Determinants of Stock Prices in the Egyptian Stock Market: Traditional Asset Pricing Models versus Behavioural Asset Pricing Models

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Abstract

The aim of this thesis is to determine a valuation model for stocks in the Egyptian stock market by comparing conventional and behavioural asset pricing models. To achieve this aim, this thesis constructs and tests the following extensions of the Fama and French three-factor model over the time period 2004-2016: (i) time-varying factor loadings; (ii) time-varying risk premia; and (iii) introducing a behavioural risk factor.

The cross-sectional tests applied on both individual stocks and portfolios double-sorted on size and the book-to-market ratio show that the Fama and French three-factor model that captures time-variation in betas using either the rolling regression approach or the DCC-GARCH model cannot fully capture the cross-sectional variation in stock returns as both specifications have high and significant pricing errors. Similarly, scaling the factor loadings in the Fama and French three-factor model using the Treasury bill rate, size, the book-to-market ratio and sentiment does not enable the model to capture some of the prominent anomalies in financial markets such as turnover and short-term momentum effects.

Modelling time-variation in risk premia, based on simple bull and bear regimes identified using a Markov-switching model, along with time-variation in risk using the DCC-GARCH provides a modest improvement to the results of the model that only captures the time-variation in risk. Specifically, although the hypothesis of time-varying risk premia is never rejected, the model is still weakened by the negative weighted average risk premia of the market factor and the high pricing errors. Finally, the results show that augmenting the Fama and French three-factor model with an additional behavioural factor does not lead to major changes in the performance of the model and that the sentiment risk factor is not significantly priced in the Egyptian stock market. However, by investigating the characteristics of stocks that are most sensitive to changes in sentiment, the results reveal that small and highly volatile are the most sensitive stocks which imply that sentiment is a non-diversifiable risk factor.

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Chapter 1

Introduction

1.1 Introduction

Asset pricing theory is a framework that aims to identify and measure risk and assign appropriate rewards for risk bearing (Harvey, 2001). It emerged to answer one of the central questions in finance literature which is how to determine the correct value of an asset that provides a stream of uncertain future cash flows (Perold, 2004). Primarily, the price of an asset is equal to the expected discounted value of its future payoffs. The rate at which these future payoffs is discounted should reflect their riskiness as investors are assumed to be risk averse and thus they require compensation for bearing any additional risk. This indicates that assets with riskier payoffs should provide higher returns than assets with less risky payoffs. This interplay between risk and returns lies at the heart of financial economics and should be given due care as it is critical not only for researchers but also for investors and practitioners as it is central to all investment decisions (Nyberg, 2009).

Asset pricing models are used in a variety of applications related to the decision making process. For example, they are used for calculations of the cost of capital associated with investment and takeover decisions, which is one of the major areas in corporate finance. In addition, they are used in performance evaluation of investment and mutual fund managers. Furthermore, managers, investors, policy makers and researchers should understand the causes of risk, how it should be measured, and its effect on the required rates of return to make effective financial decisions (Gregory *et al.*, 2013). Actually, the list of applications that use asset pricing models is vast and this justifies the increased interest of academics and practitioners in testing asset pricing models in different contexts.

However, although the theoretical genesis and initial empirical development of almost all of asset pricing models has focused mainly on the US market, this does not mean that asset pricing models that work well in the US market will work well for emerging markets. Harvey (1998) argues that with the increasing number of corporations aiming to have direct investments in emerging markets, there is a crucial need for an asset pricing model that produces appropriate hurdle rates for each of these potential investments. Nonetheless, the asset pricing literature argues that emerging markets are considered as a serious challenge for finance, and standard asset pricing models often fail to account for the specific circumstances prevalent in these markets (Dash and Mahakud, 2014). Thus, determining an appropriate asset pricing model for emerging markets remains one of the challenging areas in finance literature.

In this regard, one of the growing emerging markets that has attracted many investors recently is the Egyptian stock market. Over recent decades, there has been an increase in the number of foreign direct investments (hereafter FDIs) in Egypt due to the dynamic growth of the Egyptian economy, its strategic geographical position, low labour costs, and the success of the economic reform programs undertaken by the government. According to the UNCTAD 2017 World Investment Report, Egypt is one of the top five FDI destinations in Africa and the largest recipient in North Africa. This, in turn, intensifies the need for developing an asset pricing model for the Egyptian stock market that investors can use to evaluate different projects and investments. Nonetheless, there is a significant paucity in research studies that test asset pricing models in the Egyptian stock market. Thus to fill in this gap, this thesis aims to identify a valuation model for stocks in the Egyptian stock market by comparing between conventional and behavioural asset pricing models.

1.2 Research Background

A comprehensive study of asset pricing models should start with the Efficient Market Hypothesis (hereafter EMH) that sets the foundations of many asset pricing models by setting out the key assumptions concerning investors' preferences, human judgement, and decision making in financial markets (Xu, 2010). Fama (1970) defines an efficient market as the one in which prices fully reflect all available information. However, testing whether information is fully reflected in prices must be undertaken within the context of a pricing model. This requires a model that provides a link from economic fundamentals to asset prices. The most obvious candidate for this task is the Capital Asset Pricing Model (hereafter CAPM) which is still considered the most important asset pricing model as it supports most of our basic intuitions about the trade-off between risk and return (Ross and Dybvig, 2003).

In its elegant simplicity, the CAPM suggests that the expected return on any asset is equal to the risk-free rate plus a risk premium which is represented by the asset's market beta, multiplied by the premium per unit of beta risk measured as the average excess return of a broad market portfolio over the risk-free rate. Upon its inception in the late 1960s, significant empirical work was performed to test the predictions of the CAPM that an asset's excess return over the risk-free rate should be proportional to its exposure to overall market risk as measured by beta.

