation 6.13), the coefficient of the NSI of our TFM and the normal CAPM beta. For the last two models, a five-year period is used for estimation purposes, as this is the best period for estimating more reliably the systematic risk with monthly data (Dimson and Marsh, 1983; Chincarini and Kim, 2006). In order to evaluate how the estimated betas of the selected models fit to realized betas we make use of Spearman's rank correlation. This is a non-parametric measure without making any assumption about the linear relationship between the variables. The Spearman's measure of correlation is given as follows:

$$\rho = 1 - \frac{6\sum d_i^2}{n(n-1)} \qquad 6.18$$

where d_i is the difference between each rank of corresponding values of X (the model's x betas) and Y (the realized betas). Table 6.8 exhibits the results. The NM appears four times the highest values of correlation in relation to the other models. Furthermore, it is evident the relatively low correlation between the realized monthly betas and the realized daily betas. This happens because in monthly returns a piece of information is lost and that is why most practitioners use daily or even intraday returns to estimate more accurately betas. We also present in parentheses in table 6.8 the correlation between the estimated betas of the TFM and the CAPM and the realized monthly betas. It is noteworthy that both models present exactly the same number of superiority as bold letters indicate. Hence, we are indifferent between these models if we had to select one of them for predicting monthly betas. However, the best performance of the TFM both in time series and in cross sectional regressions enables it the preferred model.

Table 6.8: Spearman correlation with realized betas.

Panel A: Realized daily betas				
Year	exp(a)	NSI	CAPM	Realized Monthly
2003	0.79	0.76 **(0.50)**	**0.83** (0.42)	0.48
2004	**0.70**	0.68 **(0.71)**	0.68 (0.58)	0.57
2005	0.16	**0.47 (0.25)**	0.36 (0.20)	0.66
2006	0.52	**0.64** (0.16)	0.62 **(0.27)**	0.12
2007	**0.63**	0.56 (0.37)	0.58 **(0.55)**	0.22
2008	**0.74**	0.40 (0.51)	0.47 **(0.54)**	0.48
2009	**0.87**	0.69 **(0.49)**	0.68 (0.48)	0.76
2010	0.84	0.85 (0.65)	**0.89** (0.65)	0.80
2011	0.76	0.77 (0.40)	**0.84 (0.49)**	0.70

Notes: Bold letters indicate superiority.

6.5 Conclusions

In this chapter, we estimate time varying betas with daily data for stocks traded on the S&P 500. The betas are calculated by means of different univariate and bivariate GARCH models, the Kalman filter algorithm at which the random walk process is used to model the stochastic form of betas, the Schwert and Seguin model and the TFM. The accuracy of beta prediction is applied on the next year's realized returns. The MSE and the MAE are employed as accuracy measures. The forecasts are tested on three different samples for nine consecutive years. The results show that the accuracy of beta predictions differs significantly among the samples. For the two biggest samples the new method works well enough, while the Kalman filter algorithm takes the advantage of accuracy at the smallest one. The UGARCH, the BGARCH and the S&S models perform better in the 5 years period than the longest periods. On the other hand, the remaining univariate GARCH models do not seem to have adequately predictions at any sample. The findings do not change substantially when the Diebold and Mariano test is used. This specific test controls the equal forecast accuracy among the models. The KFRW model gives the best results with the models out of the GARCH family to fall short just for a little. The UGARCH model shows the best predictions among the GARCH models. The window of 5 years appeared in essence the most accurately results.

Taking into consideration the estimated parameters, they change significantly not only from period to period but also among the best and worst groups. The best stocks according to UGARCH model have significantly smaller long run volatility unlike to the worst stocks where their volatility is far away from the population average. Large differences are observed on the γ coefficient of the UTARCH model indicating that asymmetries play a significant role on the predictive accuracy. For the last univariate GARCH model, the EGARCH, it is clear that the γ coefficient is similar to all groups of stocks even though the long run volatility of stocks calculated using the window of five years is smaller than the total average. In general, the bivariate cases of the GARCH models do not present large deviations from the univariate ones. As far as the KFRW model is concerned, an important difference is pointed out on the constant parameters. A statistically significant constant deteriorates the model's results indicating the difficulty of predicting returns using betas that are associated with a significant α parameter. For the S&S model the b2 coefficient is of paramount importance as it signals the model's performance. Regarding the parameters of the new model they show that a decreasing and concave beta coefficient is appeared more efficient for predicting purposes. To note here that even though the new model does not seem to be the best one among the examined models its sufficient accuracy prediction and its use for pricing assets enables it a useful tool at investors' hands. As for the asset returns as expected they do not follow the normality assumption. However, the average J-B test is smaller for stocks with better accuracy predictions than the worst ones. At the same time significant differences are also observed on tests related to autocorrelation and heteroskedasticity. Finally, the measure of Spearman's rank correlation indicate that the estimated betas coming from the NSI and the CAPM appear exactly the same performance.

PART III

THE EFFECTS OF HERDING IN FINANCIAL MARKETS

Part III introduces the reader to concepts of herding behavior. The efficient market hypothesis states that market participants form rational expectations of future prices discounting all market information into expected prices. However, the existence of herding might aggravate volatility of returns destabilizing financial markets (Demirer and Kutan, 2006). Hence, this part of this thesis exhibits the results of the effects of herding on different volatility measures. Part III continues by reporting the reasons of selecting the herding model of Hwang and Salmon (2004) among other competitive models. Furthermore, in the light of the empirical evidence that higher co-moments are capable of explaining asset returns, it is investigated whether herding also matters towards higher co-moments in five major developed markets (i.e. USA, UK, Germany, France and China). Finally, this part explores the existence of contagion effects of herding as well as the effects of unexpected macroeconomic shocks on herding. Part III is being composed by Chapters 7 and 8.

CHAPTER 7

HERDING BEHAVIOUR AND VOLATILITY

7.1 Introduction

The existence of herding behaviour in financial markets is worth examining and documenting for a number of reasons. Initially, investors and financial managers are concerned about the way information is reflected in stock market prices. The efficient market hypothesis states that market participants form rational expectations of future prices discounting all market information into expected prices. However, the existence of herding might aggravate volatility of returns destabilizing financial markets (Demirer and Kutan, 2006).

The role of financial markets and institutions in the economy is very important since they constitute the channel of passing funds from savers to investors. A small volatility in the prices of financial assets is acceptable due to the process of allocating funds among competing uses. However, excessive or extreme market volatility could lead to structural or regulatory changes (Becketti and Sellon, 1989). Volatility has attracted growing attention by all participants in financial markets during the past two and more decades developing forecast models and explaining the sources of this variability (Yu, 2002; Poon and Granger, 2003).

Friedman (1953) first tested the link between investor behaviour and market volatility arguing that irrational investors destabilize prices. They usually buy when prices are high and sell when prices are low in contrast to rational investors that lead the prices towards their fundamentals by buying low and selling high. De long et al. (1990) have claimed that the existence of noise trading in the markets can increase price volatility and consequently the risk associated with investing in the stock market and the risk premia. The authors support the idea that rational speculators in the presence of positive feedback investors might proceed to buy today in the hope of selling to noise traders at a higher price tomorrow, moving the prices even further away from their fundamentals. Froot et al. (1992) show that investors imitate one another increasing the volatility this way, while Wang (1993) reports that uninformed investors tend to follow the market trend. Such behaviours are considered to be equal to herding as stated by Blasco et al. (2012). The authors examined the effect of herding on market volatility for the Spanish stock market. Their findings support a direct linear impact of herding on market volatility for all different volatility measures considered.

In empirical studies, the estimation of herding can be classified into two main categories (Spyrou, 2013). The first one investigates the existence of herding on specific investor types such as institutional investors. The herding measure of this category was first proposed by Lakonishok et al. (1992) and improved by Sias (2004). The second category investigates herding towards market consensus by relying on aggregate price and market activity data. This category is primarily based on measures proposed by Cristie and Huang (1995), Chang et al. (2000) and Hwang and Salmon (2004) and it is widely used in the international literature (Spyrou, 2013). In addition, the measures of the latter category are relatively easy to calculate since they are based on observed returns data and not on detailed records of individual trading activities such as the measure proposed by Lakonishok et al. (1992) (Hwang and Salmon, 2004).

Herding measures towards market consensus are based on return dispersion-based models and state space models. The first dispersion model of Christie and Huang (1995) derives by estimating the cross-sectional standard deviation of returns (CSSD). Based on daily and monthly data from the US market, the authors support the predictions of rational asset pricing models and suggest that herding is not an important factor in asset returns determination. The second dispersion model of Chang et al. (2000) employs the cross-sectional absolute deviation of returns (CSAD) as a measure of return dispersion. They advocate that in extreme market conditions a non-linear relation would exist between return dispersion and market return. Therefore, in the presence of herding, the quadratic factor of market return will be negative and statistically significant. Using data from five countries, the results indicate no evidence of herding in the U.S. and Hong Kong, partial evidence of herding in Japan and significant evidence of herding in South Korea and Taiwan both of which belong to emerging markets. For the last two countries, the existence of herding is attributed to factors related to the government intervention, the inefficiency of reliable company information and the presence of more speculative investors. The referred models have been used by a number of studies. Caparrelli et al. (2004) examine herding in the Italian stock market. The findings reveal herding behaviour from September 1988 to January 2001 when extereme market phases exist. As for the Chinese stock market, Demirer and Kutan (2006) find no evidence of herding. The authors report that the Asian crisis period had no significant impact on cross sectional standard deviations. However, Yao et al. (2014) show that for the same stock market investors exhibit different levels of herding, when it is split into the Shanghai Stock Exchange (SHSE) and Shenzhen Stock Exchange (SZSE) over the period from January 1999 to December 2008. More concretely, the SZSE strongly exhibits herding behaviour, while herding is stronger for the largest and smallest stocks, and for growth stocks relative to value stocks. Caporale et al. (2008) test the existence of herding for the Greek stock market. Using daily, weekly and monthly data, their results indicate that herding is present for the whole 1998-2007 period. However, herding is much stronger over daily time intervals, revealing the short-term nature of the phenomenon. Furthermore, the findings for this specific market show that investor behaviour seems to have become more rational since 2002 as part of the regulatory and institutional reforms that took place in the country and the increased presence of foreign institutional investors. Additionally, the findings of Tessaromatis and Thomas (2009) are along the same line for the Greek stock market over the 1998-2004 period. However, the authors find little evidence of herding when the covered period is from 1985 to 2004. More recently, Chiang and Zheng (2010) using data of 18 global markets have revealed strong evidence of herding in advanced stock markets, with the exception of the US, besides the fact that in the US and Latin American markets, supportive signs of herding during crises were evident. Philippas et al (2013) use the

CSAD model to detect herding in the US real estate investment trusts (REIT) market over the 2004-2011 period. Their findings show that deterioration of investors' sentiment and adverse macro-shocks to REIT funding conditions result in the emergence of herding behaviour. Demirer et al. (2014) examines whether herding exists to American Depository Receipts (ADRs). They conclude that herding is more extensive at the sector level than at the country level regarding the markets of the ADRs.

The second methodology of measuring herding was suggested by Hwang and Salmon (2004) and it is based on state space models. This method focuses on the cross-sectional variability of factor sensitivities. According to their model, betas of individual assets will be biased and away from their equilibrium values when investors' herding towards market portfolio is present. They show that herding exists in both bull and bear US and South Korean stock markets, while the findings of herding towards size and value factors of Fama and French (1993) model depict a range of results including evidence of significant periods of herding towards value in the US market. Demirer et al. (2010) use all three models for testing herding behaviour in the Taiwanese stock market. Herding is statistically significant when the non-linear model of Chang et al. (2000) and the state space model of Hwang and Salmon (2004) are employed. In addition, diversification is limited in this market especially when it faces losses, a result caused by the herding effect.

This chapter investigates the existence of herding in the Greek stock market, and examines whether its presence influences market volatility. The measurement of herding has been conducted using the model of Hwang and Salmon (2004). With this particular model, we are able to detect herding not only in periods of extreme market movements but also during normal market conditions. Hence, it provides a more detailed analysis of herding over time (Demirer et al., 2010). In addition, the model is free from the influence of idiosyncratic components as it focuses only on the variability of factor sensitivities (Hwang and Salmon, 2004). This study adds to the literature on the herding behaviour of investors with different ways. First, it extends investor herding studies to an emerging market by using state space models not previously applied in this specific market. Second, it employs different portfolios formed on the basis of the magnitude of beta and the size designed to identify whether herding is differentiated across these portfolios. Last but not least, it examines the implications of herding on market volatility. Generally speaking, traders use different models to evaluate stock market volatility. From this point of view, the results could provide a better understanding of which variables affect market volatility resulting in to much more accurate forecasting and, furthermore, to the adoption of new hedging strategies for more integrated risk management.

Volatility has been estimated using four different measures. The first one is the standard GARCH(1,1) model, which has generally been found to be the most appropriate of the ARCH family models (Brailsford and Faff, 1996). The TGARCH model is considered in order to gauge asymmetries in market returns. Furthermore, we employ the volatility measure of French et al. (1987) which takes into account the autocorrelation in daily returns. Finally, we decompose the latter estimated variance into upside and downside volatilities, estimated by the summation of positive and negative daily market returns respectively. The findings of this chapter also contribute to the growing literature on the ASE. Diacogiannis et al. (2005) claim that studying the Athens Stock Exchange (ASE) can offer useful inferences due to the regulatory regime and practices characterizing the Greek market. The authors report that in the ASE, despite the influence of institutional investors, traders are mainly small investors and from this point of view the ASE employs no specialists. However, the regulatory authority monitors trading activities and controls insider trading by targeting on the restriction of excessive volatility.

The rest of this chapter is deployed as follows. The next section, section 7.2, acts as a brief introduction to the Greek environment. Section 7.3 provides the methodological details and section 7.4 describes the data. In section 7.5, the empirical results are presented and in section 7.6, we conclude.

7.2 The Greek stock market environment

The Greek stock market is a liberalized market offering all the benefits stemmed from such markets (Cajueiro et al., 2009). Galindo et al. (2007) and Abiad et al. (2008) show that financial liberalization is associated with higher capital allocation efficiency and reduced variation in expected marginal returns. Furthermore, Greece is a member of the European Monetary Union and from 2001 up to November 2013 it was characterized as a developed market. However, the ASE did not have the same picture in the past. By following a range of deregulation measures both in monetary and capital sectors since the early of 1990's, the security market started attracting funds from both domestic and international investors (Alexakis and Apergis, 1994). Over the period of 1995-2000 the ASE had an impressive cumulative return reaching and surpassing 290%.

Over the last years, the market has once again attracted the attention of international organizations and market participants due to macroeconomic imbalances faced by the country (Economou et al., 2011). The participation of foreign investors reached as high as 50% of the total capitalization in December 2013 according to the monthly statistical bulletin of ASE. This is a significant increase when compared to just 33% increase reported in 2004. Furthermore, according to the 6th Annual Review of Asset Management in Europe, 56 asset management companies there were registered in the Greek stock market in 2012. However, the review states that the top 5 asset managers control as high as the 73% of the total market, indicating that this market is not well diversified compared with the UK market in which the concentration of the top 5 asset managers reaches as high as the 35%. Adding upon this, the findings of herding behaviour among market analysts (Welch, 2000) and fund managers (Theriou et al., 2010), strengthen our suspicions regarding the existence of herding in this specific market.

As far as the market volatility is concerned, a number of studies related to the ASE have shown that it does not remain constant over time (Karathanassis and Philippas, 1993; Koutmos et al., 1993; Apergis and Eleftheriou, 2001; Siourounis, 2002). Athanassiou et al. (2006) point out that the ASE has faced highly volatile periods at times, with speculative characteristics and price swings. The market rose during the 1997-1998 period of almost 100%. However, this particular rally ended with the market crash in 1999. All these signify that market may not react rationally at all times, based on the underlying fundamentals and the available information. Therefore, the magnitude of market volatility in the ASE can be strongly influenced by the existence of herding exactly as the evidence shows in the case of the Spanish stock market (Blasco et al., 2012).

7.3 Methodology

7.3.1 The model of herding measure

The model of herding measure developed by Hwang and Salmon (2004) is based primarily on the CAPM of Sharpe (1964), and Lintner (1965). When rational investors exist in a market, the CAPM in equilibrium can be expressed as follows:

$$E_t(r_{it}) = \beta_{it} E(r_{mt}) \qquad 7.1$$

where r_{it} and r_{mt} indicate the excess return of asset i and the market return respectively and β_{it} is the systematic risk. $E_t(\cdot)$ is the conditional expectation at time t. When herding occurs, equation 7.1 no longer holds, resulting in the bias of expected return and risk. The model of HS suggests that in the case of herding towards market, the following relationship holds:

$$\frac{E_t^b(r_{it})}{E_t(r_{mt})} = \beta_{it}^b = \beta_{it} - h_{mt}(\beta_{it} - 1), \qquad 7.2$$

where $E_t^b(r_{it})$ and β_{it}^b are the biased expected returns on the asset and its observed beta respectively. h_{mt} is a latent herding parameter that changes over time. When $h_{mt} = 0$, there is no herding and the CAPM holds in equilibrium. When $h_{mt} = 1$, there is perfect herding towards market indicating that all the individual assets change in accordance with the movements of the market portfolio. When $0 < h_{mt} < 1$ some degree of herding exists in the market depending on the magnitude of h_{mt}. In adverse herding should $h_{mt} < 0$.

When the market increases significantly, for an equity with $\beta_{it} > 1$ the CAPM suggests that $E_t(r_{it}) > E_t(r_{mt})$. Herding behaviour towards market of the investors will push the equity's price downward, making $0 < E_t^b(r_{it}) < E_t(r_{it})$. For that reason the equity looks less risky than it should, suggesting that $1 < \beta_{it}^b < \beta_{it}$. The same order of betas holds when the market goes down as investors will buy the equity pushing it upwards. For an equity with $\beta_{it} < 1$ the inverse process holds and the biased beta will increase when the market changes (i.e. $1 > \beta_{it}^b > \beta_{it}$) (Wang, 2008). When $\beta_{it} = 1$, the equity is neutral to herding, while for adverse herding (i.e. $h_{mt} < 0$) an equity with $\beta_{it} > 1$ means that $E_t^b(r_{it}) > E_t(r_{it}) > E_t(r_{mt})$ and for an equity with $\beta_{it} < 1$ holds that $E_t^b(r_{it}) < E_t(r_{it}) < E_t(r_{mt})$. Because herding represents market wide behaviour, it is preferable to use all assets in the market than a single asset to eliminate the effects of idiosyncratic movements in any individual β_{it}^b. The cross sectional mean of β_{it}^b (β_{it}) is 1 regardless of whether β_{it} is biased or not. Thus, the cross sectional standard deviation is:

$$Std_c(\beta_{it}^b) = Std_c(\beta_{it})(1 - h_{mt}). \qquad 7.3$$

Taking logarithms on both sides of equation 7.3 we get,

$$\log[Std_c(\beta_{it}^b)] = \log[Std_c(\beta_{it})] + \log(1 - h_{mt}). \qquad 7.4$$

Defining $H_{mt} = \log(1 - h_{mt})$ and $\mu_t = E(\log[Std_c(\beta_{it})])$ we can write when herding is absent, $\log[Std_c(\beta_{it})] = \mu_t + v_{mt}$ assuming that $v_{mt} \sim iid(0, \sigma_{mv}^2)$. In the presence of herding, the following holds:

$$\log[Std_c(\beta_{it}^b)] = \mu_m + H_{mt} + v_{mt}. \qquad 7.5$$

Allowing H_{mt} to evolve over time and assuming it follows an AR(1) process then:

$$H_{mt} = \varphi H_{mt-1} + \eta_{mt}, \qquad 7.6$$

where $\eta_{mt} \sim iid(0, \sigma_{m\eta}^2)$. The Kalman filter approach can be used for estimating equation 7.6. A significant value of $\sigma_{m\eta}^2$ indicates the existence of herding and a significant φ supports the AR(1) process, while $|\varphi_m| \le 1$ so as to not explode, making the series H_{mt} non stationary. Following Hwang and Salmon (2004) and Demirer et al. (2010), we add to equation 7.5 market volatility[12], σ_{mt}, and return, r_{mt}, as independent variables as they have been found to statistically influence the volatility of factor sensitivities. Hence, the augmented state space model 2 is defined as:

$$\log[Std_c(\beta_{it}^b)] = \mu_m + H_{mt} + c_{m1}\log\sigma_{mt} + c_{m2}r_{mt} + v_{mt}. \qquad 7.7$$

All the assumptions made above also hold for this model.