Although the early empirical tests of the CAPM support the central predictions of the Black *et al*. (1972) version of the model, which assumes that market betas are sufficient to explain expected returns and that the risk premium is positive (Fama and French, 2004), the prediction that the premium per unit of beta is equal to the expected market return minus the risk-free rate is consistently rejected. Furthermore, from the 1970s onwards, several studies have questioned the empirical validity of the CAPM by documenting the existence of several anomalies such as the size effect of Banz (1981), the value effect of Basu (1977), and the momentum in stock returns of Jegadeesh and Titman (1993).

At a fundamental level, the existence of these anomalies does not directly mean that financial markets are inefficient, but it may mean that the underlying asset pricing model (such as the CAPM) is inadequate, and this is at the core of the joint hypothesis problem which represents one of the main obstacles facing tests of market efficiency.

Fama (1991) argues that the joint hypothesis problem has enriched academic research as the eventual resolution of these anomalies will result in more precise and more general theories of market efficiency and equilibrium asset pricing models under uncertainty (Jensen, 1978).

On the one hand, the EMH proponents explain the existence of anomalies in financial markets in terms of the inadequacy of existing asset pricing models that may either miss important risk factors that determine stock returns or that are mis-specified due to ignoring time-variation in risk and risk premia (Ghysels, 1995). Consequently, this view leads to the emergence of many asset pricing models that try to accommodate the anomalies that the CAPM has failed to capture.

On the other hand, behavioural finance proponents explain the existence of anomalies in terms of the unrealistic assumptions of efficient markets, and hence they aim to provide an alternative financial paradigm that can better explain financial markets. However, to date, there is a significant debate concerning whether behavioural finance can replace the EMH as the dominant paradigm (Kai, 2004).

These two opposing views about the existence of anomalies in financial markets provide a heated debate in finance literature. The controversy between standard finance and behavioural finance is most apparent in the following quotations from Fama (1991) and Hirshleifer (2001).

"In the end, I think we can hope for a coherent story that (i) relates the cross-section properties of expected returns to the variation of expected returns through time, and (ii) relates the behaviour of expected returns to the real economy in a rather detailed way. Or we can hope to convince ourselves that no such story is possible." (Fama 1991, p.1610).

“Over time I believe that the purely rational paradigm will be subsumed by a broader psychological paradigm that includes full rationality as a significant case.” (Hirshleifer, 2001, p.1534).

These two quotations provide a roadmap for research in asset pricing literature. The first line of research argues that the existence of readily available firm characteristics that can describe average returns implies that researchers should include a range of additional factors into asset pricing models. In this regard, Shah *et al.* (2014) argue that multifactor asset pricing models provide a good starting point to explain the cross-sectional variation in stock returns. Thus, motivated by the theoretical work of Merton (1973) and Ross (1976), researchers add factors beyond market returns to describe the cross-section of expected returns by arguing that these factors are either proxies for underlying state variables that represent changes in the investment opportunity set or proxies for “factor-mimicking” portfolios in an Arbitrage Pricing Theory (APT) setting. Seminal work here includes the series of papers by Fama and French (1992, 1993) who argue that most of the well documented empirical anomalies can be captured by sensitivity to three factors which are: (i) the market factor; (ii) the size factor generated by a long position in a small market capitalization portfolio and a short position in a large market capitalization portfolio; and (iii) a book-to-market (B/M) factor that is generated by a long position in a portfolio with high B/M stocks and a short position in a portfolio with low B/M stocks.

The second line of research argues that the existence of anomalies can be attributed to the unrealistic assumptions employed in previous tests of asset pricing models about the constancy of expected returns, betas and risk premia (Iqbal *et al.*, 2010). Many researchers have criticised this assumption by arguing that betas and expected returns tend to vary over time (Jagannathan and Wang, 1996; Lettau and Ludvigson, 2001). As a result, the focus of the literature has shifted towards developing alternative approaches to capture time-variation in risk and risk premia and testing whether conditional asset pricing models can explain the cross-sectional variation in stock returns.

The third line of research takes a different perspective to provide a resolution for these anomalies. It argues that if the conventional finance model is undermined by many anomalies, then restructuring conventional asset pricing models is warranted (Statman, 1999). Campbell (2000) highlights that it is unrealistic to hope for a fully rational, risk-based explanation of all the empirical anomalies that have challenged empirical research. Thus, behavioural finance proponents have been working to supplement the conventional model with an alternative behavioural model by tracing the implications of behavioural assumptions for equilibrium prices (Statman, 1999).

Given these three lines of research, this thesis compares conditional versions of the Fama and French three-factor model and behavioural asset pricing models to determine which provide a better explanation of the cross-sectional variation in stock returns for the Egyptian stock market.

1.3 Research Aim and Objectives

A major part of the research effort in finance is devoted to understanding why different financial assets earn different expected rates of returns. As a result, several asset pricing models have emerged to explain this phenomenon. These models differ mainly in their assumptions about investors' preferences, information sets, the stochastic process governing the arrival of news to markets, and frictions in the markets for real and financial assets (Ferson and Jagannathan, 1996). These assumptions are either derived from the EMH or behavioural finance.