[12]The monthly market volatility, σ_{mt}, is calculated using within month daily returns.

7.3.2 Volatility measures

7.3.2.1 Volatility measure using within month daily returns

The first measure of market volatility is as in French, Schwert and Stambaugh (1987). Each month the variance of the market portfolio is computed using within month daily returns:

$$\sigma_{mt}^2 = \sum_{i=1}^{N_t} r_{it}^2 + 2 \cdot \sum_{i=2}^{N_t} r_{it} r_{it-1} \qquad 7.8$$

where N_t is the number of daily market returns, r_{it}, in month t. The second term on the right-hand side of equation 7.8 adjusts for autocorrelation in daily returns. This measure has also been used by Chen and Petkova (2012) for estimating idiosyncratic risk.

7.3.2.2 Upside and Downside volatility

We follow a similar approach to the above one for catching up the volatility in up and down market returns. This time the second term of equation 7.8 is omitted as in Schwert (1989). The market variance is decomposed into upside and downside variances as follows:

$$\sigma_{mt}^2 = \sum_{i=1}^{N_t^+} r_{it}^2 + \sum_{i=1}^{N_t^-} r_{it}^2 \qquad 7.9$$

where once again r_{it} is the daily market returns in month t, but now N_t^+ and N_t^- is the number of days with positive and negative market returns respectively.

7.3.2.3 The univariate GARCH (1,1) model

The GARCH model that was developed by Bollerslev (1986) allows the conditional variance to be dependent upon previous own lags (Brooks, 2002). Equation 7.10 is used for estimating the conditional market variance in month t:

$$r_{it} = \mu + r_{it-1} + u_{it} \qquad 7.10$$

In equation 7.10, r_{it} is the daily stock market returns in month t, μ is a constant, r_{it-1} captures time dependence of the returns series smoothing them of possible structural shifts over the sample period and u is the error term which follows N~ $(0,\sigma^2)$. After estimating equation 7.10, the conditional variance of a GARCH (1,1) model is calculated as follows:

$$\sigma_{mt}^2 = \alpha_0 + \alpha_1 u_{it-1}^2 + \beta\sigma_{mt-1}^2 \qquad 7.11$$

For the conditional variance, σ_{mt}^2, to be nonnegative and positive, the following conditions must be met:

$a_0 > 0; a_1 \geq 0; \beta \geq 0 and a_1 + \beta < 1$.

7.3.2.4 The Threshold ARCH model

The Threshold ARCH (TARCH) model is an extension of GARCH adding a new term to the variance equation to count for possible asymmetries. The conditional variance of a TARCH model (Zakoian, 1994) is given by the following equation:

$$\sigma_{mt}^2 = \alpha_0 + \alpha_1 u_{it-1}^2 + \beta\sigma_{mt-1}^2 + \gamma u_{it-1}^2 I_{it-1} \qquad 7.12$$

where I_{it-1}=1 if u_{it-1}<0 or zero otherwise.

If γ>0 there will be leverage effect while for non-negativity of the variance should:

7.4 Data description

The data used for the effects of herding on market volatility concerns securities traded on the ASE. Keeping in mind the problems associated with thin trading and data availability, forty one stocks are selected. All of them belong to large cap 20 and middle cap 40 indexes. Their total market capitalization reaches as high as the 95% of the 60 stocks that constitute the Athens General Index and the 81% of the whole market. To note here that the relatively low number of stocks at the very early stage of the sample can cause survivorship bias problems. To examine possible effects related to survivorship bias, we also form big and small sample portfolios. The small sample portfolio contains stocks that were available at the very early stage of the sample. The big sample portfolio contains all selected stocks. Following the method of Banz and Breen (1986), we do not find statistically significant differences in returns between the big and the small sample. The estimated t-statistic of the constant is just 0.23. The period under analysis is from February 1995 to April 2010 and covers the bull market up to early 2000 and the crisis of 2008. For the estimation of betas, we are using rolling windows of 60 monthly observations as in Hwang and Salmon (2009). In their analysis, the authors regard herding not as a short-lived phenomenon that arises rapidly but as a more slowly moving procedure where a short run relationship can be proved misleading regarding the level of stock prices. Their argument is based on the fact that the noise, that can be seen as any factors that make asset prices deviate from their fundamental values, may be highly persistent and slow-moving over time as shown by Fama and French (1988). Furthermore, by employing monthly returns instead of daily returns, we reduce the estimation error, with the trade off being the lower number of observations used in the state space models. To calculate the excess returns, a 3-month treasury bill has been employed as risk free. The simple monthly rates of return are estimated as in Karathanassis and Philippas (1993) in the case of ASE, while they are adjusted for splits and changes in capital structure. The inclusion of dividends would add little to the overall variability of the data (Lo and MacKinlay, 1988).

7.5 Empirical Evidence

7.5.1 Herding behaviour towards market

Following the procedure described above, the betas are calculated using the Ordinary Least Squares (OLS) method. The beta coefficient in the ASE is found to be priced in explaining returns of portfolios in the APT (Ross, 1976) context in Messis et al., (2006), while it is marginally rejected at the 10% level in Michailidis et al., (2006) for the same market, though a significant part of returns left unexplained as usually happens in CAPM tests (Fama and French, 1996). We use the magnitude of the estimated betas to rank the stocks and make three similar subgroups of portfolios as in Hwang and Salmon (2004). Hence, beta based portfolios are constructed each month by ranking betas at ascending order such as the high beta portfolio to consist of the top 80%, the low beta portfolio of the bottom 80% and the medium beta portfolio of the middle 80%. We follow the same method by forming this time three non-overlapping portfolios of equal weights to test any differences in the results between the two procedures. The final conclusions do not deviate though the herding pattern of the low and high non-overlapping beta portfolios appears to be more intense. Furthermore, we assume that homogeneity holds and each member faces a similar decision problem while observing at the same time the trades of other members in the group (Bikhchandani and Sharma, 2001). The total portfolio contains all stocks representing the overall market behaviour. Then we proceed to the construction of the monthly time series cross-sectional standard deviations of betas for the aforementioned portfolios. Table 7.1 depicts some statistical properties about the series of the estimated mean of OLS betas and the estimated cross sectional standard deviation of betas. $E_c(\beta^b_{imt})$ varies from 1.35 to 0.64 and $Std_c(\beta^b_{imt})$ ranges between 0.49 and 0.14. The lowest value of correlation coefficient is observed between the highest and the lowest beta based portfolios related to the estimated cross sectional standard deviation. The herd measure towards market (equation 7.5) is presented in table 7.2. It is clear that H_{mt} is highly persistent for all portfolios as the coefficient of the AR(1) model (i.e. $\hat{\varphi}_m$) is large and statistically significant at each level. In addition, it is less than one without exploding, while the same significance shows the standard deviation of $\sigma_{m\eta}$ as we expected in the case of herding.

Table 7.1: Properties of the cross-sectional mean and standard deviation of betas.

Panel A: Sample Statistics								
	Cross-sectional mean of betas				**Cross-sectional st.dev. of betas**			
Portfolio	**Total**	**High**	**Medium**	**Low**	**Total**	**High**	**Medium**	**Low**
Mean	0.97	1.08	0.97	0.85	0.35	0.29	0.27	0.31
Maximum	1.19	1.35	1.22	1.03	0.51	0.49	0.38	0.42
Minimum	0.77	0.85	0.73	0.64	0.17	0.17	0.14	0.19
Std. Dev.	0.12	0.14	0.12	0.10	0.07	0.10	0.06	0.05
Panel B: Correlation coefficients								
	Total	**High**	**Medium**	**Low**	**Total**	**High**	**Medium**	**Low**
Total	1	0.99	0.99	0.98	1	0.93	0.74	0.60
High		1	0.99	0.95		1	0.68	0.40
Medium			1	0.98			1	0.66

Notes: Panel A reports the first two moments of $E_c(\beta^b_{imt})$, the cross sectional mean of the betas, and $Std_c(\beta^b_{imt})$, the cross-sectional standard deviation of the betas in the ASE over the period 1995-2010. Panel B shows the correlation coefficients among the series.

Table 7.2: Estimates of state-space model and Herd measure (Model 1). The table reports the Kalman filtered state space model of equation (5) for all portfolios formed on betas.

Portfolio	Total	High	Medium	Low
μ	-1.093 (-8.85)*	-1.394 (-6.06)*	-1.387(-11.6)*	-1.204 (-10.2)*
φ_m	0.943 (35.9)*	0.978 (48.8)*	0.951(32.6)*	0.973 (47.5)*
$\sigma_{m\eta}$	0.071 (31.7)*	0.065 (68.1)*	0.080 (48.2)*	0.043 (107.6)*

t-statistic in parenthesis
* represents significance at 5% level

Table 7.3 presents the results of the augmented state space model 2. Once again the findings are similar to those reported for state space model 1 regarding the existence of herding. For the additional variables we observe that the terms of market return and volatility are statistically significant only for the low and high beta portfolios respectively. The results are quite interesting. Firstly, the volatility of factor sensitivities, $Std_c(\beta^b_{imt})$, for the low portfolio increases as market return increases. This finding possibly indicates that conservative investors, as regards the ones invested in low beta stocks, start participating in market when conditions are favourable. As for the high beta portfolio, the volatility of factor sensitivities decreases with market volatility. The result consistent with previous studies such those of Hwang and Salmon (2004) and Demirer et al. (2004) suggests that herding for this portfolio is more likely to occur during highly volatile periods.

Table 7.3: Estimates of state-space model and Herd measure (Model 2).

Portfolio	Total	High	Medium	Low
μ	-1.238 (-8.49)*	-1.558 (-7.42)*	-1.396(-9.91)*	-1.209 (-9.96)*
φ_m	0.937 (35.8)*	0.977 (47.8)*	0.950(29.7)*	0.973 (47.2)*
$\sigma_{m\eta}$	0.071 (31.4)*	0.066 (67.7)*	0.079 (48.1)*	0.042 (111.3)*
r_m	0.033 (0.49)	0.011 (0.26)	0.043 (0.79)	0.054 (2.13)*
$\log\sigma_m$	-0.055 (-1.17)	-0.063 (-1.97)*	-0.003 (-0.07)	-0.002 (-0.10)

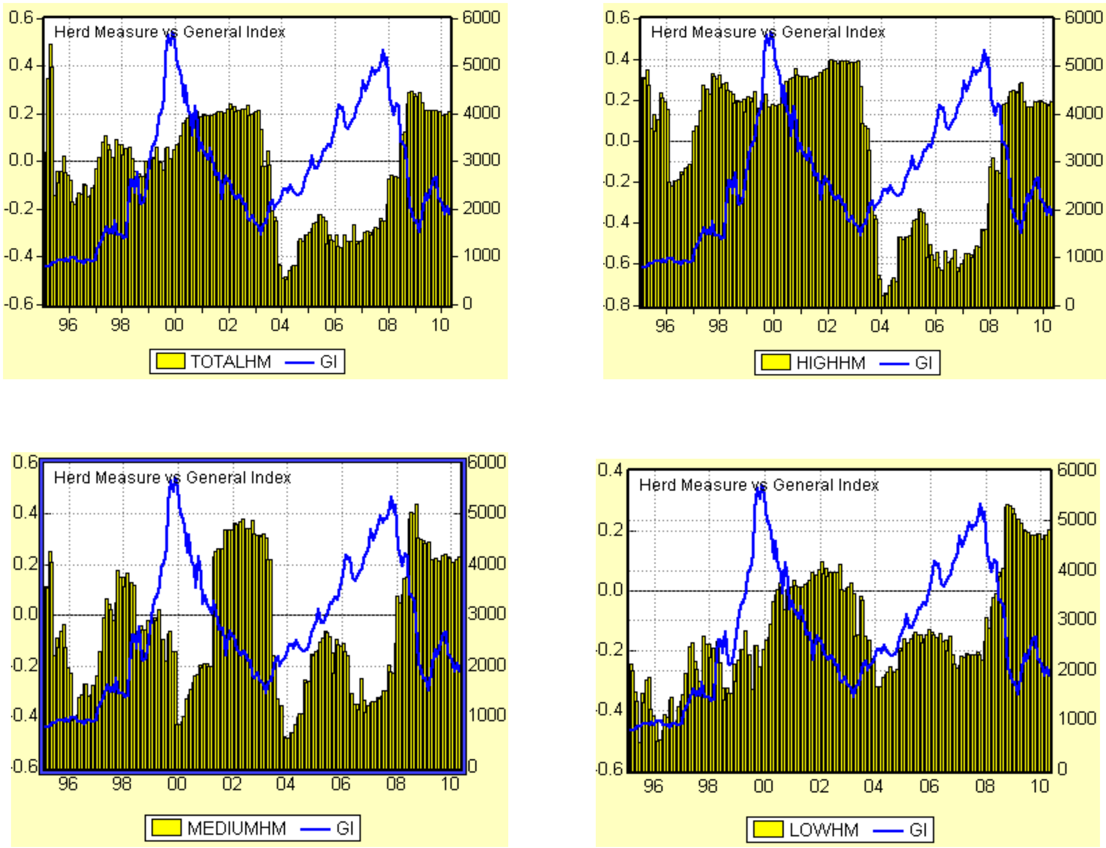
Notes: The table reports the Kalman filtered state space model of equation (6) for all portfolios formed on betas by adding market returns and volatility as independent variables.
t-statistic in parenthesis
* represents significance at 5% level

We continue by depicting the evolution of herding measure (i.e. $h_{mt} = 1 - e^{H_{mt}}$) in figure 7.1. The figure reveals several cycles of herding and adverse herding.

Starting with the total market portfolio, we observe the existence of herding during the early 1997 and the first quarter of 2003 period. However, the magnitude of herding does not reach at high levels for the first 3 years of the given period. In addition, it becomes slightly negative during the second semester of 1998. The picture changes from the early of 1999 until the first quarter of 2003 as the measure reaches as high as 0.20. These results are similar to those reported by Caporale et al. (2008) and Tessaromatis and Thomas (2009) using the alternative testing methodologies reported above even though the former study supports evidence of herding up to 2008.

As far as the existence of herding among the three portfolios is concerned, it is interesting to see that not all of them have the same behaviour. For example, the high beta portfolio (HIGHHM) has a positive herd measure that starts from the early of 1997 up to the middle of 2004. It almost presents similar characteristics to the overall market although they differ in magnitude. The herding measure of this portfolio is almost doubled and reaches as high as 0.4. The strong evidence of herding during this period coincides with major changes happened in Greece. First, the number of listed companies increased significantly while the introduction of electronic trading system improved the liquidity. Furthermore, Greece adopted the euro in 2001 while the euro banknotes and coins were introduced on 1 January 2002, after a transitional period of one year. Since then and up to the first semester of 2008 adverse herding is present. It is worth reporting here that some herding also exists even a few months before the Greek support package on 2 May 2010, which led to contagion effects to some of the EU countries as part of re-assessment of risk by investors according to the 61st European Economy occasional paper published in May 2010. As far as the low beta portfolio (LOWHM) is concerned, it exhibits adverse herding from 1995 up to late 2001, though at a decreasing rate. Around the introduction of the euro in Greece, herding of this particular portfolio also passes to positive values. When examining the medium beta portfolio (MEDIUMHM), herding is observed from the early 1997 up to late 1998 and for the whole 2001-2003 period. Although the differences observed above for the aforementioned portfolios are significant, they tend to disappear during the second observed period of herding which starts rising from the middle of 2008.

Figure 7.1: The evolution of Herding measure towards market.



7.5.2 Herding behaviour for size based portfolios

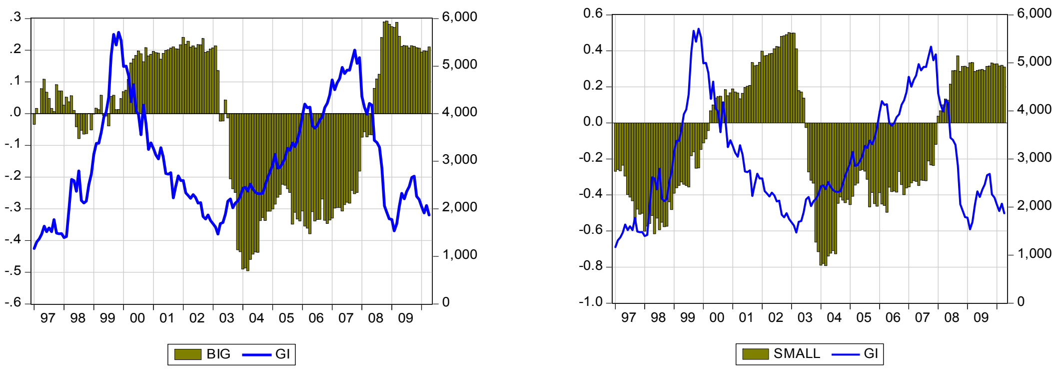
This part of the chapter examines the presence of herding or adverse herding for portfolios formed on size. ‘Size effect’ has been detected for this specific market (Theriou et al., 2005), while Wermers (1999) refers that herding is greater in small growth stocks. To construct portfolios according to size, we split the selected stocks in two groups regarding their total capitalization. The covered period starts from 1997 for achieving similar number of stocks contained at each portfolio. Table 7.4 presents the results for both state space models. The portfolios exhibit signs of herding as indicated by the $\sigma_{m\eta}$ for all cases. The volatility of factor sensitivities, $Std_c(\beta^b_{imt})$, for both portfolios is influenced by the two additional variables. It increases with the level of market returns and decreases with market volatility suggesting that herd behaviour exists independently of the particular state of the market. Figure 7.2 demonstrates as previously done the evolution of herding for the size-based portfolios. It is worth reporting that differences are observed only at the early period of the sample. More concretely, small portfolio exhibits adverse herding over the 1997-1999 period, instead of some weak signs of herding in the big portfolio. For the remaining period they tend to follow almost identical pattern.

Table 7.4: Estimates of state-space model and Herd measure for size-based portfolios.

Portfolio	μ	φ_m	$\sigma_{m\eta}$	r_m	$\log \sigma_m$
M.1 Small	-1.107 (-3.98)*	0.983 (68.0)*	0.062 (72.1)*		
M.2 Small	-1.751 (-4.61)*	0.982 (64.0)*	0.616 (78.0)*	0.070 (1.71)**	-0.254(-2.79)*
M.1 Big	-1.119 (-8.48)*	0.969 (53.6)*	0.047 (94.8)*		
M.2 Big	-2.354 (-11.1)*	0.967 (56.5)*	0.044 (104.4)*	0.020 (0.91)	-0.488 (-6.69)*

Notes: The table reports the results of both state space Kalman filtered models on portfolios formed on size.
t-statistic in parenthesis
* and ** represent significance at 5% and 10% level respectively.

Figure 7.2: The evolution of herding measure for size based portfolios.