Given the debate between the EMH and behavioural finance proponents and the different implications that each has for asset pricing generally, and the relationship between risk and return in particular, the overall aim of this thesis is to:

"*Identify the key determinants of asset prices in the Egyptian stock market based on both conventional and behavioural asset pricing models.*"

From a theoretical point of view, this thesis has the following objectives:

1. Provide a comprehensive literature review concerning the debate between the EMH and behavioural finance.
2. Discuss the relative merits of both conventional (static and conditional) and behavioural asset pricing models and summarize the empirical evidence underlying them.

From an empirical point of view, this thesis has the following objectives:

1. Construct an Egyptian version of the Fama and French three risk factors.
2. Test the conditional Fama and French three-factor model that captures time-variation in betas using the rolling regression approach, the scaled factor model approach, and multivariate GARCH with dynamic conditional correlations (DCC), and compare these three approaches.
3. Test the conditional Fama and French three-factor model that captures time-variation in betas, using the rolling regression approach and the DCC-GARCH model, and captures time-variation in risk premia using a Markov-switching regime model.
4. Test the performance of behavioural asset pricing models that incorporate the effect of sentiment into asset pricing models either as a conditioning variable or as a risk factor.

After highlighting the main objectives of this thesis, the next section highlights the main research questions that this thesis aims to address and the contribution that each adds to the literature.

1.4 Research Questions and Contribution to the Knowledge

Pricing equities is a core task for investors, and one of the most important issues in finance research. Nonetheless, there is a paucity of research studies that tackle this task in emerging markets generally and the Egyptian stock market specifically. However, Harvey (1998) emphasises that there is an acute need for more research on emerging markets in order to gain better understanding of these markets and address a number of myths about them.

In this context, traditional asset pricing models often face severe challenges when applied to emerging markets for the following reasons. Ghysels (1995) argues that one of the main obstacles that researchers face in their attempt to explain the cross-sectional and time-series variations in stock returns is to determine the appropriate state variables that should be priced in equilibrium. In this regard, researchers in emerging markets often start with the risk factors normally priced in developed markets. Nonetheless, the weak correlation between emerging and developed markets raises some doubt regarding whether these risk factors are also rewarded in emerging markets.

In this respect, the annual reports of the Egyptian stock exchange show that the coefficient of correlation between Egypt and developed markets is low compared to the coefficient of correlation between developed markets and each other. Thus, important research questions that evolve from this observation are: (i) what are the prevalent risk factors in the Egyptian stock market? (ii) are common risk factors normally rewarded in developed markets also rewarded in emerging markets such as Egypt?

Although these questions are important in a market such as Egypt, there are no clear answers as there is a dearth of studies that focus on the assessment of alternative asset-pricing models in the Egyptian context. Specifically, there are two main studies that analyse the performance of alternative asset pricing models in the Egyptian stock market. Though the results of these studies are inconclusive, they provide useful avenues to follow in determining an appropriate asset pricing model for the Egyptian stock market.

Omran (2007) tests the CAPM for the Egyptian stock market using 41 companies over the time period 2001-2002. His results show that, contrary to the predicted positive relationship between returns and beta, the coefficient of beta has a negative sign which is counterintuitive. However, Pettengill *et al.* (1995) argue that such a result is possible as a result of using realized returns rather than expected returns in CAPM tests. They highlight that the relationship between beta and realized return is conditional on the market excess returns. Specifically, when market excess returns are positive, the CAPM predicts the usual positive relation between beta and stock returns, whereas when excess realized market returns are negative, the CAPM predicts an inverse relation between beta and stock returns. Consistent with this proposition, Omran reports that the average market return during the test period is negative. Therefore, a negative beta coefficient should be expected. These results may imply that conditional rather than static CAPM is required to explain stock returns in the Egyptian stock market.

Shaker and Elgiziry (2014) compare the performance of five alternative asset pricing models[1] for 55 stocks listed on the Egyptian stock market for the time period January 2003 to December 2007. Consistent with the existing literature, they test the performance of the models using six portfolios formed on size and the book-to-market ratio. However, given the limited number of stocks used in this study, the number of stocks in each portfolio is much smaller compared to prior studies for developed markets, and thus it is considered a serious limitation in this study. They use the Gibbons, Ross, and Shanken (1989) (GRS) test in order to compare between the

[1] (i) The CAPM, (ii) the Fama and French three-factor Model, (iii) the Carhart model, (iv) the liquidity –augmented Fama and French three-factor model (Chan and Faff, 2005) and (v) the liquidity and momentum-augmented Fama and French three-factor model.

models. Their results affirm that the Fama and French three-factor model outperforms all of the other models.

However, although they support the Fama and French three-factor model, their results should be interpreted with caution for the following reasons. First, the GRS test does not address the most important question in asset pricing literature which is why different assets yield different returns. According to Goyal (2011) asset pricing models are mainly cross-sectional in nature. This, in turn, necessitates testing the model using a cross-sectional regression approach to determine whether it can explain the cross-sectional variation in stock returns. Second, since this study uses only a portfolio sorted on size and the book-to-market ratio as the main test assets, it is subject to the criticism of Lewellen *et al.* (2010) who argue that tests that use these portfolios as tests assets may overestimate the ability of the model to capture the cross-sectional variation in stock returns. They argue that the strong factor structure of these portfolios makes it more probable that betas on almost any proposed factor will be related to expected returns. Ang *et al.* (2010) argue that one way to avoid this problem is to use individual stocks as test assets in order to have more rigorous tests of asset pricing models.