7.5.3 The estimated volatility measures

The estimated within monthly volatility and autocorrelation from 1995 to 2010 are depicted in figure 7.3. From this graph, two particularly volatile periods can be easily identified, though they differ in duration. The first volatile period with intense spikes starts from early 1997 up to late 2002. During this period, as mentioned above, there was a significant increase in ASE up to 1999. The following years the uncertainty prevailed resulting in volatility to remain in high levels. The second volatile period is attributed to the global financial crisis. It started on 9 August 2007, when BNP Paribas announced that it was ceasing activity in three hedge funds that specialized in US mortgage debt and culminated with the collapse of Lehman Brothers on 15 September 2008. In October 2008, it has been observed the highest level of volatility ever. Regarding autocorrelation, it surpasses the 10% of total volatility in the referred periods and reaches as high as 20% in early 1998 and in the middle of 2008.

Figure 7.3: The estimated market volatility and autocorrelation using within monthly daily returns.

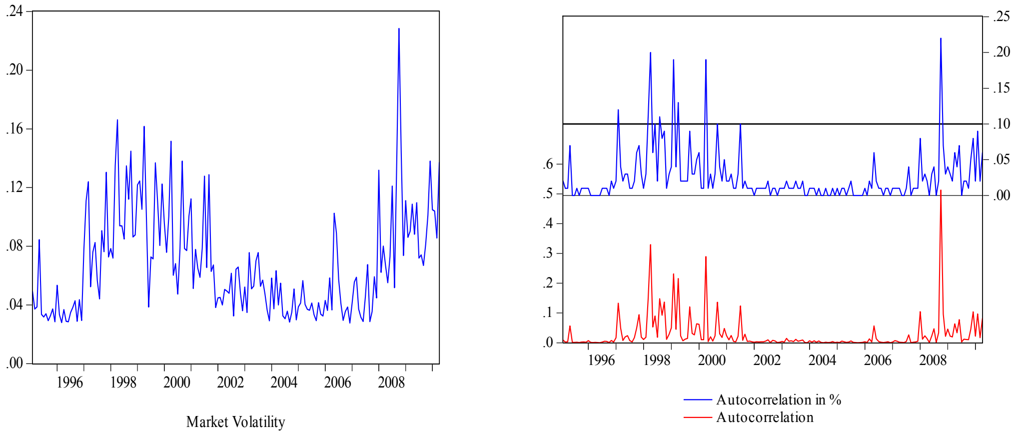
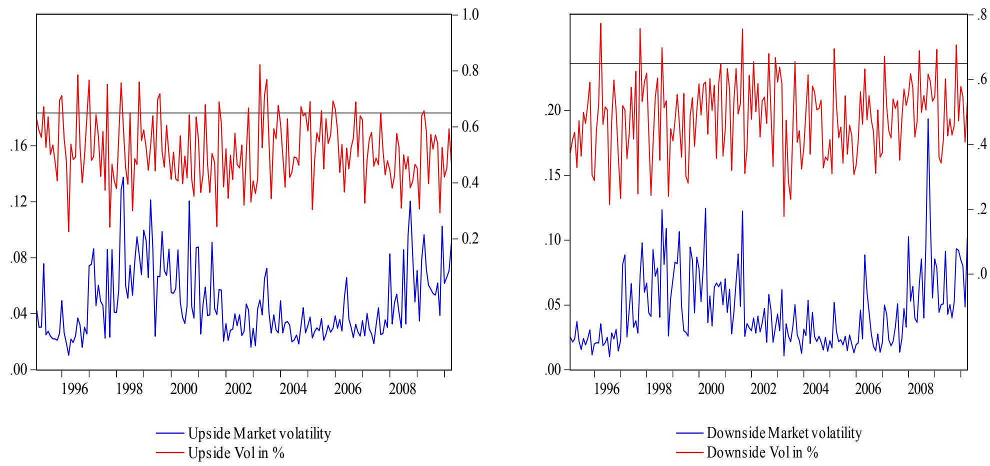


Figure 7.4 presents the decomposition of volatility into upside and downside volatilities. The upside risk accounts for more than 65% of total monthly volatility during the first period referred above in many cases. We arbitrarily chose this level in order to designate a point above which investors possibly feel comfortable and optimistic about the future prospects of the index. The last time that such a high level of upside volatility was observed was in September 1999. Since then and up to April 2001 it remained constantly below 65%. The number of cases related to downside volatility is far smaller than upside volatility. There are just three such cases during the period from 1995 up to August 1998 and another three during the global financial crisis.

Bearing in mind the high levels of upside and downside volatilities happened in some months, we test the returns following those months. We make the naïve assumption that when upside volatility of a given month is more than a critical level of the total volatility (we defined it to be at 65%) then it might exist investment opportunities. There are 24 cases of upside volatility being higher than the 65% level. The average monthly and quarterly returns followed the referenced month were 5.10% and 7.06% respectively. Both series found to be statistically significant at the 5% level. This fact could possibly indicate that it might be the existence of herding that triggers such behaviour. However, when the downside volatility is considered no investment opportunities are being observed.

Figure 7.4: The decomposition of total volatility into upside and downside volatilities.



7.5.4 The effects of herding on market volatility

Having obtained the volatility measures, we are able to examine the linear effect of herding on calculated volatility. By doing this we first need to test for stationarity. This test suggests that the first and second moments of each variable do not vary with time otherwise the model will be invalid and may contain ‘spurious regression results’ (Granger and Newbold, 1974). Deviations from stationarity can be examined by controlling for ‘unit roots’ within the data. The Augmented Dickey Fuller test (ADF) has been carried out in this study assessing whether a unit root is present or not in a variable. The initial different herding measures are found to be non stationary, hence unit root has been removed by taking the first differences (i.e. DY(t) =Y(t)-Y(t-1)). After differencing the data, the variables became stationary at all levels of significance. We then run the following regression:

$$\sigma_{zmt} = c + b_1 DH_{it} + b_2 DH_{it-1} + b_3 DH_{it-2} + \ldots + b_n DH_{it-n} + v_{it} \qquad 7.13$$

In equation 7.13, σ_{zmt} is the estimated zth measure of market volatility on month t (z=1,…5), DH_{it} is the first differences of herding measure i on month t and DH_{it-n} is the nth lagged value of herding as in Venezia et al., (2009). Table 7.5 presents the results of only statistically significant estimators at least at the 10% level. Overall, we find herding measures to have a significantly positive effect on all measures of volatility. This suggests that stocks exhibiting higher levels of herding or adverse herding will also present higher volatility. The results are consistent with those of Venezia et al. (2009) and Blasco et al. (2012).

The estimated GARCH and TARCH measures of volatility generally show that contemporaneous values of herding do not affect them. The γ coefficient of the TARCH model is on average 0.12 indicating that there are asymmetries in the news. Specifically, bad news has larger effects on the volatility of the series than good news. It is interesting to note that upside volatility is influenced by the one month lagged herding value no matter what herding measure is. This can be the reason why high levels of upside volatility in a given month lead to statistically significant positive returns in the next consecutive months. Another interesting point relates to downside volatility. The herding effects on this particular volatility measure reach up to two months lagged, signalling that investors possibly 'run in the exit' when negative conditions prevail in the market. The effects of small and large cap herding measures support our previous findings. In general, we could claim that herding in the ASE might be considered an additional risk factor, which increases market volatility as also reported by Blansco et al. (2012) for the Spanish stock market. However, a lot of variation of market volatility left unexplained by the model as the statistically significant constants indicate. We also ran Granger causality test, the results of which show that herding 'causes' volatility but not vice versa as exactly found by Venezia et al. (2009).

Table 7.5: The effects of herding on volatility.

Total	FSS Vol.	Upside Vol.	Downside Vol.	GARCH	TGARCH
c	0.068 (0.00)*	0.047 (0.00)*	0.046 (0.00)*	0.060 (0.00)*	0.055 (0.00)*
b_1	0.067 (0.03)*	0.065 (0.02)*	0.067 (0.03)*		
b_2	0.103 (0.04)*		0.082 (0.03)*	0.066 (0.03)**	0.054 (0.03)**
b_3				0.064 (0.04)**	
High	**Sq. returns**	**Upside Vol.**	**Downside Vol.**	**GARCH**	**TGARCH**
c	0.068 (0.00)*	0.047 (0.00)*	0.046 (0.00)*	0.060 (0.00)*	0.055 (0.00)*
b_1	0.051 (0.02)**		0.054 (0.02)*	0.057 (0.03)*	
b_2	0.082 (0.03)*	0.048 (0.02)*	0.071 (0.02)*		0.054 (0.03)**
b_3					

Table 7.5 continued

Low	Sq. returns	Upside Vol.	Downside Vol.	GARCH	TGARCH
c	0.067 (0.00)*	0.045 (0.00)*	0.044 (0.00)*	0.060 (0.00)*	0.052 (0.00)*
b_1	0.116 (0.05)*		0.104 (0.04)*		
b_2	0.208 (0.07)*	0.111 (0.04)*	0.184 (0.06)*		
b_3			0.089 (0.05)**	0.169 (0.08)*	0.075 (0.06)
Small	Sq. returns	Upside Vol.	Downside Vol.	GARCH	TGARCH
c	0.072 (0.00)*	0.049 (0.00)*	0.049 (0.00)*	0.064 (0.00)*	0.058 (0.00)*
b_1			0.071 (0.04)**		
b_2	0.075 (0.04)**	0.052 (0.03)**			
b_3				0.056 (0.04)	0.026 (0.04)
Big	Sq. returns	Upside Vol.	Downside Vol.	GARCH	TGARCH
c	0.071 (0.00)*	0.049 (0.00)*	0.048 (0.00)*	0.064 (0.00)*	0.056 (0.00)*
b_1	0.106 (0.05)**		0.118 (0.05)*	0.055 (0.09)	0.020 (0.08)
b_2	0.199 (0.07)*	0.120 (0.04)*	0.168 (0.06)*		
b_3					

Notes: The table reports the regression results of the estimated herding measures on the estimated volatilities as shown in equation 7.13.
Standard error in parenthesis.
* and ** represent significance at 5% and 10% level respectively.

7.6 Conclusions

In this chapter, the cross sectional variance of betas is used for investigating primarily the herd behaviour towards General Market Index of the ASE and how volatility is affected by its presence. The selected stocks represent almost the 95% of the total capitalization of the Athens General Index and the 81% of the whole market. Different portfolios are formed based on the magnitude of the estimated betas as well as on size. The total beta portfolio counts for the overall market behaviour. There is evidence of herding over the 1998-2003 period, a result consistent with previous studies, while herding also exists from the very early of 2008 up to the last selected month. As far as the beta based portfolios are concerned, we find different periods of herding. The high beta portfolio has a positive herd measure that starts from the early of 1997 until the middle of 2004 depicting similar characteristics to the overall market. The low beta portfolio exhibits from the very beginning of 1995 and up to 2001 adverse herding, though at a decreasing rate. When examining the medium beta portfolio, herding is observed from the early 1997 up to late 1998 and for the whole

2001-2003 period. Although the differences observed above for the aforementioned portfolios are significant, they tend to disappear during the second observed period of herding which starts rising from the middle of 2008. For the size based portfolios, they show differences only for the first three years of the selected sample.

The results associated with the augmented state space model 2 exhibit that market return and volatility are statistically significant only for the low and high beta portfolios respectively. There is evidence that the volatility of factor sensitivities, $Std_c(\beta_{imt}^b)$, for the low portfolio increases as market return increases. This fact possibly indicates that conservative investors, as regards the ones invested in low beta stocks, start participating in market when conditions are favourable. For the high beta portfolio, the volatility of factor sensitivities decreases with market volatility. The result consistent with previous studies suggests that herding for this specific portfolio is more likely to occur during highly volatile periods.

The presence of herding as mentioned earlier has important implications on market volatility. We use four different measures of market volatility such as the GARCH(1,1) and the TGARCH, the volatility measure of French et al. (1987) which takes into consideration the autocorrelation in daily returns as well as the upside and downside volatility coming from the summation of positive and negative daily market returns respectively. The results, consistent with previous studies, indicate that herding positively affect volatility measures. Hence, stocks exhibiting higher levels of herding or adverse herding will also present higher volatility. From this point of view, herding is considered to be an additional risk factor that can lead market participants and investors to a better understanding of market risk, asset pricing and of course asset allocation.

CHAPTER 8

HIGHER MOMENT CAPM, CONTAGION OF HERDING AND MACROECONOMIC SHOCKS

8.1 Introduction

The Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965) is important in finance as it gives the simplest systematic explanation of risk and return. However, as we mentioned earlier in this thesis, the model has come under scrutiny since empirical findings indicate that asset returns cannot be explained by the market beta alone. For example, a number of studies show that average returns are also determined by the firm size, earnings yield, leverage, book-to-market and prior return (*inter alia*: Basu, 1977; Banz, 1981; Bhandari, 1988; Jegadeesh, 1990; Fama and French, 1992). These pricing anomalies, though debatable, suggest that the mean variance CAPM is not a satisfactory description of market equilibrium.

The international literature also demonstrates that apart from the pricing of the first co-moment of stock returns with the market return, differences in average returns across assets relate to systematic third and fourth moments of the return distribution. Kraus and Litzenberger (1976) were the first to suggest that higher co-moments may also be significant in explaining stock returns. The authors argued that if the normality assumption of market returns is rejected, investors should also take into consideration portfolio skewness and kurtosis. If this happens then each stock's contribution to systematic skewness (co-skewness) and systematic kurtosis (co-kurtosis) may determine the attractiveness of a stock and consequently the required return (Hung et al., 2004). Harvey and Siddique (2000) show that co-skewness along with a market portfolio proxy becomes a significant factor in explaining the cross-section of returns for stocks traded on the US market. The authors report that the systematic skewness requires an average annual risk premium of 3.6%. Fang and Lai (1997) depict evidence that the expected excess rate of returns are also related to both systematic skewness and systematic kurtosis. Dittmar (2002) presents a framework of a 4-moment CAPM in a conditional setting and shows that cokurtosis and coskewness factors are priced. Smith (2007) finds the price of coskewness risk to be large when market skewness is negative. More recently, Poti and Wang (2010) find that, while coskewness and cokurtosis risk help price different strategies and portfolios, momentum strategies and portfolios managed on the basis of available information neither CAPM nor its higher versions can give consistent results without generating high levels of SDF volatility. Hwang and Satchell (1999) refer that both systematic risks are significant in emerging markets while similar results are reported by Messis et al. (2007) for the Greek market. Moreno and Rodriguez (2009) conclude that coskewness factor is economically and statistically meaningful in evaluating mutual fund performance. Coskewness has also been used in the pricing of real estate (Vines et al., 1994), in explaining the return generating process in futures markets (Christie-David and Chaudhry, 2001) or in the estimation of conditional VaR (Bali et al., 2008).

In such models of equilibrium, the simultaneous execution of a large number of trades produces efficient outcomes. However, the existence of herding behaviour from market participants makes the equilibrium inefficient, even in the long run (Avery and Zemsky, 1998). Moreover, in cases where extreme market conditions are present, diversification may become unattainable since asset returns become almost perfectly correlated (Chang et al., 2000; Baur, 2006).

In empirical studies, the estimation of herding can be classified into two main categories (Spyrou, 2013). The first one investigates the existence of herding on specific investor types such as institutional investors. The herding measure of this category was first proposed by Lakonishok et al. (1992) and improved by Sias (2004). The second category investigates herding towards market consensus by relying on aggregate price and market activity data. This category is primarily based on measures proposed by Cristie and Huang (1995), Chang et al. (2000) and Hwang and Salmon

(2004) and is widely used in the literature (Spyrou, 2013). In addition, the measures of the latter category are relatively easy to calculate since they are based on observed returns data and not on detailed records of individual trading activities such as the measure proposed by Lakonishok et al. (1992) (Hwang and Salmon, 2004).

This part of the thesis contributes in the literature with different ways. In the light of the above that higher co-moments are capable of explaining asset returns, we firstly investigate whether herding also matters towards those additional factors in five major developed markets (i.e. USA, UK, Germany, France and China). To our knowledge this is done for first time since most of the papers test herding towards the factors of Fama and French (1993) model. Second, a number of studies have documented that unexpected variations in different macroeconomic variables or uncertainty shocks such as the 9/11 terrorist attacks influence stock prices and increase volatility (*inter alia*: Fama, 1981; Pearce and Roley, 1985; Wasserfallen, 1989; Gjerde and Saettem, 1999; Hondroyiannis and Papapetrou, 2001, Bloom, 2009). This fact motivates us to empirically examine the effects of unexpected components of some selected macroeconomic variables on the estimated herding measures. To achieve our goal and catch any macroeconomic shocks we make use of the Box-Jenkins methodology. Finally, we investigate whether contagion of herding between the selected countries exists. If this happens, the benefits of international portfolio diversification diminish. For example, Economou et al. (2011) argue that there is a great degree of co-movements in herding measures across four different European countries. We extend the analysis by investigating whether contagion of herding matters due to macroeconomic shocks or crises period. Estimated conditional correlations are used for this purpose. Next section provides methodological details and section 3 describes the data. In section 4, we present the empirical results and in section 5, we conclude.

8.2 Methodology

8.2.1 CAPM and Higher Moment CAPM

According to Modern Portfolio Theory, which was first introduced by Markowitz (1952), investors have an aversion to risk, they are looking for assets in terms of the distribution of returns, while the following conditions are satisfied (Alexander,2002):

$\partial U / \partial \mu > 0, \partial U / \partial \sigma < 0; \partial^2 U / \partial \mu^2 < 0, \partial^2 U / \partial \sigma^2 < 0$.

The CAPM which specifies the relationship between risk and return has the following form:

$$R_{it} - R_{ft} = a_i + \beta_i (R_{mt} - R_{ft}) + e_{it} \qquad \text{MODEL 1} \qquad 8.1$$

with $R_{it} - R_{ft}$ being the excess return of asset i, $R_{mt} - R_{ft}$ the market excess return, β_i the systematic risk and α_i and e_{it} are assumed to be zero according to the model.

Kraus and Litzenberger (1976) and Harvey and Siddique (2000) developed asset pricing models incorporating coskewness term into CAPM. Loadings on market premium and premium squared can be estimated as follows:

$$R_{it} - R_{ft} = a_i + \beta_i (R_{mt} - R_{ft}) + \gamma_i (R_{mt} - R_{ft})^2 + e_{it} \qquad \text{MODEL 2} \qquad 8.2$$

where β_i is the same as above, while γ_i depicts systematic skewness.

Model 3 except for systematic variance and systematic skewness incorporates systematic kurtosis. Thus, for the model's empirical estimation we run the following time series regression as in Fang and Lai (1997) and Hung et al. (2004):

$$R_{it} - R_{ft} = a_i + \beta_i (R_{mt} - R_{ft}) + \gamma_i (R_{mt} - R_{ft})^2 + \delta_i (R_{mt} - R_{ft})^3 + e_{it} \qquad \text{MODEL 3} \qquad 8.3$$

where δ_i is the loading of cokurtosis factor for asset i.

The measures of coskewness and cokurtosis are robust to portfolio (dis)aggregation because although non-linear in the market they are both linear in the stock component itself and consistent with asset pricing models (Hung et al., 2004). Investors tend to have negative preference to variance and kurtosis and positive preference to right-skewed securities (Arditti, 1967; Fang and Lai, 1997; Harvey and Siddique, 2000).

8.2.2 The measure of Herding

The model used for the measurement of herding is that of Hwang and Salmon (2004), as herding behaviours can also be present under normal market conditions. In equilibrium and according to CAPM equation 8.4 should hold:

$$E_t(r_{i,t}) = b_{i,t} E(r_{m,t}) . \qquad 8.4$$

However, when herding towards market exists, instead of the above equilibrium relationship, the authors suggest the following relationship:

$$\frac{E_t^b(r_{it})}{E_t(r_{mt})} = \beta_{imt}^b = \beta_{imt} - h_{mt}(\beta_{imt} - 1), \qquad 8.5$$

where $E_t^b(r_{it})$ and β_{imt}^b are the biased expected returns on the asset and the observed beta respectively. h_{mt} is a latent herding parameter that changes over time.