Enlightened by the results of Shaker and Elgiziry and the argument of Culp and Cochrane (2003) that the Fama and French three-factor model represents the most popular multifactor model that emerged to respond to the challenges facing the CAPM due to its ability to capture most of the variations of average returns (Fama and French, 1996), this thesis uses the Fama and French three-factor model as the main asset pricing model for the Egyptian stock market. This leads us to the second challenge facing testing asset pricing models in emerging markets which is related to whether local or global risk factors are rewarded in emerging markets. This challenge results in the emergence of two schools of thought (Garcia and Ghysels, 1998). The first school proposes that if these markets are segmented from developed markets, then their returns should be associated with local rather than global risk factors

(Griffin, 2002). The second school proposes that if these markets are integrated, then their expected returns are better described by their exposure to global risk factors. Consistent with the first school of thought, Cakici *et al.* (2013) point out that returns on emerging markets are better described by exposure to local risk factors. In addition, Griffin (2002) and Fama and French (2012) argue that the local versions of asset pricing models provide a better description of local stock returns compared to global versions. Thus, Griffin recommends the use of country-specific risk factors when performing cost-of-capital calculations, performance measurement and risk analysis.

Besides Griffin's recommendation, there are different factors that may negatively impact the degree of integration of the Egyptian stock market with other markets. First, political instability is one of the main reasons behind diminishing integration efforts, as many international investors are reluctant to invest in the country during these unstable political periods. After the Egyptian revolution in 2011, uncertainty concerning the economic outlook of the country increased, leading to an international deterioration of confidence in the economy. World Bank indicators show that foreign direct investment decreased significantly from \$11.6 billion in 2007 to \$4.8 billion in 2014. Furthermore, the share of foreign investors in the Egyptian market decreased from 31.8% of the total value traded in December 2004 to only 18.58% in December 2016.

In addition, the prevailing deficiencies in both the regulatory and operational institutions governing economic integration, investment and the capital market in Egypt may make many investors reluctant to invest in such an environment where corruption and a lack of transparency are prevalent (Alshorbagy and Elsaman, 2011).

Thus, enlightened by the above discussion, this thesis employs the Egyptian version of the Fama and French factors (Market, SMB, and HML) as the main risk factors. Since Fama and French SMB and HML portfolios are not readily available for the Egyptian stock market, these portfolios are constructed by the author using the Fama and French (1993) approach and are made publicly available for future researchers. This, in turn, constitutes the first contribution of this thesis.

After highlighting the main risk factors, the next step is to test whether the Fama and French three-factor model can explain the cross-sectional variation in stock returns in the Egyptian stock market. The absence of a reliable answer to such a question leaves managers and decision makers in a difficult position and constitutes a significant gap in research that this thesis aims to fill. Specifically, this thesis aims to contribute in addressing some of the gaps in the literature about the Egyptian stock market by answering the following empirical questions.

Q1: In the conditional Fama French three-factor model, does the rolling regression approach, the scaled factor approach, and/or the DCC-GARCH model explain the cross-sectional variation in stock returns? Which of these approaches provide the best way to capture the time-variation in betas in the Egyptian stock market?

Following Ghysels (1995), the search for appropriate model specification is more important than the search for the relevant state variables. While early research assumed that expected returns, betas and risk premia are constant over time, both theoretical arguments and empirical results cast doubts on the validity of these assumptions. From a theoretical point of view, it is sensible to assume that investors' attitude towards risk and the riskiness of firms change over time as economic conditions change. Furthermore, there is substantial empirical evidence that stock returns are predictable over time (Fama and French, 1989; Chen, 1991). In addition, many researchers have documented significant evidence that betas tend to vary over time in both developed and emerging markets (Ferson and Harvey, 1991; Bollerslev *et al.*, 1988). Thus, conditional asset pricing models that allow for variations in risk and risk premia based on both macroeconomic and microeconomic information are more interesting and realistic than static models that assume a stable and linear relation between risk and returns. The reason is that such models not only mirror the way in which investors actually behave, but also because such models are built upon a solid economic framework without which asset pricing theory may become vacuous (Cochrane, 2001).

However, despite the increased interest in testing conditional asset pricing models, there is a significant dearth in studies that test conditional asset pricing models in emerging markets generally and the Egyptian stock market specifically. This lack of studies, in turn, warrants further research given the argument of Iqbal *et al*. (2010) that the assumption of constant betas and expected returns is more questionable in emerging markets. Specifically, they argue that the highly volatile political, economic and institutional conditions prevalent in emerging markets imply that the parameters of asset pricing models and expected returns are unlikely to remain constant over time. This, in turn, suggests that applying unconditional asset pricing models to emerging markets may result in model misspecification.

Thus, given the increased support for conditional asset pricing models, the first empirical question that this thesis aims to answer is whether the conditional Fama and French three-factor model that captures time-variation in betas using the rolling regression approach, the scaled factor model approach, and the DCC-GARCH model can explain the cross-sectional variation in stock returns. The contribution of this empirical question emerges from the following aspects.

First, this thesis is among the first studies that test the performance conditional models in the Egyptian stock market. Such a test seems appealing given the rich sample period that this thesis covers. Specifically, the time span of this thesis from 2004 to 2016 covers significant breakpoints including the Global Financial Crisis, the Arab Spring and the Egyptian revolutions. This rich sample period with different episodes of up and down markets strongly challenges the assumption normally applied in previous tests of asset pricing models that beta and risk premia are constant over time.

Second, since there is no consensus in asset pricing literature on which approach is better in modelling time-variation in betas, this thesis uses the simple rolling regression approach, the scaled factor model approach, and the DCC-GARCH model as the main approaches to model time-variation in betas and compares between them. This comparison offers useful insights about the performance of each of these approaches to determine which one is more appropriate in capturing time-variation in betas in the Egyptian stock market.

Third, since most of the studies that employ the DCC-GARCH to capture time-variation in betas do this within the context of the CAPM (Vendrame *et al*., 2018; Bali and Engle, 2010), this thesis extends these studies by modelling time-variations in the betas of the Fama and French three factors using the DCC-GARCH model.

Although the focus of this empirical question is on modelling time-variation in betas only, Ferson and Harvey (1991) argue that a constant beta model might be a good approximation of reality as long as the time-variation of risk premia is taken into consideration. This leads us to the second empirical question.

Q2: Does the rolling regression, the DCC-GARCH, and/or the Markov-switching approaches provide better explanation of the cross-sectional variation in stock returns?

Despite the arguments of Ferson and Harvey (1991) that time-variation in risk premia constitutes the main source of predictability in stock returns, the empirical coverage of asset pricing models that capture time-variation in risk premia is relatively weak. The main approach used to model time-variation in risk premia is regime switching techniques that have received increased interest over recent decades in both asset pricing and asset allocation literature. In such techniques, the main assumption is that the risk-return relationship is time-varying and depends on the prevailing regime. Specifically, it is expected that the risk-return relationship is positive during the bull regime, while it tends to be negative during the bear regime. This observation can help explain many of the puzzles that conventional asset pricing models fail to capture (Ghysels *et al.*, 2014).

Consistent with the argument that the risk-return relationship is nonlinear, Ghysels *et al.* (2014) find that the risk-return relationship is positive during the bull regime, whereas the relationship is reversed during the bear regime. In the same spirit, Vendrame *et al*. (2018) test a conditional CAPM that models time-variation in betas, using the DCC-GARCH model, and models time-variation in risk premia, using a Markov-switching model. Their main proposition is that there are two risk premia: one associated with the bull regime and one associated with the bear regime. These regimes are assumed to be random variables that can only be inferred using a certain probability estimated using a Markov switching model. Consistent with the results of Ghysels *et al.* (2014), they find that the bull risk premia is positive, whereas the bear risk premia is negative. Furthermore, they find that their conditional CAPM provides a better explanation of the cross-sectional variation in stock returns compared to its static counterpart. However, the model is weakened by its failure to explain the value and momentum anomalies.

In the light of the above results, it is apparent that the assumption, that risk-return relationship is linear, is highly restrictive and may be the main reason behind the failure of conventional asset pricing models to explain the cross-sectional variation in stock returns. Thus, to relax this assumption, the second empirical question of this thesis aims to determine whether modelling the time-variation in risk premia using the Markov switching model can provide better explanation of the cross-sectional variation in stock returns.

Answering this question contributes to the literature in the following sense. Since the previous studies that model time-variation in risk premia focus mainly on the CAPM, this thesis aims to extend these results by modelling time-variation in risk premia within the context of multifactor asset pricing models. Specifically, this thesis tests whether the conditional Fama and French three-factor, that models time-variation in risk using either the rolling regression approach or the DCC-GARCH and models time-variation in risk premia, using a Markov switching model, can explain the cross-sectional variation in stock returns in the Egyptian stock market. The introduction of switching regimes to a multifactor factor model framework is an important innovation given the wide use of multifactor models in academic research and given their success to explain the cross-sectional variation in stock returns compared to the CAPM.

The above empirical questions focus on analysing whether the conventional Fama and French three-factor model, that derives its assumptions from standard finance theories, can explain the cross-sectional variation in stock returns in the Egyptian stock market. However, Shefrin and Statman (1994) argue that market efficiency and conventional asset pricing models are expected to prevail in markets that are dominated by rational investors. Since both rational and noise traders participate in real financial markets, Shefrin and Statman argue that the failure of conventional asset pricing models to explain the cross-sectional variation in stock returns may be attributed to ignoring the effect of noise traders on stock prices. Thus, in order to provide better explanations for the cross-sectional variation in stocks returns and gain better understanding of real financial markets, Hirshleifer (2001) argues that the fully rational paradigm should be replaced by a broader psychological paradigm. Thus, within this context, this thesis aims to test whether behavioural asset pricing models can provide better explanation of the cross-sectional variation in stock returns in the Egyptian stock market.

Q3: Within behavioural asset pricing models, does incorporating the effect of sentiment either as a conditioning variable or as a risk factor provide better explanation of the cross-sectional variation in stock returns in the Egyptian stock market?

Although the EMH proponents attempt to explain the existence of anomalies in financial markets by either searching for additional risk factors that can better explain the cross-sectional variations in stock returns or by searching for accurate ways to model time-variation in risk and risk premia, Campbell (2000) argues that hoping for a fully rational, risk-based explanation for all of the anomalies in financial markets is merely impossible. This leads behavioural finance proponents to attribute the existence of anomalies to the unrealistic assumptions upon which conventional asset pricing models are built (Chandra and Thenmozhi, 2017).

The evidence about the role of investor sentiment on stock prices leads behavioural proponents to argue for behaviouralizing asset pricing models (Shefrin, 2005). This leads to the emergence of several attempts to augment conventional asset pricing models with behavioural factors in order to provide better explanations for the cross-sectional variation in stock returns (Potì and Shefrin, 2014; Ho and Hung, 2009). Following this line of reasoning, this thesis aims to extend the results of these papers and provide further evidence on the performance of behavioural asset pricing models in the Egyptian stock market which act as a useful example of a growing emerging market.