Because herding represents market wide behaviour, it is preferable to use all assets in the market than a single asset to eliminate the effects of idiosyncratic movements in any individual β_{it}^b. The cross section mean of β_{it}^b (β_{it}) is 1 regardless of whether β_{it} is biased or not. Thus, the cross sectional standard deviation is:

$$Std_c(\beta_{it}^b) = Std_c(\beta_{it})(1 - h_{mt}). \qquad 8.6$$

Taking logarithms on both sides of equation 8.6 we have,

$$\log[Std_c(\beta_{it}^b)] = \log[Std_c(\beta_{it})] + \log(1 - h_{mt}). \qquad 8.7$$

Defining $H_{mt} = \log(1 - h_{mt})$ and $\mu_t = E(\log[Std_c(\beta_{it})])$ we can write when herding is absent, $\log[Std_c(\beta_{it})] = \mu_t + v_{mt}$ assuming that $v_{mt} \sim iid(0, \sigma_{mv}^2)$. In the presence of herding, the following holds:

$$\log[Std_c(\beta_{it}^b)] = \mu_m + H_{mt} + v_{mt}. \qquad 8.8$$

Allowing H_{mt} to evolve over time and assuming it follows an AR(1) process then:

$$H_{mt} = \varphi H_{mt-1} + \eta_{mt}, \qquad 8.9$$

where $\eta_{mt} \sim iid(0, \sigma_{m\eta}^2)$. The Kalman filter approach can be used for estimating equation 8.9. A significant value of $\sigma_{m\eta}^2$ indicates the existence of herding and a significant φ supports the AR(1) process, while $|\varphi_m| \le 1$ so as to not explode, making the series H_{mt} non stationary.

At the same context and having previously estimated the OLS sensitivities for the higher-moment CAPM, herding towards coskewness at time t, h_{cskt}, can be captured by equation 8.10 :

$$\gamma_{it}^b = \gamma_{it} - h_{cskt}(\gamma_{it} - E_c[\gamma_{it}]), \qquad 8.10$$

with $E_c[\gamma_{it}]$ being the cross-sectional expected beta for coskewness at time t. When h_{csk}=1, there is perfect herding and thus $\gamma_{it}^b = E_c[\gamma_{it}]$ for all i, implying that all securities will respond in unison given changes in the factor. As far as herding towards cokurtosis (i.e. h_{ckurt}) is concerned, it is defined in the same way with the difference being that coefficient δ of equation 8.3 is currently being considered. All the assumptions used in the case of CAPM also hold here.

8.3 Data description

The data set used in this study concerns the constituents of five major indexes. The indexes are the S&P 500 for US, the FTSE 100 for UK, the DAX for Germany, the CAC for France and the HSI for China. The covered period is from June 2003 to August 2011. The monthly continuous compounding adjusted returns have been used. To calculate the excess returns, we employ the 1M-Treasury Bill for the US market, the 1M Euribor rate for the Germany and France markets, the 1M- Libor rate for the UK market and the 3M-Deposit rate for the Chinese stock market. For the estimation of betas, we are using rolling windows of 24 monthly observations as in Hwang and Salmon (2009). In their analysis, the authors regard herding not as a short-lived phenomenon that arises rapidly but as a more slowly moving procedure where a short run relationship can be proved misleading regarding the level of stock prices. Their argument is based on the fact that the noise, that can be seen as any factors that make asset prices deviate from their fundamental values, may be highly persistent and slow-moving over time as shown by Fama and French (1988). Furthermore, by employing monthly returns instead of daily returns, we reduce the estimation error, with the trade off being the lower number of observations used in the state space models. Securities that have not covered an adequate period of trading for the estimation of betas have been excluded from the sample. In addition, we omit a small number of extreme betas estimates in order to avoid outliers that could possibly affect numerically the beta herd measure. At the same time, the available estimated betas should cover at least the 85% of the constituents of each index. Thus, the starting date of herding measure is June 2003. The summary statistics with regard to indexes are presented in table 8.1. Table 8.1 also demonstrates the number of stocks used to estimate herding measures along with correlation coefficients. From the table, it is clear that minimum return ranges from -13.3% to -23.5%, while the maximum return ranges from 8.61% to 18.7%. All market returns are non-gaussian at the 5% level given the J-B test. The highest correlation coefficient is observed between the CAC and the DAX indexes and the lowest between the DAX and the HSI. The number of stocks starts with 625 in June 2003 and reaches to 709 in August 2011. As for the macroeconomic variables used for testing the effects of shocks on herding measures, they are the Industrial Production Index (IP), the Consumer Price Index (CPI), the Gross Domestic Product (GDP) and the 10Y-Bond rate of each country. The choice of variables has been made arbitrarily, in the sense that they influence the securities in the same degree, implying that all securities operate in the same economic environment and that the particular variables are important to the whole economy. The macro data retrieved from the Eurostat and the Federal Reserve system.

Table 8. 1: Properties of monthly excess market returns and correlation coefficients for all indexes over the period June 2003 to August 2011.

Index	Mean return	Min	Max	Std. Dev.	Skewness	Excess Kurtosis	J-B test	Number of shares Min	Max	Avrg
CAC	0.05%	-17.2%	10.2%	5.13%	-0.894	0.753	15.5	34	40	37.8
DAX	0.55%	-21.3%	15.9%	5.76%	-1.157	2.844	55.4	27	29	27.9
FTSE 100	0.27%	-13.3%	8.61%	4.09%	-0.820	1.206	17.1	72	99	88.7
HSI	0.82%	-23.5%	18.7%	6.79%	-0.443	1.223	9.42	32	42	39.1
S&P 500	0.23%	-18.5%	8.97%	4.37%	-1.164	2.927	21.8	460	499	481.3

Correlation coefficients

	CAC	DAX	FTSE 100	HSI	S&P 500
CAC	1.000	0.862	0.421	0.351	0.451
DAX		1.000	0.410	0.332	0.441
FTSE 100			1.000	0.655	0.812
HSI				1.000	0.723

8.4. Empirical findings

8.4.1 Herding towards the selected factors

Following the procedure described above for the empirical estimation of herding, the first step is the application of OLS method for estimating sensitivities of the three aforementioned models and calculate the cross-sectional standard deviation of the estimated betas to be used in the state space model. We assume that homogeneity holds and each member faces a similar decision problem observing at the same time the trades of other members in the group (Bikhchandani and Sharma, 2001). Table 8.2

shows some statistical properties of the estimated cross-sectional standard deviations of betas for the estimated risk factors. Most of the series are non normal according to the Jarque –Bera test, although the values of the test are generally reduced when the log-cross sectional standard deviation of betas are considered, a finding similar to that of Hwang and Salmon (2004).

Table 8.3 depicts the results of the estimation of H_{mt} (equation 8.8). H_{mt} is highly persistent for all countries as the coefficients of the AR(1) model (i.e. $\hat{\varphi}_m$) are large and statistically significant at each level. Furthermore, they are less than one without exploding, while the same significance shows the $\sigma_{m\eta}$ as we expected in the case of herding. Similar characteristics present the other two risk factors (i.e. coskewness and cokurtosis) apart from the case of FTSE towards coskewness, resulting in to conclude that investors do take into consideration these particular factors.

Figure 8.1 presents the evolution of herding measures $(h_t = 1 - \exp(H_t))$. Starting with the $h_{mt,}$ the herding towards market index, the figure shows several cycles of herding and adverse herding among the countries. In the case of the US market, there was never extreme values of herding or adverse herding as they bounded above and below of almost by 0.2. The same characteristics and the same pattern follow the UK market, although the measure is almost doubled. In relation to the DAX index, it gradually passed from negative values of herding in the middle of 2003 to positive values peaking at the first semester of 2008 where the financial crisis was broken out. Since then it plunged reaching at its lowest level some months before the end of the sample. In the French market, herding seems to follow its own pattern. For example, even though the rest of the countries exhibit an increasing measure of herding since the early period of the sample, the CAC index shows an increasing adverse herding behaviour which took place around late 2004 up to December 2005. Another interesting herd pattern is presented by the HSI. The specific measure continued to grow even when the global financial crisis was in progress, as the shaded area depicts, showing that capital transmission might have been taken place in that country from the other countries.

Table 8. 2: Properties of the cross-sectional standard deviation of betas.

	Cross sectional standard deviation of OLS betas						Log-cross sectional standard deviation of OLS betas					
	MODEL 1	MODEL 2		MODEL 3			MODEL 1	MODEL 2		MODEL 3		
	Market	Market	Skew	Market	Skew	Kurt	Market	Market	Skew	Market	Skew	Kurt
(A) CAC (France)												
Mean	0.886	0.913	2.547	1.025	3.014	12.23	-0.131	-0.098	0.893	0.012	1.071	2.392
Std. dev.	0.130	0.116	0.717	0.168	0.789	5.676	0.144	0.124	0.296	0.159	0.252	0.481
Skewness	0.484	0.569	0.067	0.560	0.704	0.393	0.357	0.424	-0.310	0.432	0.341	0.008
Kurtosis	1.847	2.105	1.739	1.867	2.669	1.722	1.705	1.955	2.060	1.715	1.993	1.562
JB stat	9.355	8.654	6.632	10.46	8.632	9.288	9.024	7.478	5.236*	9.891	6.099	8.527
(B) DAX (Germany)												
Mean	0.774	0.775	5.590	0.941	7.375	115.8	-0.278	-0.265	1.561	-0.088	1.852	4.314
Std. dev.	0.166	0.112	3.150	0.219	3.801	104.1	0.216	0.150	0.571	0.239	0.562	0.963
Skewness	0.240	-0.246	0.656	0.206	0.399	0.874	-0.075	-0.468	0.077	-0.240	-0.265	0.158
Kurtosis	2.117	1.976	2.108	2.449	1.852	2.480	1.968	2.277	1.875	2.255	2.188	1.809
JB stat	4.170*	5.329*	10.39	1.952*	8.058	13.71	4.484*	5.770*	5.312*	3.241*	3.880*	6.257
(D) FTSE 100 (UK)												
Mean	0.810	0.831	13.96	1.147	19.42	457.2	-0.233	-0.207	2.434	0.123	2.736	5.688
Std. dev.	0.167	0.170	9.042	0.195	14.13	411.9	0.218	0.221	0.632	0.170	0.662	0.947
Skewness	-0.265	-0.455	0.734	0.352	1.184	0.751	-0.435	-0.617	0.350	-0.022	0.471	0.322
Kurtosis	1.585	1.727	1.979	2.668	3.136	1.891	1.726	1.851	1.566	2.435	1.959	1.518
JB stat	9.419	10.09	13.19	2.505*	23.23	14.37	9.809	11.72	10.49	1.320*	8.122	10.76
(C) HSI (China)												
Mean	0.698	0.698	3.993	1.075	5.301	103.1	-0.416	-0.396	1.250	0.010	1.480	4.193
Std. dev.	0.215	0.182	1.886	0.370	2.895	83.74	0.354	0.286	0.548	0.359	0.655	1.044
Skewness	-0.463	-0.329	0.159	0.204	0.159	0.734	-0.687	-0.610	-0.410	-0.156	-0.400	-0.329
Kurtosis	1.671	1.825	1.583	1.774	1.875	2.653	1.891	2.006	1.712	1.705	1.644	1.705
JB stat	10.81	7.496	8.298	6.885	5.635*	9.390	12.86	10.22	9.613	7.318	10.22	8.705
(E) S&P 500 (US)												
Mean	1.190	1.225	16.03	1.499	20.40	654.4	0.168	0.200	2.476	0.384	2.754	5.711
Std. dev.	0.122	0.102	11.94	0.313	13.72	697.5	0.101	0.082	0.785	0.199	0.750	1.340
Skewness	0.530	0.609	0.586	0.734	0.360	0.783	0.387	0.439	0.233	0.525	0.005	0.141
Kurtosis	2.245	2.732	1.680	2.300	1.478	2.021	2.082	2.599	1.365	1.941	1.268	1.417
JB stat	6.994	6.435	12.86	10.90	11.69	14.08	5.955*	3.849*	11.92	9.175	12.41	10.65

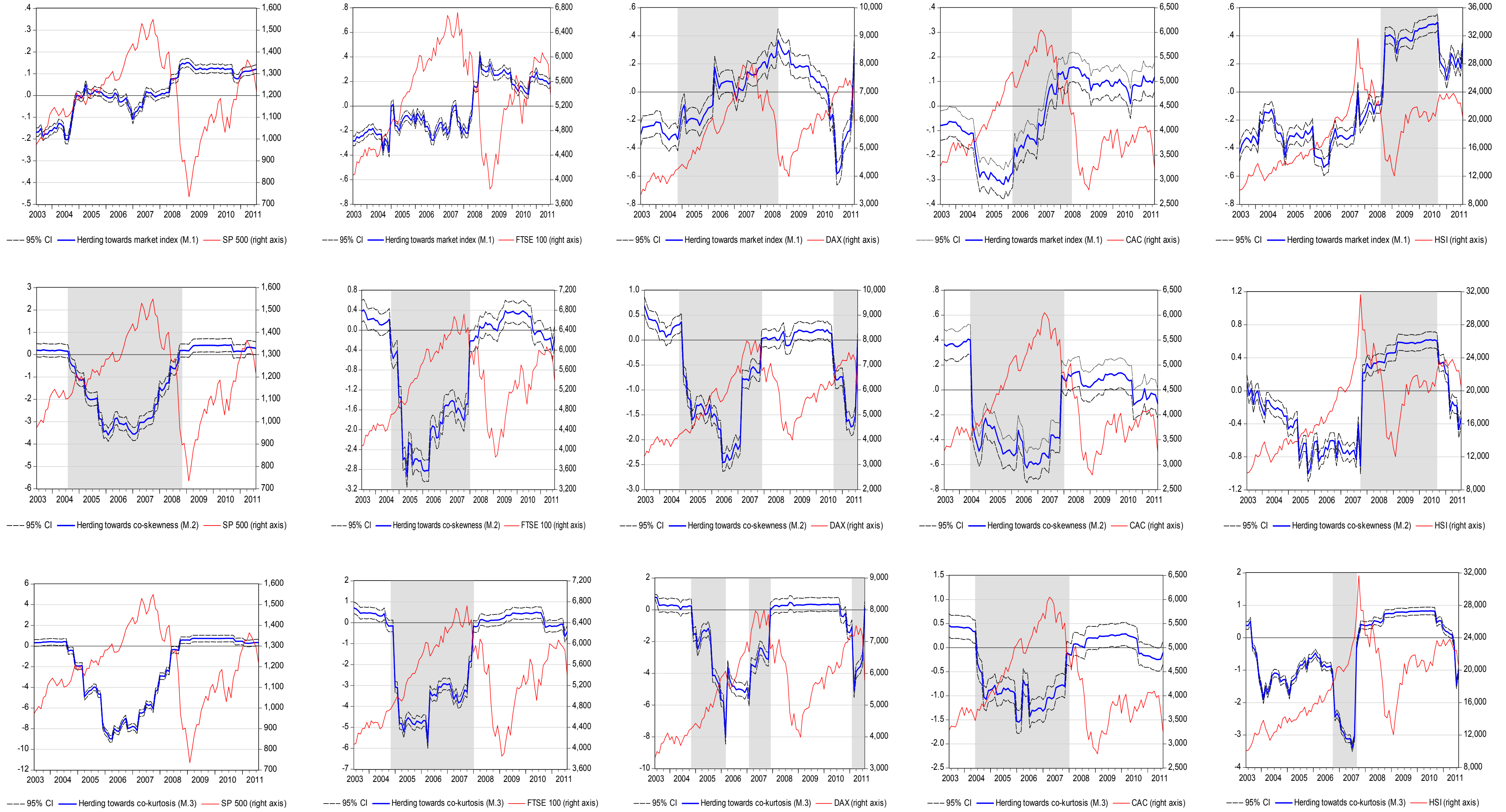
Notes: * represents normality according to J-B test at 5% level. Betas on each model are calculated using OLS method and a 24 months rolling window. The estimated betas of each model were used to obtain their corresponding cross-sectional standard deviation.

Table 8.3: Estimates of state-space model and Herd measure.

	MODEL 1	MODEL 2		MODEL 3		
	Beta coef	Beta coef	Skew coef	Beta coef	Skew coef	Kurt coef
CAC						
μ	-0.136 (0.431)	-0.105 (0.333)	0.816 (0.282)*	0.012 (0.086)	0.994 (0.341)*	2.246 (0.0.425)*
φ	0.971 (0.212)*	0.972 (0.266)*	0.962 (0.056)*	0.988 (0.032)*	0.967 (0.075)*	0.972 (0.053)*
σ_v	0.063 (0.022)*	0.069 (0.024)*	0.107 (0.049)*	0.160 (0.047)*	0.099 (0.043)*	0.101 (0.041)*
σ_η	0.005 (0.002)*	0.003 (0.001)*	0.023 (0.010)*	0.001 (0.000)*	0.015 (0.006)*	0.043 (0.019)*
DAX						
μ	-0.229 (0.333)	-0.242 (0.247)	1.488 (0.485)*	-0.081 (0.249)	1.773 (0.474)*	3.949 (0.663)*
φ	0.965 (0.131)*	0.959 (0.221)*	0.958 (0.104)*	0.942 (0.107)*	0.955 (0.073)*	0.971 (0.022)*
σ_v	0.088 (0.031)*	0.092 (0.036)*	0.215 (0.086)*	0.116 (0.052)*	0.256 (0.104)*	0.165 (0.074)*
σ_η	0.012 (0.004)*	0.006 (0.002)*	0.042 (0.015)*	0.018 (0.007)*	0.041 (0.015)*	0.146 (0.069)
FTSE 100						
μ	-0.234 (0.241)	-0.253 (0.557)	2.241 (0.607)*	0.116 (0.286)	2.443 (0.432)*	5.331 (0.626)*
φ	0.982 (0.084)*	0.985 (0.078)*	0.976 (0.049)*	0.966 (0.244)*	0.975 (0.032)*	0.979 (0.034)*
σ_v	0.095 (0.042)*	0.074 (0.028)*	0.104 (0.045)*	0.078 (0.019)*	0.145 (0.068)*	0.121 (0.057)*
σ_η	0.008 (0.003)*	0.008 (0.002)*	0.055 (0.024)*	0.007 (0.001)*	0.064 (0.035)	0.099 (0.048)*
HSI						
μ	-0.418 (0.512)	-0.406 (0.379)	1.305 (0.617)*	-0.091 (0.545)	1.514 (0.623)*	4.269 (0.721)*
φ	0.986 (0.051)*	0.974 (0.069)*	0.971 (0.039)*	0.978 (0.053)*	0.968 (0.046)*	0.968 (0.032)*
σ_v	0.101 (0.039)*	0.085 (0.032)*	0.106 (0.052)*	0.114 (0.043)*	0.139 (0.068)*	0.131 (0.064)*
σ_η	0.018 (0.008)*	0.015 (0.006)*	0.045 (0.018)*	0.021 (0.007)*	0.066 (0.024)*	0.125 (0.053)*
S&P 500						
μ	0.171 (0.241)	0.208 (0.139)	2.205 (2.070)*	0.218 (0.170)*	2.401 (2.424)	5.347(2.37)*
φ	0.975 (0.470)*	0.992 (0.033)*	0.976 (0.087)*	0.995 (0.031)*	0.977 (0.093)*	0.979(0.053)*
σ_v	0.068 (0.023)*	0.026 (0.010)*	0.135 (0.046)*	0.014 (0.006)*	0.167 (0.071)*	0.178 (0.074)*
σ_η	0.002 (0.001*	0.003 (0.001)*	0.051 (0.017)*	0.006 (0.003)*	0.048 (0.021)*	0.100 (0.037)*

Notes: *represents significance at 5% level. The table reports the Kalman filtered state space model of equation (8) for all factors and markets. The first, second and fourth columns represent the market betas coming from each model, while the third and fifth columns depict the coskewness. The last column refers to cokurtosis. Each one of the state space models has been estimated using 99 observations, from June 2003 to August 2011.