Specifically, supported by the results of Ho and Hung (2009) that using investor sentiment as a conditioning variable helps explain the anomalies that conventional asset pricing models fail to explain, this thesis tests whether using investor sentiment as a conditioning variable can provide better explanation for the size, value, liquidity, and momentum effects which act as examples of the most prominent anomalies in financial markets compared to using macroeconomic and microeconomic conditioning variables. Furthermore, supported by the results of Ho and Hung (2012), and Berger and Turtle (2012) that investor sentiment is a non-diversifiable risk factor that warrants an additional premium in equilibrium, this thesis augments the Fama and French three-factor model with a behavioural factor, constructed as the difference between the returns of portfolios of high sentiment beta and low sentiment beta stocks, to determine whether this model can provide better explanation of the cross-sectional variation in stock returns in the Egyptian stock market.

The results of this empirical question contribute to the literature in several ways. First, most of the studies that test behavioural asset pricing models focus mainly on developed markets and there is a significant dearth in studies that test the performance of these models in emerging markets generally and the Egyptian stock market specifically. Despite the empirical success of behavioural asset pricing models in developed markets, it is essential to test these models in other markets in order to provide out-of-sample tests before concluding that they provide good description of average returns. In this regard, Drew and Veeraraghavan (2002) and Dash and Mahakud (2014) argue that testing the performance of asset pricing models in emerging markets context is a very good approach to provide an out-of-sample evidence as their market structures are significantly different from developed markets. Ansari and Khan (2012) find that there is a significant difference in the quality of information available in developed and emerging markets since developed markets have stronger property rights as well as better corporate governance which should encourage arbitrage-based trading on fundamentals. In contrast, in emerging markets noise-based trading is more prevalent. Thus, this implies that testing behavioural asset pricing models in emerging markets may reveal new insights about the performance of these models.

Second, the Egyptian stock market provides an interesting environment to test the performance of behavioural asset pricing models due to the following reasons. First, The Egyptian stock market is dominated by retail investors who are more affected by behavioural biases compared to institutional investors (Jackson, 2003) as shown in Table 1.1 that shows the percentage of retail investors in the Egyptian stock market in terms of total value traded. Schmitz *et al.* (2006) state that individual or retail investors fit the definition of noise traders as they are less likely to have access to better information than other market participants (institutional investors). They also do not have the time nor money to obtain timely information, nor the ability to interpret this information. Hence, they might be more prone to use heuristics, rules of thumb or other simplifying decision rules in their investment decisions.

Table 1.1: The Percentage of Retail Investors in the Egyptian Stock Market (2004-2016)

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Retail Investors (%)	54	53	60	61	66	63	48	41	50	51	71	61	65

Source: EGX Annual Reports (2004-2016)

Second, Metwally and Darwish (2015) show that the Egyptian stock market is a highly speculative market that is affected by noise trading and psychological biases. Specifically, they document the existence of overconfidence bias in the Egyptian stock market. According to Schmeling (2009), countries that are more vulnerable to herd-like behaviour and overreaction are subject to stronger sentiment-return relationship. Thus, this implies that sentiment may have a significant effect on stock prices in the Egyptian stock market.

Finally, the Egyptian stock market like other emerging market is highly restrictive due to its strict institutional settings such as short-sale constraints. These constraints deter institutional investors from participating in price stabilizing activities by trading against irrational investors to drive prices back to their fundamental values. Thus, this implies that prices tend to deviate from their fundamental values for extended periods of time and provides opportunity for irrational investors to have significant impact on stock prices. Thus, it is apparent that the Egyptian stock market provides a rich environment to study the effect of investor sentiment on stock prices. Consequently, testing the performance of behavioural asset pricing models in the Egyptian context may provide new insights about their performance that can contribute towards universal validation of these models.

1.5 Structure of the Thesis

This thesis is structured as follows. Chapter 2 provides a detailed discussion on the EMH, the CAPM, and behavioural finance as they constitute major building blocks in finance literature. Specifically, this chapter compares between the main assumptions of the EMH and behavioural finance. Furthermore, it provides an overview on the size, value, and momentum effects as they are the most prominent asset pricing anomalies.

Chapter 3 provides a comprehensive overview on the Fama and French three factor model that acts as the main asset pricing model in this thesis. It discusses the development of the model and its empirical results in both developed and emerging markets. Furthermore, the chapter discusses the different schools of thought that emerged to justify the inclusion of the SMB and HML factors in the model.

Chapter 4 discusses two major breakthroughs in asset pricing literature. First, the chapter illustrates the development of conditional asset pricing models. Then, it highlights the relative merits of the different approaches emerged to capture time-variation in risk and risk premia. Furthermore, it summarizes the empirical evidence on the performance of conditional asset pricing models in both developed and emerging markets. Second, this chapter discusses the development of behavioural asset pricing models and summarizes the empirical evidence on their performance.

Chapter 5 highlights the main variables used in this thesis with a special focus on the construction of the Fama and French three risk factors and the sentiment risk factor for the Egyptian stock market. The chapter then proceeds by discussing the relevant methodological techniques employed in this thesis, together with the traditional methodologies applied in asset pricing tests. Specifically, the chapter covers the time-series and cross-sectional tests of asset pricing models with a special focus on the Fama-Macbeth cross-sectional regression approach as the main methodology used in this thesis. The chapter also provides a detailed overview on the approaches employed to capture time-variation in betas and risk premia, that is, the rolling regression approach, the scaled factor model approach, the multivariate GARCH with dynamic conditional correlations, and switching regimes.

Chapter 6 provides the descriptive statistics of the Fama and French factors. Then, the construction of the portfolios sorted on market capitalization, the book-to-market ratio, and double sorted on both market capitalization and the book-to-market ratio is explained. Finally, the chapter presents the descriptive statistics for these portfolios and individual stocks as the main tests used in this thesis.

Chapter 7 presents the results of the conditional versions of the Fama and French three-factor model, which uses the rolling regression approach, the scaled factor model approach, and the DCC-GARCH as the main techniques to capture time-variation in betas. Then, a comparison between the different specifications of the model is held to determine which model provides a better explanation of the cross-sectional variation in stock returns.

Chapter 8 discusses the results of the Markov switching model and analyses whether the model captures the main events the Egyptian stock market passed by during the sample period. The chapter then presents the results of the conditional Fama and French three-factor model that captures time-variation in betas using the rolling regression approach and the DCC-GARCH model, and captures time-variation in risk premia using the Markov switching model and compares between both specifications. Finally, the chapter provides the descriptive statistics of the Egyptian consumer confidence index as the main proxy for investor sentiment. Then, it presents the results of behavioural asset pricing models that use investor sentiment as a conditioning variable and as a risk factor.

Chapter 9 concludes the thesis and readdresses the research questions to determine whether the conventional or the behavioural asset pricing models provide better explanation of the cross-sectional variation in stock returns. The chapter also highlights the main limitations of this thesis along with providing recommendations for future research.

Chapter 2
Efficient Markets and Behavioural Finance

2.1 Introduction

Since the main aim of this thesis is to evaluate alternative valuation models for the Egyptian stock market, it is important to review the various aspects of the asset pricing literature. The first step towards achieving this aim is to review the literature on the EMH, behavioural finance, and the CAPM as they represent an essential starting point before analysing the wide array of asset pricing models (whether conventional or behavioural) that have emerged to capture the cross-sectional variation in stock returns.

Until relatively recently, the EMH has been widely accepted by financial economists who believed that the market prices of financial securities fully reflect all the available information. Since its inception, the EMH has been extensively applied in theoretical models and tested in empirical studies of financial securities prices. However, testing whether information is fully reflected in prices must be undertaken within the context of a pricing model. The fact that the EMH has to be tested within the context of an asset pricing model leads to the emergence of the joint hypothesis problem which represents one of the main obstacles facing tests of market efficiency.

Specifically, the existence of anomalies, that traditional finance theories fail to capture, does not necessarily create the need to revise or replace the EMH with a better paradigm due to the joint hypothesis problem. On the one hand, the EMH proponents explain the existence of anomalies in financial markets in terms of the inadequacy of existing asset pricing models that may miss important risk factors that determine stock returns. On the other hand, behavioural finance proponents explain the existence of anomalies in terms of the unrealistic assumptions of efficient markets, and hence they aim to provide an alternative financial paradigm that can better explain financial markets (Asness and Liew, 2014).

These two opposing views about the existence of anomalies in financial markets have created a heated debate in the finance literature. On the one hand, Fama (1998), in his critique of behavioural finance, argues that most of the anomalies split randomly between overreaction and under-reaction which in turn supports the argument that these anomalies are due to chance and hence they cannot be considered as evidence against market efficiency. In addition, Fama highlights that some apparent anomalies can be attributed to bad model problem rather than market inefficiency and that most of them are captured by multifactor asset pricing models. Furthermore, Fama emphasises that replacing the EMH requires introducing an alternative model that can better characterise financial markets and provide rejectable predictions. Overall, Fama (1998) conjectures that behavioural models are incapable of replacing the EMH.

On the other hand, Shiller (2003) argues that although the EMH can illustrate and characterise an ideal world, it cannot be maintained in its pure form as an accurate descriptor of real markets. Accordingly, behavioural finance should play a considerable role in understanding financial markets and economists should incorporate evidence from behavioural finance in their models to be able to better describe current financial markets.

Although to date behavioural finance cannot be considered as a viable alternative to the EMH, it has achieved a remarkable progress in highlighting the importance of behavioural factors in financial markets. As a result, Debondt *et al.* (2008) state that a major paradigm shift is underway in finance. They claim that this new paradigm will combine the best aspects of the standard finance theories and behavioural finance. It will replace the unrealistic assumptions about the rationality of individual behaviour with descriptive insights about human behaviour revealed by the behavioural finance proponents. They argue that asset pricing theory should also combine new, more realistic, assumptions about human behaviour along with the rigorous methods and techniques of standard finance.

The outline of this chapter is as follows. First it starts with a brief review of the EMH along with identifying its main implications for asset pricing. Then Section 2.3 provides an overview of the development of the CAPM and its empirical evidence. Section 2.4 summarizes the development of behavioural finance and the main differences between standard finance and behavioural finance and the implications of these differences for asset pricing. Section 2.5 deals with the most commonly cited financial market anomalies. Finally, Section 2.6 concludes.

2.2 The Efficient Market Hypothesis

The EMH can be defined in many ways. Fama (1970) argues that an efficient market is one in which prices fully reflect all available information. Jensen (1978) states that a market is considered efficient with respect to an information set if investors cannot achieve economic profits by trading on the basis of this information set. Fama (1965) states that an efficient market is a market where there are large numbers of rational profit-maximizing investors who actively compete, with each trying to predict future market values of individual securities, and where important current information is almost freely available to everyone.

Many implications can be derived from these definitions. First, Shleifer (2000) argues that sufficient but not necessary conditions for market efficiency are:

1) A large number of rational profit-maximizing investors who actively compete in the market and hence value securities rationally.
2) Even if there are some irrational investors in the market, their irrational trades are random and hence tend to cancel each other out, and even if their trades are correlated, rational arbitrageurs eliminate any mispricing that they cause. Therefore, irrational investors will not influence prices.