Figure 8. 1: Evolution of herding towards different measures of risk for all indexes.



With regard to herding behaviour towards coskewness and cokurtosis factors, we can clearly observe its existence. As we mentioned earlier, all standard deviations of residuals of these factors apart from one case (i.e.η_{skt} and η_{kurt}) are highly significant. It is interesting to note that when markets were starting to rise, the specific herding measures went down, showing that stocks with higher than average sensitivities went down further, depicting a fact that investors might have bought stocks with lower skewness or kurtosis. In addition, because of the rise in the markets was at its early stage, investors couldn't afford high levels of kurtosis as they might not have been yet confident about the long run market direction. In a later stage, when the indexes were continuing to rise, herding towards systematic skewness and systematic kurtosis started to climb, as investors preferred stocks with higher skewness and kurtosis betas for taking the advantage of extreme market conditions under the presumption that positive events will be more frequent than negative ones.

8.4.2 The effects of macroeconomic shocks on herding

The main issue we explore in this section is the effects of macroeconomic shocks on the estimated herd measures towards market. However, the first thing needs to be done is to catch unexpected components of the selected macroeconomic variables. For this purpose, we employ the Box-Jenkins methodology of an ARIMA (p,d,q) model. According to Wasserfallen (1989), the in-sample residuals from ARIMA models can be used as proxies for unexpected components, implying that expectations are partly rational. However, the underlying forecast is only based on the history of the series itself. In addition, we should have in mind that the use of estimated ARIMA residuals as explanatory variables can give consistent parameter estimates but overstated levels of significance (Pagan, 1984). The effects of macroeconomic shocks on the estimated herd measures are evaluated using the Box-Jenkins methodology of an ARIMA (p,d,q) model.

To begin with, the general form of an ARIMA (p,d,q) model is as follows:

$$A(L)(1-L)^d Y_t = \delta + \Theta(L)\varepsilon_t, \qquad 8.11$$

where L is the lag operator, d is the number of differences for becoming the stochastic variable Y stationary, $A(L) = 1 - \alpha_1 L - ... - a_p L^p$ and $\Theta(L) = 1 - \theta_1 L - ... - \theta_q L^q$. Table 8.4 presents the structure of the estimated ARIMA models for the examined macroeconomic variables, the residuals of which are going to be used for investigating the effects of macroeconomic shocks on herding. From the table it seems that the selected variables are integrated of order 1, while the orders p and q vary significantly. The highest R squared value appears to have the Gross Domestic Product and the lowest the 10YB.

Table 8.4: The structure of the estimated ARIMA models of all macroeconomic variables being considered.

	USA	UK	Germany	France
Industrial Production Index				
ARIMA structure	(2,1,0)	(3,1,2)	(3,1,3)	(1,1,2)
SBC	-6.04	-6.40	-5.07	-5.48
Rsq.	0.384	0.082	0.235	0.146
Harmonised CPS/BY 2005				
ARIMA structure	(2,1,1)	(2,1,1)	(2,1,2)	(2,1,2)
SBC	-7.30	-8.14	-8.16	-8.44
Rsq.	0.251	0.086	0.147	0.057
Gross Domestic Product				
ARIMA structure	(3,1,1)	(4,1,2)	(3,1,2)	(4,1,3)
SBC	-7.50	-5.22	-5.45	-6.50
Rsq.	0.738	0.837	0.758	0.954
10YB/Constant maturity rate				
ARIMA structure	(1,1,2)	(1,1,0)	(0,1,1)	(0,1,1)
SBC	-2.01	-3.04	-3.07	-3.41
Rsq.	0.119	0.185	0.093	0.081

Notes: Parentheses depict the orders of p, d and q respectively.

With the estimated residuals of the ARIMA models at hands and following Hwang and Salmon (2004), we include them as explanatory variables in equation 8.8. Table 8.5 presents the results. The findings show that there are cases where macroeconomic shocks influence herd behaviour. For example, the $Std_c(\beta_{imt}^b)$ of DAX increases when positive shocks on IP and 10YB happen as the positive and statistically significant coefficients indicate. However, $Std_c(\beta_{imt}^b)$ decreases in the case of the S&P index with the level of IP shocks as the negative sign depicts. The finding might show an overheated US economic activity during the examined period, resulting in negative shocks on IP being taken as good news from investors (Boucher, 1999).

Table 8.5: Effects of macroeconomic shocks on herding.

Portfolio	CAC	DAX	FTSE 100	S&P 500
μ	-0.151 (0.235)	-0.283 (0.131)*	-0.226 (0.129)**	0.189 (0.098)**
φ	0.981 (0.048)*	0.946 (0.044)*	0.944 (0.034)*	0.986 (0.022)*
σ_v	0.025 (0.009)*	0.002 (0.001)*	0.001 (0.000)*	0.000 (0.000)*
σ_η	0.091 (0.003)*	0.071 (0.041)**	0.069 (0.040)**	0.021 (0.009)*
IP shocks	0.152 (0.598)	0.542 (0.321)**	-0.424 (0.748)	-0.198 (0.103)**
GDP shocks	0.389 (1.241)	0.172 (0.915)	0.110 (1.231)	0.291 (1.216)
INFL shocks	0.434 (1.685)	0.353 (1.271)	-0.179 (1.634)	-0.016 (0.422)
10YB shocks	0.040 (0.683)	0.226 (0.133)**	-0.021 (0.145)	0.002 (0.024)

Notes: *, ** represent significance at 5% and 10% level respectively. The estimated herding measures towards market are regressed on macroeconomic shocks of the selected economic variables. Unexpected shocks of each variable are proxied by the respective ARIMA-residuals.

Due to the fact that volatility and market returns have been found to have significant effects on herding, we also present in table 8.6 the results of an augmented state space model as previously done, but this time these two variables are taken as exogenous (Hwang and Salmon, 2004). The monthly return volatility, σ_{mt}, is calculated using squared daily returns (Schwert, 1989; Hwang and Salmon, 2004). Once again, the findings are similar to those reported for the state space model with no exogenous variables regarding the existence of herding. For the additional variables, we observe that the terms of market return and volatility are statistically significant only in two cases these of the FTSE 100 and the DAX respectively. The volatility of factor sensitivities, $Std_c(\beta^b_{imt})$, in the case of FTSE 100 increases as market return increases, while concerning the DAX, $Std_c(\beta^b_{imt})$ decreases when the market becomes riskier. The result of finding only one case with statistically significant volatility is not coming as a surprise. For example, Blasco et al. (2012) and Messis and Zapranis (2014b) support in their studies a direct linear impact of herding on market volatility for the Spanish and the Greek stock market respectively and hence herding might be considered an additional risk factor.

Table 8. 6: Effects of volatility and market returns on herding.

Portfolio	CAC	DAX	FTSE 100	S&P 500
μ	-0.277 (0.322)	-0.512 (0.237)*	-0.288 0.133)*	0.158 0.107)
φ	0.979 (0.036)*	0.969 (0.054)*	0.946 (0.041)*	0.988 (0.023)*
σ_v	0.026 (0.011)*	0.045 (0.019)*	0.003 (0.001)*	0.004 (0.001)*
σ_η	0.081 (0.003)*	0.026 (0.008)*	0.067 (0.035)**	0.015 (0.007)*
r_m	0.105 (0.598)	0.368 (0.263)	0.324 (0.159)*	0.019 (0.065)
$\log \sigma_m$	-0.021 (0.036)	-0.048 0.027)**	-0.010 (0.012)	-0.005 (0.005)

Notes: *, ** represent significance at 5% and 10% level respectively. Results of regressions are shown with exogenous variables being the market returns and volatility calculated using within month daily returns.

8.4.3 Conditional correlations and contagion of herding

In the last part of this chapter, we examine whether contagion of herding between the selected countries exists when adverse economic conditions prevail in a specific country. Economou et al. (2011) using return dispersion models for measuring herding for four different European countries show that there is a great degree of co-movement in returns' dispersion across them. Hence, the authors argue that 'herding forces' diminish the benefits of international portfolio diversification when these particular markets are considered. In order to test for contagion of herding, we estimate conditional correlations of the estimated herding measures between a given originator and the rest of the countries (Chiang et al., 2007; Coudert and Gex, 2010). The bivariate GARCH (1,1) model developed by Bollerslev (1986) and used for calculating correlations has the following form (Choudhry, 2005):

$$Y_t = M + E_t, E_t \sim N(0, H_t) \qquad 8.12$$

where $Y_t = \begin{bmatrix} y_{i,t} \\ y_{k,t} \end{bmatrix}$ is a (2x1) vector containing the first differences of herding measures[13] with k being the originator country and i being one of the remaining countries. M is a 2x1 vector of intercepts in the conditional mean ($M = \begin{bmatrix} \mu_{y_i} \\ \mu_{y_k} \end{bmatrix}$) and Ht is a 2x2 conditional covariance matrix. The conditional variance-covariance equations of a diagonal VECH bivariate GARCH(1,1) model may be written:

$$VECH(H_t) = C + AVECH(\mathrm{E}_{t-1}E'_{t-1}) + BVECH(H_{t-1}H'_{t-1}) \qquad 8.13$$

where C is 3x1 vector containing the intercepts in the conditional variance-covariance equations, A and B are 3x3 diagonal matrices containing the parameters on the lagged disturbance squares and on the lagged variances or covariances respectively. More illustrative, the diagonal bivariate VECH model is simply:

$$h_{11,t} = c_{01} + a_{11}e^2_{1,t-1} + b_{11}h_{11,t-1} \qquad 8.13a$$

$$h_{12,t} = c_{02} + a_{22}e_{1,t-1}e_{2,t-1} + b_{22}h_{12,t-1} \qquad 8.13b$$

[13] The first differences of the estimated herding measures are considered since the initial measures of herding found to be non stationary according to Augmented Dickey Fuller test. The stationarity condition ensures the model's validity without containing 'spurious regression results' (Granger and Newbold, 1974).

$$h_{22,t} = c_{03} + a_{33}e_{2,t-1}^{2} + b_{33}h_{22,t-1} \quad 8.13c$$

The coefficient α_{11} depicts the ARCH process in the residuals from country i and the α_{33} coefficient represents the ARCH process in the originator country (k) equation residuals. The parameters α_{22} and b_{22} show the covariance GARCH parameters between country i and k respectively.

In a similar manner, the conditional correlation is calculated as follows (Alexander, 2001):

$$\hat{\rho}_t^{ki} = \hat{\sigma}_{ki,t} / \hat{\sigma}_{k,t}\,\hat{\sigma}_{i,t} \quad 8.14$$

where k and i's are the same as above.

Using different variables allow us to investigate the feature of the correlation changes associated with macroeconomic shocks and crises periods. Along with the ordinary macroeconomic shocks captured by residuals, we also introduce into analysis extreme macroeconomic shocks with the use of dummy variables. Extreme shocks are considered to be the 10% of the sample with worst realized values relative to the ARIMA models' predictions. Table 8.7 presents the number of extreme shocks that happened each year. It also depicts the number of months during which more than one extreme shock took place. For example, in the case of France in 2008, there were two months with one extreme shock in some of the macroeconomic variables and three months with two extreme shocks during the same month (i.e 2/1, 3/2).

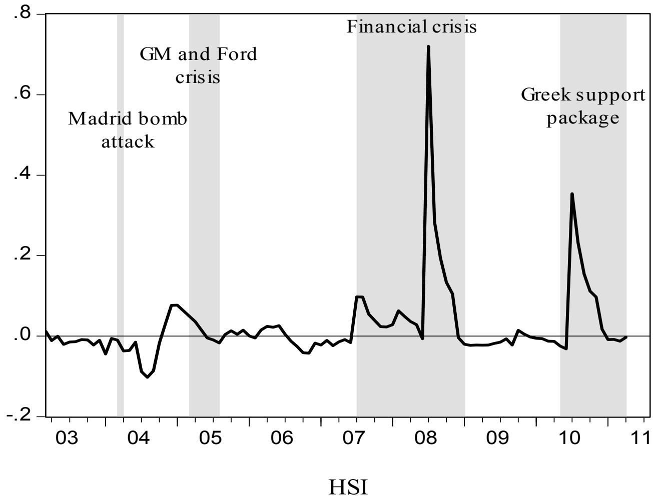
Table 8.7: Number of extreme shocks each year.

	2003	2004	2005	2006	2007	2008	2009	2010	2011
FRANCE	0	1/1	6/1	0	0	2/1,3/2	3/1	1/1,1/2	2/1, 2/2
GERMANY	0	0	3/1, 1/2	0	0	3/1, 3/2, 1/3	2/1, 1/2	2/1	4/1
UK	0	0	0	0	0	6/1, 3/2	4/1, 1/2	2/1	6/1
USA	1/1	2/1	2/1	2/1, 1/2	3/1	6/1, 1/2, 2/3	3/1	0	1/1

Notes: Extreme shocks are considered to be the ones belonged to the 10% of the sample with worst realized values relative to the models' predictions.

As far as the crises periods are concerned, they defined to be March 2004, July 2005, March to August 2005, August 2007 to April 2009 and May 2010 up to the end of the sample. The first two dates correspond to the terrorist bomb attacks in Madrid and London, which are considered to be in many respects the European equivalent of 9/11 albeit on a much smaller scale taking into consideration the number of victims (Kollias et al., 2011). The next date accounts for the General Motors and Ford crisis which triggered a surge in all CDS premia (Coudert and Gex, 2010). The crisis between August 2007 and April 2009 is attributed to the global financial crisis. It started on 9 August 2007 when BNP Paribas announced that it was ceasing activity in three hedge funds that specialized in US mortgage debt and culminated with the collapse of Lehman Brothers on 15 September 2008. The last crisis period refers to the Greek support package on 2 May 2010, which led to contagion effects to some of the EU countries as part of re-assessment of risk by investors according to the 61st European Economy occasional paper published in May 2010. We use these specific crises in order to test contagion effects to the China's market herd measure. This particular country is used here as another candidate country, apart from the three European countries and the US market, for international portfolio diversification purposes since it accommodates some specific characteristics such as its significant economic growth and the attraction of international investors (Valukonis, 2013). Hence, the Chinese stock market due to its unique features (Wong, 2006) might be unaffected from crises or macroeconomic shocks happened to the rest of the countries. To begin with, figure 8.2 depicts the average correlation between the EU and US countries with the China market. It is evident that correlation of herding measures appears significantly increasing values particularly during the last two crises meaning that contagion of herding does also exist in this particular market.

Figure 8.2: Average correlation between the EU countries and the US with the China market.



However, in order to test econometrically the hypothesis that correlation of herding measures between the selected countries changes during crises periods as well as during macroeconomic shocks, we run panel data and OLS regressions. The panel data method is used for examining whether adverse economic conditions and crises happened in the EU countries and in the US result in to contagion effects of the China's herding measure. Equation 8.15 which links the correlations to their lagged values and some of the selected variables (Chiang et al., 2007; Coudert and Gex, 2010) has the following form:

$$\rho_t^{ki} = c^{ki} + a^k \rho_{t-1}^{ki} + b^k D_{Ct} + d1^k D_{IPt} + d2^k D_{GDPt} + d3^k D_{INFLt} + d4^k D_{10YBt} + u_t^{ki} \qquad 8.15$$

where D_{Ct}, D_{IPt}, D_{GDPt}, D_{INFLt} and D_{10YBt} are the dummies of crises and extreme shocks on Industrial Production, Gross Domestic Product, Inflation and and 10 years bond respectively[14]. Furthermore, in equation 8.15, k = CAC, DAX, FTSE and S&P 500 and i is the HSI. Table 8.8 depicts the results of panel regressions. The findings indicate that the correlation coefficient of China's herding measure was increased during periods of crises and during extreme shocks on IP and GDP happened in the selected EU and US countries, as it is indicated by the statistically significant coefficients. If we look at the last column of the table where only statistically significant variables are presented, the correlation was increased of about 8.9% and 17% due to turbulent periods and shocks on IP respectively. Following the same procedure and after regressing conditional correlations on the macroeconomic shocks, we found no signs of increasing correlation. Thus, extreme shocks on some macro-variables and turbulent periods in the EU and the US countries result in changes in correlation coefficient. From this point of view, the unique characteristics of the Chinese stock market do not protect investors from contagion of herding and of course from trading strategies according to the performance of the rest markets. At this point, it is worth mentioning that another one variable of interest could be the effects of Assets under Management (AuM) on herding as capital outflows could lead to market inefficiency and thus to more herding. For example, Poti and Siddique (2013) use AuM as a proxy for risk capital for finding out factors that drives currency predictability. However, it is left for future research.

[14] We also run similar regressions to equation 8.15 by employing as independent variables just the macroeconomic shocks as well as another dummy that takes into considerations all extreme shocks according to table 8.7.

Table 8.8: Panel data regressions of the estimated correlations on their lagged values and dummy variables.

Coefficient	All dummies	Crisis Dummy	Macro shocks dummies	Only significant dummies
Constant	0.005 (0.012)	0.009 (0.013)	0.017 (0.012)	0.006 (0.012)
Lagged endogenous variable	0.529 (0.044)*	0.543 (0.042)*	0.549 (0.043)*	0.529 (0.043)*
Crisis dummy	0.042 (0.019)*	0.045 (0.019)*		0.042 (0.018)*
IPextr_shocks	0.073 (0.023)*		0.080 (0.023)*	0.072 (0.023)*
GDPextr_shocks	0.032 (0.023)		0.039 (0.023)**	
INFLextr_shocks	-0.026 (0.021)		-0.023 (0.022)	
10YBextr_shocks	-0.023 (0.019)		-0.021 (0.021)	
Rsq.	0.717	0.704	0.713	0.714

* and ** represent 5% and 10% statistically significant level respectively.

Table 8.9 refers to findings coming from OLS regressions. These regressions are employed for investigating what macroeconomic shocks in one of the three EU countries and in the US lead to changes in pair-wise correlation coefficient. We chose to report only the statistically significant results at least at the 10% level of correlation changes. Chiang et al. (2007) point out that any public news about one country may be interpreted as information regarding the entire region as a result of herding behaviour. Therefore, we might expect that the more integrated two specific markets are, the more intense the effects of contagion of herding will be. For example volatility spillovers have been attributed to the behaviour of market traders who encourage contagion effects, such that a movement in one market encourages speculation in another market (McMillan et all., 2010). From the table, we observe the correlation changes between DAX and these of CAC and HSI when unexpected macroeconomic shocks take place in Germany. The finding of contagion of herding between the two Eurozone countries is consistent with the results of Mylonidis and Kollias (2010). The authors argue that both of them appear to be the ones with a higher degree of convergence among four major European stock markets. In relation to the Chinese stock market, it seems to be extensively influenced by a number of different macroeconomic shocks happened in Germany. On the other side, contagion of herding is observed in Germany by shocks occurred in the US and in the UK, while the US country with one or another way affects all European countries except for China. All the above might indicate that significant deviations between two herding measures might signal trading opportunities. This fact could be related to the wake-up call hypothesis, where investors realize similarities between two markets' fundamentals after crises or shocks (Chiang et al., 2007).

Table 8.9: Tests of changes in correlations between herding towards market on behalf of unexpected variations in macroeconomic variables in one of the EU and the US countries.

From DAX to	CAC	FTSE	SP500	HSI
Constant	0.391 (0.087) *			0.081 (0.011)*
Lagged endogenous variable	0.737 (0.069)*			0.113 (0.110)
IPextr_shocks				0.220 (0.053)*
GDPextr_shocks	0.311 (0.117)*			0.067 (0.037)*
INFLextr_shocks				-0.089 (0.046)**
Rsq.	0.522	0.704		0.341
From FTSE to	CAC	DAX	SP500	HSI
Constant		0.123 (0.156)	-0.044 (0.037)	-0.211 (0.025)*
Lagged endogenous variable		0.896(0.046)*	0.910 (0.031)*	0.772 (0.067) *
IPextr_shocks		0.124 (0.059)*		
GDPextr_shocks			-0.040 (0.013)*	
INFLextr_shocks				0.036 (0.008) *
Rsq.		0.806	0.893	0.602
From SP500 to	CAC	DAX	FTSE	HSI
Constant	-0.237 (0.100) *	0.062 (0.074)	-0.052 (0.037)	
Lagged endogenous variable	0.914 (0.041)*	0.645 (0.079)*	0.906 (0.033)*	
GDP_shocks		-0.130 (0.067)**		
10YB	-0.024 (0.012)*			
Allextr_shocks			0.010 (0.005)**	
Rsq.	0.841	0.417	0.888	

* and ** represent 5% and 10% statistically significant level respectively.

8.5 Conclusions

In this 8th chapter of the thesis, using the model of Hwang and Salmon (2004) we have tried to investigate herd behaviour towards three different measures of risk, coming from the CAPM and the Higher Moment CAPM. These risk measures, in a number of studies, have been found to be significant in explaining stock returns. The model has been applied to five major developed markets such as the US market, the UK market, the Germany market, the French market and the China market. The results demonstrate the existence of herding not only towards market index but also towards the factors of coskewness and cokurtosis. Most of herding measures follow their own patterns particularly towards the market index, while herding patterns towards coskewness and cokurtosis reveal an opposite direction in relation to their corresponding market behavior.

By taking residuals of ARIMA models for measuring unexpected components in some selected macroeconomic variables and using them as exogenous factors on augmented state space models, we find that shocks on Industrial Production index and 10 years bond influence the magnitude of herding. In particular, the $Std_c(\beta^b_{imt})$ of the DAX increases as positive shocks on IP and 10YB happen, while in the case of S&P 500 it decreases with the level of IP shocks. The latter might depict an overheated US economic activity during the given period, resulting in negative shocks on IP to be taken as good news from investors. In addition, turbulent periods in the EU and the US markets and extreme negative shocks on the expected values of their macroeconomic variables influence the China's herding measure as the conditional correlation indicates. Moreover, the results show a great degree of co-movement in herding measures across the selected countries. Different shocks in the US macroeconomic variables result in changes in pair-wise correlation coefficient with all European countries, while the China's herding measure seems to be extensively affected by a number of shocks in Germany. The findings exhibit that possible benefits of international portfolio diversification are rather small when these specific market are taken into account. Hence, the unique characteristics of the Chinese stock market do not protect investors from contagion of herding and thus, future international studies should test for other countries with lower effects of contagion of herding in order to increase the benefits of international diversification.

PART IV

CONCLUSIONS, APPENDICES AND BIBLIOGRAPHY

Part IV contains the conclusions of this thesis, the Appendices and the corresponding bibliography. As for the conclusions, a summary of our main contributions to academia and the finance industry is also provided, along with a discussion of directions for further work. In appendices are presented the main theoretical steps used in the development of the CAPM.

CONCLUSIONS

This chapter presents a summary of our main conclusions and discusses directions for further work. In addition it contains the contribution which our new methodology and the empirical findings on herding behavior make to all market participants.

To begin with, the theory of asset pricing relies heavily on the principles of present value calculations and the hypothesis of efficient capital markets. However, substantial differences observed in the values of different assets, making financial economists to develop theoretical and empirical oriented models to address this substantive ‘anomaly’. The Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965) is by far the most famous model for asset pricing. The model predicts that the expected return of an asset is proportional to its beta coefficient. The coefficient measures the sensitivity of an asset’s return to the aggregate market return. However, the considerable evidence against the CAPM points to the fact that variables other than the market portfolio accommodate significant risk premia. Over the years, researchers have made many attempts to refine the theoretical foundations and improve the empirical performance of the CAPM. A number of static and dynamic models focus on a better explanation of asset returns. Some of the basics assumptions of the CAPM do not hold. Among them, the instability of betas have been widely recognised as a basic source of CAPM’s failure.

Motivated by the fact that betas are time varying, we develop a novel approach for capturing the time variation of betas by treating the pattern as a function of market return. Hence, we proceed to the construction of a new two-factor model (TFM) which incorporates variables targeting to absorb the information conveyed by betas’ instability. The model is free from subjective bias problems related to the selection of a critical threshold. The results are very promising both in the times series and in the cross-sectional contexts.

As for the time series tests, the models is compared against the CAPM and the FF3FM on five different kinds of portfolios. Each specific portfolio is formed on the basis of some specific characteristics. For example, some portfolios have been constructed using the estimated coefficients of the nonlinear regression used to build the TFM. Furthermore, momentum portfolios are also included in the analysis, since these portfolios are the main drawback of the FF3FM in empirical tests. In time series regressions, the tested hypothesis is that all alphas of the selected portfolios are equal to zero. For this purpose, the GRS test is used. The test shows that neither CAPM nor FF3FM explain the variation of portfolio returns. On the contrary, the TFM displays the lowest test's values, lower mispricing errors and $R^{2'}$s similar to those of FF3FM. The SMISI factor is priced in several cases while the second factor, the NSI, appears high t-statistics indicating its importance in explaining stock returns.

We started constructing our model by claiming that 'Superior' stocks should gain higher returns than 'Inferior' stocks. To remind here that the former stocks have positive b_coefficients and the latter negative b_coeeficients as they were estimated from the equation 3.3. The results clearly indicate the spread in returns between 'Superior' and 'Inferior' portfolios. Furthermore, we assumed that a 'Superior' stock should contain all those characteristics that make it to appear higher returns than its competitors. For example, it could be a stock with relatively low leverage and in bad states of the world its beta coefficient to not increase as much as another stock with high leverage values (Jagannathan and Wang, 1996). To examine if these stocks possess better fundamental characteristics we used the z-score on different fundamental ratios. We find that 'Superior' stocks have lower P/E, D/C ratios and higher BVG and SG. Although the picture changes for the D/C and SG ratios during the 2002-2011 sub-period, it seems to because of 'Inferior' portfolio increases more than average its values. The aggregate z-scores also exhibit that 'Superior' portfolio dominates 'Inferior' at least for the years preceding the formation period. Our empirical findings reported analytically in chapter 4, have significant implications. Firstly, they indicate that this specification outperforms alternative models such as CAPM and FF3FM in explaining returns in time series regressions. Furthermore, we provide evidence that the particular portfolios used to model's construction are not being necessarily riskier. Hence, the new risk factors give valuable information of better understanding the characteristics of returns, targeting the reinforcement of stock market efficiency. Investors, banks, fund managers and other interested parties would be able to make their portfolio choices and form their investment strategies according to the amount of risk they can or wish to undertake. We left for further research the model's empirical examination to other countries and with other competitive models such as the APT.

The cross section regression constitutes the second approach of testing asset pricing models. The Fama and MacBeth (1973) two step procedure is mainly followed in the international literature. To enhance our findings and strengthen the model's performance we also conducted tests in the context of cross-sectional regressions. Once again, we used three well-known models for comparing them against our new TFM. The examined portfolios were formed on the basis of BVps ratios and betas. In general, the results depict that in the cross-sectional analysis both conditionally and unconditionally, the stock market prices different risk factors. In relation to the BVps portfolios, the SMISI factor is priced and the market risk premium has the expected positive sign apart from the case of FF3FM though not significant at any level. The conditional cross-sectional regressions in the case of BVps portfolios identify the power of the TFM variables in explaining asset returns even though a proportion of them left unexplained. This also happens with CAPM, while the market and the HML factors in the FF3FM appear to be significant with the constant not being statistically different from zero. For the beta sorted portfolios, we should refer that almost no risk premia are priced apart from the case of PL-model. In extreme market conditions, the selected portfolios appear to have a different reaction. For example, the lowest portfolios are less influenced than the highest ones in downward movement of the markets. However, in upward movements the lowest BVps portfolio does not differentiate from the highest one though this is the case between the two extreme beta sorted portfolios. The findings of the models' performance in extreme conditions present that all of them in down moths leave unexplained returns but they do better in up months. Due to the fact that all models accommodate the market risk, we have proceeded with the estimation of risk premium when beta sorted portfolio returns were used as dependent variables in the conditional-cross sectional regressions. The TFM gave the most accurately results. Hence, the results also indicate the appropriateness of the TFM in the cross sectional context. From this point of view, the two new risk factors can provide useful information to both academics and practitioners and provide the market with another one tool in the 'battle' of market efficiency.

After the successful empirical implementation of the TFM in the above two testing approaches, we assess the predictive accuracy of the model and compare it along with other modelling techniques that rely heavily on time series regressions. The different versions of the GARCH models and the Kalman filter algorithm are two of the most documented methods. As far as this part of this thesis is concerned, the contribution to the international literature is multiple. First, the predictive accuracy of betas is examined by employing different versions of the reported models. Second, we use nine out of sample consecutive years and three different samples of returns intervals. This way, we are in a position of selecting the best fitted time interval and use it for future predictions without wondering what time interval is the most appropriate. Third, we provide evidence that the estimated models' parameters vary significantly not only from period to period but also among the best and worst groups sorted on the models' predictive accuracy. Finally, the fact that the CAPM model is firmly based on the assumption that asset returns are iid normal (i.e. identically, independently and normally distributed) motivates us to apply a few diagnostic tests for finding out if the existence of iid normal returns is accompanied by better results.

More concretely, the time varying betas are estimated by means of different univariate and bivariate GARCH models, the Kalman filter algorithm at which the random walk process is used to model the stochastic form of betas, the Schwert and Seguin model and our TFM. The accuracy of beta prediction is applied on the next year's realized returns. As measures of accuracy the MSE and the MAE tests are employed. The forecasts are tested on three different in magnitude samples for nine consecutive years. The results show that the accuracy of beta predictions differs significantly among the samples. For example, the predictive accuracy of the TFM's betas do well enough in longer samples, while the Kalman filter algorithm takes the advantage of accuracy at the smaller sample. This happens not because our model's beta deteriorates in accuracy, since by construction remains the same, but because in longer samples the alternative models work poorly. Hence, one of our main findings is that a five-year time interval for predicting betas is the most appropriate. The findings do not change dramatically when the Diebold and Mariano test is used.

Taking into consideration the estimated parameters, they change significantly not only from period to period but also among the best and worst groups. The best stocks according to UGARCH model have significantly smaller long run volatility in contrast to the worst stocks whose their volatility is far away from the population average. Large differences are also observed on the γ coefficient of the UTARCH model indicating that asymmetries play a significant role on the predictive accuracy. Generally speaking, the bivariate GARCH models do not present large deviations from the univariate ones. As far as the KFRW model is concerned, a significant difference is indicated on the constant parameters. A statistically significant constant deteriorates the results of the model indicating the difficulty of predicting returns using betas that are associated with a significant α parameter. As for the S&S model, the b2 coefficient is of paramount importance as it signals the model's performance. Regarding the parameters of the TFM, a decreasing and concave beta coefficient appears to be more efficient for predicting purposes. Even though the TFM does not seem to be the best one among the examined models its sufficient accuracy prediction and its use for pricing assets enables it a useful tool at investors' hands. As for the asset returns as expected they do not follow the normality assumption. However, the average J-B test is smaller for stocks with better accuracy predictions than the worst ones. At the same time, significant differences pointed out on tests related to autocorrelation and heteroskedasticity.

As reported earlier in the scope of this thesis, we are also interested about the existence of herding behavior in financial markets. Its presence can aggravate volatility of returns destabilizing financial markets. Furthermore, its presence relates to observed monlinearities of asset returns. Hence, we empirically test the existence of herding in different financial markets and examine what are the consequences on different aspects of financial activity. To begin with, we test herding effects on volatility and betas for the Greek stock market. This specific market has been selected because the Athens Stock Exchange (ASE) can offer useful inferences due to the regulatory regime and practices characterizing the Greek market (Diacogiannis et al.2005). The use of herding measure developed by Hwang and Salmon (2004) allows us to detect herding not only in periods of extreme market movements but also during normal market conditions. Hence, it provides a more detailed analysis of herding over time (Demirer et al., 2010). In addition, the model is free from the influence of idiosyncratic components as it focuses only on the variability of factor sensitivities (Hwang and Salmon, 2004). The findings contribute to the literature on the herding behaviour of investors with different ways. First, it extends investor herding studies to an emerging market by using state space models not previously applied. Second, it employs different portfolios formed on the basis of the magnitude of beta and the size designed to identify whether herding is differentiated across these portfolios. Last but not least, it examines the implications of herding on market volatility. Our results demonstrate that herding exists in the Greek stock market over the 1998-2003 period, a result consistent with previous studies, while herding also appears from the very early of 2008 up to the last selected month in 2010. This finding is rather unexpected since this particular period the world financial crisis was broken out while a couple of years later, Greece had faced macroeconomic difficulties. The Greek support package on 2 May 2010 led to contagion effects to some of the EU countries as part of re-assessment of risk by investors according to the 61st European Economy occasional paper. As far as the market volatility is concerned, we used four different measures. The results, consistent with previous studies, indicate that herding positively affect volatility measures. Hence, stocks exhibiting higher levels of herding or adverse herding will also present higher volatility. From this point of view, herding is considered to be an additional risk factor that can lead market participants and investors to a better understanding of market risk, asset pricing and of course asset allocation.

Another one contribution of this thesis is the examination of the existence of herding towards factors other than the market risk. In the light of the findings that higher co-moments are capable of explaining asset returns, we investigate whether herding also matters towards co-skewness and co-kurtosis in five major developed markets (i.e. USA, UK, Germany, France and China). To our knowledge this is done for first time as most of the papers test herding towards the factors of FF3FM. Furthermore, different studies have shown that unexpected variations in different macroeconomic variables or uncertainty shocks such as the 9/11 terrorist attacks influence stock prices and increase volatility. This fact motivated us to examine their effects on the estimated herding measures. Once again, the herding measure of Hwang and Salmon (2004) is applied. The results show that herding towards market exists only in the case of Germany. However, herding exists towards co-skewness and co-kurtosis in all examined countries. It is indicative that skewness and kurtosis play an important role in investors' criteria when selecting securities. With the use of ARIMA models for measuring unexpected macroeconomic shocks, we find that shocks and extreme shocks to variables such as Industrial Production, Consumer price index and the rate of the 10 years bond seem to affect the magnitude of herding. In addition, turbulent periods in the EU and the US markets and extreme negative shocks on the expected values of their macroeconomic variables influence the China's herding measure as the conditional correlation indicates. Hence, the unique characteristics of the Chinese stock market do not protect investors from contagion of herding and thus, future international studies should test for other countries with lower effects of contagion of herding in order to increase the benefits of international diversification.

APPENDICES

APPENDIX A: Von Neumann-Morgenstern preferences

The formal theory of choice under risk relies on the work of John Von-Neumann and Oscar Morgenstern (1953). The return of a financial asset forms part of a historical time series. This fact makes financial investment to be classified as being risky rather than uncertain. The time series data must satisfy some probability distribution. As far as the case of capital investment is concerned, the investment decision falls into the uncertain category. Let's start by giving some definitions of a gamble.

Definition 1 - Simple Gamble: G(X,Y;p).

Here X and Y denote outcomes and p is the probability that X occurs and Y occurs with probability (1-p).

Definition 2 - A Fair Gamble.

A fair gamble has the property that the expected return is zero. The expected value of payoffs is equal to weighted average of payoffs, the weights being equal to the probabilities with which payoff occurs.

Thus, $\sum_{i=1}^{n} p_i x_i$ = expected value, where $\sum_{i=1}^{n} p_i = 1,\ p_i > 0$

Definition 3 - The state of nature refers to events outside the control of decision maker.

Let's denote with S, the set of states that can occur at any date. The individual events $s_i \in S$, i = 1 … n, are assumed to be mutually exclusive, finite in number and collectively exhaustive. Each $s_i \in S$ occurs with a non-zero probability

$p_i > 0, \sum_{i=1}^{n} p_i = 1.$

Definition 4 - Acts and Consequences.

The course of action chosen by the decision maker is represented by the set A of discrete, mutually, exclusive, state contingent acts, $a(s_i) \in A$. The 'game against nature' has consequences represented by the matrix of payoffs/prospects.

The notion of rationality of decisions under uncertainty is derived axiomatically from ordinal preference relationships that are expressed pair-wise on the outcome space defined by the payoffs for same state under different acts. The binary preference relationships can take the following form:

(a) $x \succ y$ or $y \succ x$ Strong Preference (i.e. X (Y) is strongly preferred to Y (X))

(b) $x \cong y$ Indifference (i.e.We are indifferent between X or Y)

(c) $x \geq y$ Weak Preference (i.e. X is preferred to Y but Y is not necessarily less preferred to X)

Axioms of rationality pertaining to ordinal binary preference/relationships are the following:

<u>Axiom I</u>: Comparability (completeness). For any pair of alternatives, X or Y in the entire set of payoffs (P) an individual must be able to say one of the following:

$X \succ Y$ or $Y \succ X$ or $X \sim Y$.

For being this true, the outcomes X and Y must be finite/bounded and comparable.

<u>Axiom II: T</u>ransitivity (consistency). The axiom of consistency means that if $X \succ Y$ and $Y \succ Z$, then $X \succ Z$. i.e. $X \succ Y \succ Z$. A violation of this axiom occurs when an individual states that he prefers wine to beer and beer to beverage but concludes that over the set wine and beverage, he prefers beverage to wine.

<u>Axiom III</u>: Independence of irrelevant alternatives. This axiom states that the binary relationship that holds between any two events X or Y is not affected when each is combined in a gamble with an arbitrary third event, Z. Thus if:

$X \sim Y$ and two gambles such as $G_1\,(X,Z;\alpha_1)$ and $G_2\,(Y,Z;\alpha_1)$ exist, then

$G_1\,(X,Z;\alpha_1) \sim G_2\,(Y,Z;\alpha_1)$.

<u>Axiom IV: </u>Continuity (measurability). If Y is preferred less than X but more than Z ($X \succ Y \succ Z$) then there is a unique probability α such that the individual is indifferent between Y and the gamble where X occurs with probability α and Z with (1-α).

<u>Axiom V: </u>Ranking (dominance). If an individual's preferences for outcomes Y and U lie somewhere between X and Z, then it is possible to establish a set of gambles such that the individual is:

Indifferent between Y and a gamble involving X and Z occurring with some probabilities α and (1-α) respectively.
Indifferent between U and a gamble involving X and Z occurring with probabiliy α_2 and (1- α_2) respectively. Furthermore, if $\alpha_1 > \alpha_2$, then Y $\succ$ U . Or if $\alpha_1 = \alpha_2$, then Y ~ U.
<u>Axiom VI: </u>More is preferred to less. Everybody prefers more to less.

Von Neumann and Morgenstern were able to establish a cardinal utility function from what are essentially ordinal preference orderings. They prove the fundamental theorem: under uncertainty rational individuals maximise expected utility of wealth.

APPENDIX B: Mean-Variance rule

The mean variance rule has been formalized by Markowitz (1952, 1959). The rule states that if the distribution of returns offered by assets is jointly normal, or if the utility function is quadratic, then investors maximise expected utility simply by selecting assets that yield the best combinations of mean and variance of returns. In other words:
1. If there are two payoffs X and Y then:

X $\succ$Y if $E(X) \geq E(Y)$ and $Var(X) < Var(Y)$.

2. Returns from an investment should follow the normal distribution. The returns from an investment are defined as:

$$R_i = P_1 / P_0 - 1$$

where P_1 is the price of ith asset at the end of period and P_0 is initial price. Hence, if $P_i \sim N(\overline{P_i}, \sigma_p^2)$, then $R_i \sim N(\overline{P_i}, \sigma_p^2)$. In words, if asset's price P_i at the end of period is normally distributed, then so are the returns R_i.
If asset returns are normally distributed, then the mean-variance rule corresponds to maximisation of $E(U(R_i))$. The indifference curve for a risk averse investor in the mean variance plane is upward-sloping and convex. The former means that there is a positive trade off between risk and return. Thus, the person is prepared to put up with

some more risk and the first derivative of the expected utility of the investment with respect to risk is positive, i.e. $\left(\frac{\mathrm{dE(U(R))}}{\mathrm{d\sigma_R}} > 0\right)$.

As for convexity, it implies that investors are prepared to put up with some more risk only if they are compensated in terms of expected returns at an increasing rate, i.e. $\left(\frac{\mathrm{d^2E(U(R}_i\mathrm{))}}{\mathrm{d\sigma_R^2}} > 0\right)$.

So, if $E(X) = E(Y)$, then only if $Var(X) < Var(Y)$ will it imply that the combination $\left[E(X), Var(X)\right]$ yields a higher utility than combination $\left[E(Y), Var(Y)\right]$.

Furthermore, if $E(X)$ is strictly greater than $E(Y)$, then as long as $Var(X)$ is not greater than $Var(Y)$, asset X yields greater utility than asset Y.

APPENDIX C: Deriving the CAPM

Let $(\sigma_m, E(R_m))$ denote the point corresponding to the market portfolio m. All portfolios chosen by rational investors will have a point $(\sigma_i, E(R_i))$ that lies on the so-called capital market line

$E(R_i) = R_f + \frac{((E(R_m) - R_f)}{\sigma_m}\sigma_i$, which is the efficient frontier for investments.

The price of risk, which represents the change in expected return $E(R_i)$ per one unit change in standard deviation σ_i is given by

$$\frac{((E(R_m) - R_f)}{\sigma_m}. \qquad \text{C.1}$$

The CAPM states that for any asset i, the equilibrium expected return of this asset is

$$E(R_i) = R_f + ((E(R_m) - R_f)\frac{\sigma_{im}}{\sigma_m^2}. \qquad \text{C. 2}$$

To prove C.2 we assume that investor holds w% a portfolio of asset I and the market portfolio m (i.e. w, 1-w). This portfolio will have return defined by

$$E(R_p) = wE(R_i) + (1-w)E(R_m) = \\ w[E(R_i) - E(R_m)] + E(R_m) \quad . \tag{C.3}$$

The risk is

$$\sigma(R_p) = \sqrt{w^2\sigma_i^2 + (1-w)^2\sigma_m^2 + 2w(1-w)\sigma_{im}} \\ = \sqrt{w^2(\sigma_i^2 + \sigma_m^2 - 2\sigma_{im}) + 2w(\sigma_{im} - \sigma_m^2)\sigma_m^2} \quad . \tag{C.4}$$

The risk return trade off of portfolio in C.3 and C.4 is determined by

$$\frac{\partial E(R_p)/\partial w}{\partial \sigma(R_p)/\partial w}.$$

However market equilibrium follows only at w=0. Hence, differentiating C.3 and C.4 and evaluating at w=0 yields

$$\left.\frac{\partial E(R_p)/\partial w}{\partial \sigma(R_p)/\partial w}\right|_{w=0} = \frac{E(R_i) - E(R_m)}{(\sigma_{im} - \sigma_m^2)/\sigma_m}. \tag{C.5}$$

After equating C.5 with C.1 (i.e. the price of risk) we get

$$\frac{E(R_i) - E(R_m)}{(\sigma_{im} - \sigma_m^2)/\sigma_m} = \frac{((E(R_m) - R_f)}{\sigma_m} \tag{C.6}$$

and solving for $E(R_i)$ we take the CAPM formula for asset i.

$$E(R_i) = R_f + \beta((E(R_m) - R_f) .$$

APPENDIX D: From theoretical foundation to empirical estimation of CAPM

In Appendix C, we have seen the ex-ante from of CAPM, i.e.

$$E(R_i) = R_f + \beta((E(R_m) - R_f) . \tag{D.1}$$

The first step necessary to empirically test the theoretical (i.e. ex ante) CAPM is to transform it from expectations into a form that uses observed data. By assuming that on average the realized rate of return of an asset is equal to the expected rate of return we can write:

$$R_{i,t} = E(R_{i,t}) + \beta_i \varphi_{m,t} + e_{i,t} \tag{D.2}$$

Where $\varphi_{m,t} = R_{m,t} - E(R_{m,t}), E(\varphi_{m,t}) = 0$ and $e_{i,t}$ is the disturbance error with $E(e_{i,t}) = 0$ and $Cov(e_{i,t}, \varphi_{m,t}) = 0$.

By taking expectations of both side of equation D.2 we observe that it is a fair game, since the average realized return is equal to the expected return. Hence, substituting $E(R_i)$ from the CAPM into equation D.2, we obtain:

$$\begin{aligned} R_{i,t} &= R_{f,t} + [E(R_{m,t}) - R_{f,t}]\beta_i + \beta_i [R_{m,t} - E(R_{m,t})] + e_{i,t} \\ &= R_{f,t} + (R_{m,t} - R_{f,t})\beta_i + e_{i,t}. \end{aligned} \tag{D.3}$$

Finally, if we subtract $R_{f,t}$ from both sides of equation D.3, we have:

$$R_{i,t} - R_{f,t} = (R_{m,t} - R_{f,t})\beta_i + e_{i,t}. \tag{D.4}$$

The above equation is the ex post form of the CAPM. It is the model's empirical version in a sense that is expressed in terms of ex post observations of return data instead of ex ante expectations.

BIBLIOGRAPHY

Abiad, A., Oomes, N. and Ueda, K. (2008). The quality effect: Does financial liberalization improve the allocation of capital?. J*ournal of Development Economics*, 87, 270–282.

Alexakis, P. and Apergis, N. (1994). Monetary policy in Greece: the impact of EC membership. Edited by Kazakos, P. and Ioakimidis, P., *Pinter Publications, London*.

Alexander, C. (2001). Market models: A guide to financial data analysis. John Wiley & Sons, England.

Andersen, T., Bollerslev, T., Diebold, F. and Wu, J. (2006). Realized beta: Persistence and predictability. *Advances in Econometrics*, 20, 1-39.

Apergis, N. and Eleftheriou, S. (2001). Stock returns and volatility: evidence from the Athens stock market index. *Journal of Economics and Finance*, 25, 50-61.

Aquino, R. (2006). A variance equality test of the ICAPM on Phillipine stocks: Post-Asian financial crisis period. Applied Economics, 38, 353-362.

Arditti, F. (1967). Risk and the Required Return on Equity. *Journal of Finance,* 22, 19-36.

Athanassiou, E., Kollias, C. and Syriopoulos, T. (2006). Dynamic volatility and external security related shocks: The case of the Athens stock exchange. *International Financial Markets, Institution and Money*, 16, 411-424.

Avery, C., and Zemsky, P. (1998). Multidimensional uncertainty and herd behavior in Financial markets. *American Economic Review*, 88, 724-748.

Bali, T., and Engle, R. (2010). The intertemporal capital asset pricing model with dynamic conditional correlations. *Journal of Monetary Economics*, 57, 377-390.

Bali, T., Mo, H., and Tang, Y. (2008). The role of autoregressive conditional skewness and kurtosis in the estimation of conditional VaR. *Journal of Banking and Finance*, 32, 269-282.

Banerjee, A. (1992). A Simple Model of Herd Behavior. *Quarterly Journal of Economics,* 107, 797-818.

Banz, R. (1981). The relation between return and market value of common stocks. *Journal of Financial Economics*, 9, 3-18.

Banz, R., and Breen, W. (1986). "Sample-dependent results using accounting and market data: Some evidence". *Journal of Finance*, 41, 779-793.

Basu, S. (1977). Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis. *Journal of Finance,* 32, 663-682.

Baur, D. (2006). Multivariate market association and its extremes. *Journal of International Financial Markets, Institutions and Money*, 16, 355-369.

Becketti, S. and Sellon, G. (1989). Has financial market volatility increased?. *Economic Review*, Federal Reserve Bank of Kansas City (June 1989), 17-30.

Beenstock, M., Chan, K. (1988). Economic forces in the London stock market. *Oxford Bulletin of Economics and Statistics*, 50, 27-39.

Berk, J. (1995). A critique of size related anomalies. *Review of Financial Studies*, 8, 275-286.

Bhandari, L. (1988). Debt/Equity ratio and expected common stock returns: Empirical Evidence. *Journal of Finance,* 43, 507-528.

Bhardwaj, R., and Brooks, L. (1993). Dual betas from bull and bear markets: Reversal of the size effect. *Journal of Financial Research*, 16, 269-283.

Bikhchandani, S. and Sharma, S. (2001). Herd behavior in financial markets. IMF Staff Papers, 47, 279-310.

Bikhchandani, S., Hirshleifer, D. and Welch, H. (1992). A Theory of Fads, Fashion, Custom and Cultural Changes as Informational Cascades. *Journal of Political Economy,* 100, 992-1026.

Black, F. (1972). Capital market equilibrium with restricted borrowing. *Journal of Business*, 45, 444-454.

Black, F., and Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy*, 81, 637-654.

Black, F., Jensen, M., and Scholes, M. (1972). The capital asset pricing model: Some empirical tests. Studies in the Theory of Capital Markets. Michael C. Jensen, ed. Praeger. New York.

Blasco, N., Corredor, P. and Ferreruela, S. (2012). Does herding affect volatility? Implications for the Spanish stock market. *Quantitative Finance*, 12, 311-327.

Bloom, N., (2009). The impact of uncertainty shocks. *Econometrica*, 77, 423-685.

Blume, M. (1970). Portfolio theory: A step towards its practical application. *Journal of Business,* 43, 152-174.

Bodie,Z., Kane,A., and Marcus, A. (2002). Investments. 5th ed. Mc Graw-Hill.

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroscedasticity. *Journal of Econometrics,* 31, 307-327.

Bollerslev, T., Engle, R. and Wooldridge, J. (1988). A capital asset pricing model with time-varying covariances. *Journal of Political Economy,* 96, 116-131.

Bos, T. and Newbold, P. (1984). An empirical investigation of the possibility of stochastic systematic risk in the market model. *Journal of Business,* 57, 35-41.

Boucher, M., 1999. The hedge fund edge. John Wiley & Sons.

Brailsford, T. and Faff, R. (1996). An evaluation of volatility forecasting techniques. *Journal of Banking and Finance*, 20, 419-438.

Braun P., Nelson, D. and Sunier, A. (1995). Good news, bad news, volatility and betas. *Journal of Finance,* 50, 1575-1603.

Breeden, D. (1979). An intertemporal asset pricing model with stochastic consumption and investment opportunities. *Journal of Financial Economics*, 7, 265-296.

Brennan, M., Wang, A., and Xia, Y. (2004). Estimation and test of a simple model of intertemporal capital asset pricing. *Journal of Finance,* 59, 1743–1775.

Brenner, M. and Smidt, S. (1977). A simple model of non-stationarity of systematic risk. *Journal of Finance,* 32, 1081-1092.

Brooks, C. (2002). Introductory econometrics for finance. *Cambridge University Press, Cambridge.*

Brooks, R., Faff, R. and Mckenzie, M. (2002). Time Varying Country Risk: An Assessment of Alternative Modelling Techniques. *European Journal of Finance,* 8, 249-274.

Campbell, J. (1996). Understanding risk and return. *Journal of Political Economy*, 104, 298-345.

Campbell, J. (2000). Asset pricing at the millennium. *Journal of Finance,* 55, 1515-1567.

Campbell, J., Lo, A., and MacKinlay, A.-C. (1997). The econometrics of financial markets. Princeton University Press. *Princeton. New Jersey*.

Caparrelli, F., D' Arcangelis, A., M. and Cassuto, A. (2004). Herding in the Italian Stock Market: A Case of Behavioral Finance. *Journal of Behavioral Finance,* 5, 222-230.

Caporale, G. M., Economou, F. and Philippas, N. (2008). Herd behaviour in extreme market conditions: The case of the Athens Stock Exchange. Working paper [08-29], Brunel University, London, October 2008.

Carhart, M. (1997). On persistence in mutual fund performance. Journal of Finance, 52, 57-82.

Celik, S. (2012). Theoretical and empirical review of asset pricing models: A structural synthesis. *International Journal of Economics and Financial Issues*, 2, 141-178.

Chan, K., and Chen, N.-F. (1988). An unconditional asset pricing test and the role of firm size as an instrumental variable for risk. *Journal of Finance*, 43, 309-325.

Chan, L., and Lakonishok, J. (1993). Are the reports of beta's death premature? *Journal of Portfolio Management*, 19, 51-62.

Chan, L., Hamao, Y., and Lakonishok, J. (1991). Fundamentals and stock returns in Japan. *Journal of Finance*, 46, 1467-1484.

Chang, E., Cheng, J., Khorana, A. (2000). An examination of herd behaviour in equity markets: an international perspective. *Journal of Banking and Finance*, 10, 1651-1679.

Chen, N. (1983). Some empirical tests of the Theory of Arbitrage Pricing. *Journal of Finance*, 38, 1393-1414.

Chen, N., Roll, R., and Ross, S. (1986). Economic forces and the stock market. *Journal of Business*, 59, 383-403.

Chen, Z. and Petkova, R. (2012). Does idiosyncratic volatility proxy for risk exposure?. *Review of Financial Studies*, 25, 2745-2787.

Chiang, T. C. and Zheng, D. (2010). An empirical analysis of herd behavior in global stock markets. *Journal of Banking and Finance* , 34, 1911-1921.

Chiang, T., Jeon, B. And Li, H. (2007). Dynamic correlation analysis of financial contagion: evidence from Asian markets. *Journal of International Money and Finance*, 26, 1206-1228.

Chincarini, L., and Kim, D. (2006). Quantitative equity portfolio management: An active approach to portfolio construction and management. McGraw-Hill Companies, New York.

Choudhry, T. (2005). September 11 and time-varying beta of United States companies. *Applied Financial Economics,* 15, 1227-1242.

Choudhry, T. and Wu, H. (2008). Forecasting ability of GARCH vs Kalman filter method: Evidence from daily UK time-varying beta. *Journal of Forecasting,* 27, 670-689.

Choudhry, T. and Wu, H. (2009). Forecasting the weekly time-varying beta of UK firms: GARCH models vs. Kalman filter method. *European Journal of Finance,* 15, 437-444.

Christie, W. and Huang, R. (1995). Following the pied piper: Do individual returns herd around the market?. *Financial Analysts Journal,* 51, 31-37.

Christie-David, R., and Chaudhry, M. (2001). Coskewness and cokurtosis in futures markets. *Journal of Empirical Finance*, 8, 55-81.

Clare, A., and Thomas, S. (1994). Macroeconomic factors, the APT and the UK stock market. *Journal of Business Finance and Accounting*, 21, 309-330.

Clinebell J., Squires, J., and Stevens, J. (1993). Investment Performance Over Bull and Bear Markets: Fabozzi and Francis Revisited. *Quarterly Journal of Business and Economics,* 32, 14-25.

Cochrane, J. (1996). A cross-sectional test of an investment-based asset pricing model. *Journal of Political Economy*, 104, 572-621.

Cochrane, J. (2005). Asset pricing: Revised edition. Princeton University Press. New Jersey.

Copeland, T., Weston, J.-F., and Shastri, K. (2005). Financial theory and corporate policy. 4th Edition. Pearson Addison Wesley, Pearson Education.

Coudert, V. and Gex, M. (2010). Contagion inside the credit default swaps market: The case of the GM and Ford crisis in 2005. *Journal of International Financial Markets, Institutions and Money*, 20, 109-134.

Cuthbertson, K., and Nitzsche, D. (2004). Quantitative financial economics. 2nd ed. John Wiley & Sons. England

Daniel, K., and Titman, S. (1997). Evidence on the characteristics of cross sectional variation in stock returns. *Journal of Finance,* 52, 1-33.

Daves, P., Ehrhardt, M. and Kunkel, R. (2000). Estimating systematic risk: The choice of return interval and estimation period. *Journal of Financial and Strategic Decisions,* 13, 7-13.

Davis, J. (1994). The cross-section of realized stock returns: The pre-COMPUSTAT evidence. *Journal of Finance*, 49, 1579-1593.

De Long, J.B., Shleifer, A., Summers, L. and Waldman, R. (1990). Positive feedback investment strategies and destabilizing rational speculation. *Journal of Finance*, 45, 379-395.

Demirer, R. and Kutan A. (2006). Does herding behaviour exist in Chinese stock markets?. *Journal of International Financial Markets, Institutions and Money,* 16, 123–142.

Demirer, R., Kutan, A., and Chen, C-D. (2010). Do investors herd in emerging stock markets?: Evidence from the Taiwanese market. *Journal of Economic Behavior and Organization*, 76, 283-295.

Demirer, R., Kutan, A., and Zhang, H. (2014). Do ADR investors herd?: Evidence from advanced and emerging markets. *International Review of Economics and Finance*, 30, 138-148.

Diacogiannis, G. P., Patsalis, N., Tsangarakis, N. V. and Tsiritakis, E. (2005). Price limits and overreaction in the Athens Stock Exchange. *Applied Financial Economics,* 15, 53-61.

Diebold, F. (2012). Comparing predictive accuracy, twenty years later: a personal perspective on the use and abuse of Diebold-Mariano tests. PIER Working Paper No. 12-035, University of Pennsylvania, Philadelphia.

Diebold, F. and Mariano, R. (1995). Comparing Predictive Accuracy. *Journal of Business and Economic Statistics,* 13, 253-263.

Dimson, E., and Marsh, P. (1983). The stability of UK risk measures and the problem of thin trading. Journal of Finance, 38, 753-783.

Dittmar, R. (2002) Non linear pricing kernels, kurtosis preference, and evidence from the cross-section of equity returns. *Journal of Finance,* 57, 369-402.

Economou, F., Kostakis, A. and Philippas, N. (2011). Cross-country effects in herding behaviour: Evidence from four south European markets. *Journal of International Financial Markets, Institutions and Money*, 21, 443-460.

Eisenbeiss M., Kauermann, G. and Semmler, W. (2007). Estimating beta-coefficients of German stock data: A non-parametric approach. *European Journal of Finance*, 13, 503-522.

Engle, R. and Kroner, K. (1995). Multivariate simultaneous GARCH. *Econometric Theory,* 11, 122-150.

Fabozzi, F., and Francis, F. (1977). Stability tests for alphas and betas over bull and bear market conditions. *Journal of Finance,* 32, 1093-199.

Faff, R. and Brooks, R. (1998). Time varying beta risk for Australian industry portfolios: an exploratory analysis. *Journal of Business Finance and Accounting,* 25, 721-745.

Faff, R., and Chan, H. (1998). A test of the intertemporal CAPM in the Australian equity market. *Journal of International Financial Markets, Institutions and Money*, 8, 175-188.

Faff, R., Hillier, D. and Hillier, J. (2000). Time varying beta risk: An analysis of alternative modelling techniques. *Journal of Business Finance and Accounting,* 27, 523-554.

Faff, R., Lee, J. and Fry, F. (1992). Time stationarity of systematic risk: some Australian evidence. *Journal of Business Finance & Accounting,* 19, 253-270.

Fama, E. and French, K. (1988). Permanent and temporary components of stock prices. *Journal of Political Economy*, 96, 246-273.

Fama, E. and French, K. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33, 3-56.

Fama, E. and French, K. (1996). The CAPM is wanted, dead or alive. *Journal of Finance,* 51, 1947-1958.

Fama, E. (1981). Stock returns, real activity, inflation and money. *American Economic Review*, 71, 545-565.

Fama, E., and French, K. (1992). The cross-section of expected stock returns. *Journal of Finance*, 47, 427-465.

Fama, E., and French, K. (1995). Size and Book-to-Market factors in earnings and returns. *Journal of Finance* , 50, 131-155.

Fama, E., and French, K. (1996). Multifactor explanations of asset pricing anomalies. *Journal of Finance*, 51, 55-84.

Fama, E., and French, K. (2004). The Capital Asset Pricing Model: Theory and evidence. *Journal of Economic Perspectives*, 18, 25-46.

Fama, R., and MacBeth, J. (1973). Risk, return and equilibrium: Empirical tests. *Journal of Political Economy*, 81, 607-636.

Fang, H., and Lai, T. Y. (1997). Co-Kurtosis and Capital asset pricing. *The Financial Review,* 32, 293-307.

Farrell, J. (1997). Portfolio management: Theory and applications. 2nd Edition, McGraw-Hill International Editions. Singapore.

Ferson, W. (1989). Changes in expected security returns, risk and the level of interest rates. *Journal of Finance,* 44, 1191-1214.

Ferson, W., and Harvey, C. (1991). The time variation of economic risk Premiums. *Journal of Political Economy*, 99, 385-415.

Ferson, W., and Korajczyk, R. (1995). Do Arbitrage Pricing Models explain the predictability of stock returns? *Journal of Business,* 68, 309-349.

Fletcher, J. (2000). On the conditional relationship between beta and return in international stock returns. *International Review of Financial Analysis*, 9, 235-245.

Fraser, P., Hamelink, F., Hoesli, M., and MacGregor, B. (2004). Time-varying betas and the cross-sectional return-risk relation: evidence from the UK. *The European Journal of Finance*, 10, 255-276.

French, K., Schwert, W. and Stambaugh, R. (1987). Expected stock returns and volatility. *Journal of Financial Economics*, 19, 3-29.

Friedman, M. (1953). The case for flexible exchange rates. *Essays in Positive Economics*, University of Chicago Press: Chicago.

Friend, I., and Blume, M. (1970). Measurement of portfolio performance under uncertainty. *American Economic Review*, 60, 607-636.

Froot, K., Scharfestein, D. and Stein, J. (1992). Herd on the street: Information inefficiencies in a market with short-term speculation. *Journal of Finance*, 47, 4, 1461-1484.

Galindo, A., Schiantarelli, F. and Weiss, A. (2007). Does financial liberalization improve the allocation of investments? Micro-evidence from developing countries. *Journal of Development Economics*, 83, 562-587.

Gibbons, M. (1982). Multivariate tests of financial models: A new approach. *Journal of Financial Economics*, 10, 3-27.

Gibbons, R., Ross, S., and Shanken, J. (1989). A test of the efficiency of a given portfolio. *Econometrica*, 57, 1121-1152.

Gjerde, O., and Saettem, F. (1999). Causal relations among stock returns and macroeconomic variables in a small, open economy. *Journal of International Financial Markets Institutions and Money*, 9, 61-74.

Glosten, L., Jagannathan, R. and Runkle, D. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance,* 48, 1779-1801.

Gonzalez-Rivera, G. (1996). Time varying risk: The case of the American computer industry. *Journal of Empirical Finance,* 2, 333-342.

Granger, C.W.J. and Newbold, P. (1974), Spurious regressions in econometrics. *Journal of Econometrics,* 2, 111-120.

Graves, J. and McDonald, B. (1989). Nonnormalities and Tests of Asset Pricing Theories. *The Journal of Finance,* 34, 889-908.

Gregory, A., Harris, R., and Michou, M. (2001). An analysis of contrarian investment strategies in the UK. *Journal of Business Finance and Accounting*, 28, 1193-1228.

Groenewold, N., and Fraser, P. (1997). Share prices and macroeconomic factors. *Journal of Business Finance & Accounting*, 24, 1367-1383.

Groenewold, N. and Fraser, P. (1999). Time-Varying Estimates of CAPM Betas. *Mathematics and Computers in Simulation,* 48, 531-539.

Groenewold, N. and Fraser, P. (2001). Tests of asset-pricing models: how important is the iid-normal assumption? *Journal of Empirical Finance,* 8, 427-449.

Hafner, C. and Herwartz, H. (2008). Testing for causality using multivariate GARCH models. *Annals of Economics and Statistics,* 89, 215-241.

Hansen, L.P., and Singleton, K. (1982). Generalized instrumental variables estimation of nonlinear rational expectations models. *Econometrica*, 55, 1269-1286.

Hansen, L.P., and Singleton, K. (1983). Stochastic consumption, risk aversion, and the temporal behavior of asset returns. *Journal of Political Economy*, 91, 249-265.

Harvey, C., and Siddique, A. (2000). Conditional skewness in asset pricing tests. *Journal of Finance,* 55, 1263-1295.

Hondroyiannis, G., and Papapetrou, E. (2001). Macroeconomic influences on the stock market. *Journal of Economics and Finance*, 25, 33-49.

Howton, S., and Peterson, D. (1998). An examination of cross-sectional realized stock returns using a varying-risk beta model. *Financial Review,* 33, 199-212.

Huang, H-C. (2001). Tests of CAPM with nonstationary beta. *International Journal of Finance and Economics,* 6, 255-268.

Hull, J. (2006). Options, futures and other derivatives. *Prentice Hall*. 6th Edition.

Hung, D., Shackleton, M., and Xu, X. (2004). CAPM, Higher co-moment and factor models of UK stock returns. *Journal of Business Finance & Accounting,* 31, 87-112.

Hussain, S., and Toms, J. (2002). Industry returns, single and multifactor asset pricing tests. *European Finance Association*, Berlin meetings discussion paper.

Hwang, S. and Salmon, M. (2004). Market Stress and herding. *Journal of Empirical Finance,* 11, 585-616.

Hwang, S. and Salmon, M. (2009). Sentiment and beta herding. Available at SSRN: http://dx.doi.org/10.2139/ssrn.299919.

Hwang, S., and Satchell, S. (1999). Modelling emerging market risk premia using higher moments. *International Journal of Finance and Economics*, 4, 271-296.

Isakov, D. (1999). Is beta still alive? Conclusive evidence from the Swiss stock market. *The European Journal of Finance*, 5, 202-212.

Jacoby, G., Fowler, D., and Gottesman, A. (2000). The Capital Asset Pricing Model and the liquidity effect: A theoretical approach. *Journal of Financial Markets*, 3, 69-81.

Jagannathan, R., and Wang, Z. (1996). The conditional CAPM and the cross-section of expected returns. *Journal of Finance*, 51, 3-53.

Jegadeesh, N. (1990). Evidence of predictable behavior of security returns. *Journal of Finance,* 45, 881-898.

Jegadeesh, N. (1992). Does market risk really explain the size effect? *Journal of Financial and Quantitative Analysis*, 27, 337-351.

Jegadeesh, N., and Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance*, 48, 65-91.

Karathanassis, G. and Philippas, N. (1993). Heteroscedasticity in the market model: some evidence from the Athens stock exchange. *Managerial and Decision Economics*, 14, 563-567.

Kollias, C., Kyrtsou, C. and Papadamou, S. (2013). The effects of terrorism and war on the oil price-stock index relationship. *Energy Economics,* 40, 743-752.

Kollias, C., Papadamou, S. and Stagiannis, A. (2012). The financial spillovers of the gulf of Mexico oil accident. *The Empirical Economics Letters,* 11, 633-643.

Kollias, C., Papadamou, S., and Stagiannis, A. (2011). Terrorism and capital markets: The effects of the Madrid and London bomb attacks. *International Review of Economics and Finance*, 20, 532-541.

Koutmos, G., Lee, U. and Theodosiou, P. (1994). Time varying betas and volatility persistence in International stock markets. *Journal of Economics and Business,* 46, 101-112.

Koutmos, G., Negakis, C. and Theodossiou, P. (1993). Stochastic behaviour of the Athens stock exchange. *Applied Financial Economics*, 3, 119-126.

Kraus, A., and Litzenberger, R. (1976). Skewness preference and the valuation of risk assets. *Journal of Finance*, 31, 1085-1100.

Kroner, K. and Ng, V. (1998). Modeling asymmetric comovements of asset returns. *Review of Financial Studies,* 11, 817-844.

Lakonishok, J., and Sharpino, A. (1986). Systematic risk, total risk, and size as determinants of stock market returns. Journal of Banking and Finance, 10, 115-132.

Lakonishok, J., Shleifer, A. and Vishny, R.W. (1992), The impact of institutional trading on stock prices. *Journal of Financial Economics,* 32, 23-43.

Lakonishok, J., Shleifer, A., and Vishny, R. (1994). Contrarian investment, extrapolation, and risk. *Journal of Finance* 49, 1541-1578.

Lehmann, B., and Modest, D. (1988). The empirical foundations of the Arbitrage Pricing Theory. *Journal of Financial Economics*, 21, 213-254.

Lengwiler, Y. (2004). Microfoundations of financial economics: An introduction to general equilibrium asset pricing. Princeton University Press. New Jersey.

Lettau, M., and Ludvigson, S. (2001). Resurrecting the (C) CAPM: A cross-sectional test when risk premia are time-varying. *Journal of Political Economy*, 109, 1238-1287.

Levis, M., and Liodakis, M. (2001). Contrarian strategies and investor expectations: The U.K. evidence. *Financial Analysts Journal*, 57, 43-56.

Levy, R. (1974). Beta coefficients as predictors of returns. *Financial Analysts Journal*, 30, 61-69.

Lin, W., Chen, Y. and Boot, J. (1992). The dynamic and stochastic instability of betas: Implications for forecasting stock returns. *Journal of Forecasting,* 11, 517-541.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budget. *Review of Economics and Statistics,* 47, 13-37.

Lo, A. and MacKinlay, C. (1988). Stock prices do not follow random walks: Evidence from a simple specification test. *Review of Financial Studies,* 1, 41-66.

Lux, T. (1995), Herd behaviour, bubbles and crashes, The *Economic Journal*, 105, 881-896.

Mankiw, N. G., and Shapiro, M. (1986). Risk and return: Consumption beta versus market beta. *Review of Economics and Statistics*, 68, 452-459.

Maringer, D. (2004). Finding the relevant risk factors for asset pricing. *Computational Statistics and Data Analysis*, 47, 339-352.

Markowitz, H. (1959). Portfolio selection: Efficient diversification of investments. John Wiley and Sons. New York.

Markowitz, H. (1952). Portfolio selection. *Journal of Finance,* 7, 77-91.

McClain K., Humphreys, H. and Boscan, A. (1996). Measuring risk in the mining sector with ARCH models with important observations on sample size. *Journal of Empirical Finance,* 3, 369-391.

McMillan, D., Ruiz, I., and Speight, A. (2010). Correlations and spillovers among three euro rates: evidence using realized variance. *European Journal of Finance*, 16, 753-767.

Merton, R. (1973). An intertemporal asset pricing model. *Econometrica*, 41, 867-887.

Messis, P., Alexandridis, A., and Zapranis, A. (2014). Testing and comparing conditional CAPM with a new approach in the cross-sectional framework. Proceedings of the conference on Time Series Analysis-ITISE 2014 (June 2014, Granada, Spain).

Messis, P., and Zapranis, A. (2014a). Asset pricing with time-varying betas. *Applied Economics*, 46, 4508-4518.

Messis, P., and Zapranis, A. (2014b). Herding and volatility in the Athens stock exchange. *Journal of Risk Finance*, 15, 572-590.

Messis, P., and Zapranis, A. (2014c). Herding towards Higher Moment CAPM, contagion of herding and macroeconomic shocks: Evidence from five major developed markets. *Journal of Behavioral and Experimental Finance*, 4, 1-13.

Messis, P., Iatridis, G. and Blanas, G. (2006). Fama and French three-factor model versus arbitrage pricing theory on estimating the expected returns on value strategies: Evidence from the Athens stock market. *International Journal of Finance*, 18, 4072-4104.

Messis, P., Iatridis, G., and Blanas, G. (2007). CAPM and the efficacy of higher moment CAPM in the Athens stock market: An empirical approach. *International Journal of Applied Economics*, 4, 60-75.

Michailidis, G., Tsopoglou, S., Papanastasiou, D. and Mariola, E. (2006). Testing the Capital Asset Pricing Model (CAPM): The case of the emerging Greek securities market. *International Research Journal of Finance and Economics*, June, 78-91.

Mitchell, M., and Stafford, E. (2000). Managerial decisions and long-term price performance. *Journal of Business*, 73, 287-329.

Moreno, D., and Rodriguez, R. (2009). The value of coskewness in mutual fund performance evaluation. *Journal of Banking and Finance,* 33, 1664-1676.

Mylonidis, N. and Kollias, C. (2010). Dynamic European stock market convergence: Evidence from rolling cointegration analysis in the first euro-decade. *Journal of Banking and Finance,* 34, 2056-2064.

Nelson, D. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica*, 59, 349-370.

Pagan A. and Schwert, G. (1990). Alternative models for conditional stock volatility. *Journal of Econometrics,* 45, 267-290.

Pagan, A. (1984). Econometric issues in the analysis of regressions with generated regressors. *International Economic Review*, 25, 221-247.

Pearce, D., and Roley, V. (1985). Stock prices and economic news. *Journal of Business*, 58, 49-67.

Perold, A. (2004). The Capital Asset Pricing Model. *Journal of Economic Perspectives*, 18, 3-24.

Pettengill, G., Sundaram, N., and Mathur, I. (1995). The conditional relation between beta and returns. *Journal of Financial and Quantitative Analysis*, 30, 101-116.

Philippas, N., Economou, F., Babalos, V., and Kostakis, A. (2013). Herding behavior in REITs: Novel tests and the role of financial crisis. *International Review of Financial Analysis*, 29, 166-174.

Poon, S-H., and Granger, C. (2003). Forecasting volatility in Financial markets: A review. *Journal of Economic Literature*, 41, 478-539.

Poti, V., and Siddique, A. (2013), What drives currency predictability? *Journal of International Money and Finance*, 36, 86-106.

Potì, V., and Wang, D. (2010). The coskewness puzzle. *Journal of Banking and Finance,* 34, 1827-1838.

Reinganum, M. (1981). A new empirical perspective on the CAPM. *Journal of Financial and Quantitative Analysis*, 16, 439-462.

Reyes, M. (1999). Size, time-varying beta, and conditional heteroscedasticity in UK stock returns. *Review of Financial Economics*, 8, 1-10.

Roll, R. (1977). A critique of the asset pricing theory's tests: Part I: on past and potential testability of the theory. *Journal of Financial Economics*, 4, 129-176.

Rosenberg, B. and Guy, J. (1976a). Prediction of beta from investment fundamentals. Part 1. *Financial Analysts Journal*, 32, 60-72.

Rosenberg, B. and Guy, J. (1976b). Prediction of beta from investment fundamentals. Part 2. *Financial Analysts Journal*, 32, 62-70.

Ross, S. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory,* 13, 341-360.

Schwert, G. (1989). Why does stock market volatility change over time?. *Journal of Finance*, 44, 1115-1153.

Schwert, G. and Seguin, P. (1990). Heteroscedasticity in Stock Returns. *Journal of Finance*, 4, 1129-1155.

Shanken, J. (1990). Intertemporal asset pricing: an empirical investigation. *Journal of Econometrics,* 45, 99-120.

Sharpe, W. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance,* 19, 425-442.

Sias, R. (2004). Institutional herding. *Review of Financial Studies*, 17, 165-206.

Siourounis, G. (2002). Modelling volatility and testing for efficiency in emerging capital markets: the case of the Athens stock exchange. *Applied Financial Economics*, 12, 47-55.

Smith, D. (2007). Conditional skewness and asset pricing. *Journal of Empirical Finance*, 14, 91-119.

Solnik, B. (1974a). The international pricing of risk: An empirical investigation of the world capital market structure. *Journal of Finance*, 29, 365-378.

Solnik, B. (1974b). An equilibrium model of the international capital market. *Journal of Economic Theory*, 8, 500-524.

Spyrou, S. (2013). Herding in financial markets: A review of the literature. *Review of Behavioral Finance*, 5, 175-194.

Stambaugh, R. (1982). On the exclusion of assets from tests of the two-parameter model: A sensitivity analysis. *Journal of Financial Economics*, 10, 237-268.

Stock, J., and Watson, M. (1989). New indexes of coincident and leading economic indicators. In Olivier Jean Blanchard and Stanley Fischer , editors. NBER Macroeconomics Annual 1989.

Tang, G., and Shum, W. (2003). The conditional relationship between beta and returns: Recent evidence from international stock markets. *International Business Review*, 12, 109-126.

Taylor, S. (1986). Forecasting the volatility of currency exchange rates. *International Journal of Forecasting,* 3, 159-170.

Terasvirta, T. (1994). Specification, estimation and evaluation of smooth transition autoregressive models. *Journal of the American Statistical Association*, 89, 208-218.

Tessaromatis. N. and Thomas, V. (2009). Herding behavior in the Athens stock exchange. *Investment Management and Financial Innovations,* 6, 156-164.

Theriou, N., Maditinos, D. and Sevic, Z. (2010). Herding by mutual fund managers in the Athens stock exchange. Working paper [520], University of A Coruna, A Coruna, September 2010.

Theriou, N., Maditinos, D., Chadzoglou, P. and Anggelidis, V. (2005). The cross section of expected stock returns: An empirical study in the Athens stock exchange. *Managerial Finance,* 31, 58-78.

Valukonis, M. (2013). China’s stock market trends and their determinants analysis using market indices. *Economics and Management*, 18, 651-660.

Venezia, I., Nashikkar, A., and Shapira, Z. (2009). Herding in trading by amateur and professional investors", Available at SSRN: http://dx.doi.org/10.2139/ssrn.1358623.

Vines, T., Hsieh, C.-H., and Hatem, J. (1994). The role of systematic covariance and coskewness in the pricing of real estate: Evidence from equity REITs. *Journal of Real Estate Research*, 9, 421-429.

Von-Neumann and Morgenstern, O. (1953). Theory of games and economic behaviour. 2nd edition, Princeton University Press, Princeton (New Jersey).

Walras, L. (1874). Ilments d’Iconomie Politique Pure, ou Thıorie de la Richesse *Sociale*, Corbaz, Lausanne.

Wang, D. (2008). Herd behavior towards the market index: Evidence from 21 financial markets. Working paper [776], University of Navara, Barchelona, December 2008.

Wang, J. (1993). A model of intertemporal asset prices under asymmetric information. *Review of Economic Studies*, 60, 249-282.

Wasserfallen, W. (1989). Macroeconomic news and the stock market: Evidence from Europe. *Journal of Banking and Finance,* 13, 613-626.

Welch, I. (2000). Herding among security analysts. *Journal of Financial Economics,* 58, 369-396.

Wells, C. (1994). Variable betas on the Stockholm exchange 1971-1989. *Applied Economics,* 4, 75-92.

Wermers, R. (1999). Mutual fund herding and the impact on stock prices. *Journal of Finance,* 54, 581-622.

Wiggins, J. (1992). Betas in up and down markets. *Financial Review*, 27, 107-123.

Wong, S. (2006). China’s stock market: A marriage of capitalism and socialism. *Cato Journal*, 26, 389-424.

Woodward, G., and Anderson, H. (2009). Does beta react to market conditions? Estimates of ‘bull’ and ‘bear’ betas using a nonlinear market model with an endogenous threshold parameter. *Quantitative Finance*, 9, 913-924.

Yao, J., Ma, C., and He, W.-P. (2014). Investor herding behaviour of Chinese stock market. *International Review of Economics and Finance*, 29, 12-29.

You, L., and Daigler, R. (2010). Is international diversification really beneficial? *Journal of Banking and Finance*, 34, 163-173.

Yu, J. (2002). Forecasting volatility in the New Zealand stock market. *Applied Financial Economics*, 12, 193-202.

Zakoian, J.-M., (1994). Threshold heteroscedastic models. *Journal of Economic Dynamics and Control*, 18, 931-955.

Zarowin, P. (1990). Size, seasonality, and stock market overreaction. *Journal of Finance and Quantitative Analysis*, 25, 113-125.

Zhang, J. and Wirjanto, T. (2006). Modeling and Forecasting Volatility in China's Stock Markets. *Journal of Chinese Economic and Business Studies*, 7, 307 - 324.