3) Information is costless and widely available to all market participants. Additionally, investors agree on the implications of this information and they react quickly and fully to it, leading prices to adjust accordingly.

The assumption that information and trading costs must be zero is unrealistic and cannot describe real financial markets; hence a weaker and more realistic version of market efficiency relaxes this assumption by showing that prices should reflect information to an extent that the marginal benefits of acting on information do not exceed the marginal costs of this information (Fama, 1991).

The second implication that can be derived from the definitions of the EMH is related to the two main components of market efficiency. The first component is that there is no systematic way that investors can beat the market. Barberis and Thaler (2003) refers to this component as "*No Free Lunch*" component of market efficiency which means that the average investor cannot earn abnormal returns by trading in the markets based on publicly available information. The logic behind this component is that when information appears in the market, the competition among rational investors leads to that information becoming incorporated into the prices of securities without delay. Hence, neither technical analysis, which is the study of past stock prices to predict future prices, nor fundamental analysis, which is the analysis of financial information to help the investors determine undervalued or overvalued stocks, would enable investors to achieve any abnormal return greater than the return of a randomly selected portfolio of individual stocks with comparable risk (Malkiel, 2003).

The second component of market efficiency is that investors are rational, which means that prices should reflect only fundamental or utilitarian factors such as risk, but not psychological characteristics such as sentiment (Statman, 1999). Barberis and Thaler (2003) calls this second component "*The Price is Right*" component of market efficiency which means that prices fully reflect all the available information and hence they provide accurate signals for resource allocation. The logic behind this component is that in an efficient market, the competition among market participants leads actual prices at any point in time to reflect all available information in the market and hence the actual prices of stocks will be a good estimate of their intrinsic value (Fama, 1965). However, the intrinsic value of a stock is hard to determine, which may leave room for disagreement among investors, and hence give rise to discrepancies between actual prices and intrinsic values, though the competition among rational investors in an efficient market tends to neutralize these discrepancies and cause stock prices to wander randomly around their intrinsic values.

However, the definition of the EMH that stock prices should fully reflect all the available information is so general that it has no empirically testable implications (Fama, 1970). Hence, in order to operationalize the concept of market efficiency, Fama defines three main forms of efficiency, each of which depends on the type of information that is reflected in stock prices. The first form is weak form efficiency which means that the current stock price incorporates information contained in the historical prices. The second is semi-strong form efficiency which suggests that current prices fully incorporate all publicly available information which includes any fundamental information about individual companies, or the stock market as a whole, as well as the past history of prices (Malkiel, 2011). The third is strong form efficiency which means that current stock prices fully incorporate all existing information, whether public or private (including insider information).

However, testing whether information is fully reflected in prices and making observable and testable predictions about market efficiency must be undertaken within the context of a pricing model that determine how prices are set (Asness and Liew, 2014). The most obvious candidate for this task is the CAPM.

2.3 The Capital Asset Pricing Model

Evaluating the level of risk along with expected changes in stock prices is of crucial importance to investors who want to invest in the stock market. Hence, they must understand the factors which can affect the prices of stocks and their associated returns. In this regard, Sharpe (1964) asserts that when investors attempt to determine the price of an asset, they face two prices. The first price is the price of time which reflects the pure interest rate or the risk free rate of return. Sharpe clarifies that there are rigorous models to describe equilibrium risk-free rates. The second price is the price of risk which reflects the additional expected return earned per unit of risk borne. The main problem that Sharpe highlighted is the absence of a theory that determines the price of risk which makes it difficult for investors to understand the relationship between the price of a single asset and its risk. Motivated by this gap, Sharpe (1964) and Lintner (1965) derived the CAPM that marks the birth of asset pricing theory. Schulmerich *et al.* (2015) emphasise that the CAPM should be considered as the basic asset pricing model that must be well understood before analysing more complex models.

2.3.1 The CAPM: Brief Review and Empirical Tests

A fundamental issue in finance is determining the relationship of the risk of an investment with its expected return. The CAPM developed by Sharpe (1964), Lintner (1965) and Mossin (1966) provides the first coherent framework for addressing this issue (Perold, 2004). This section sets out the key concepts underpinning the CAPM and summarizes its empirical tests along with the main challenges facing it.

Sharpe (1964) derived the CAPM as a single factor model that assists investors in determining the equilibrium rates of return of assets in an efficient market (Hodnett and Hsieh, 2012). Specifically, Sharpe highlights that the following relationship holds for all expected asset returns:

$$E(R_i) = R_f + \beta_i(E(R_M) - R_f) \tag{2.1}$$

where $\beta_i = \frac{Cov(R_i,R_M)}{\sigma_M^2}$

The interpretation of Equation 2.1 is that the expected return on any asset i is equal to the risk-free rate, R_f, plus a risk premium which is represented by the asset's market beta, β_i, multiplied by the premium per unit of beta risk, $E(R_M) - R_f$. According to the CAPM formula, any variation in the expected return of an asset is due to variation in its beta, or more precisely, variation in the covariance of the asset's return with the return on the market portfolio or variation in the expected risk premia per unit of beta risk or both.

Tests of the CAPM focus on three implications of the relation between expected return and market beta as implied by the model:

1) There is a linear relation between expected returns on all assets and their betas. In addition, beta is a complete measure of the risk of a stock, which means that no other measure of risk should be able to explain the differences in average returns across stocks that are not explained by the CAPM.
2) The beta premium is positive which means that the expected return on the market portfolio is more than that of assets that are uncorrelated with the market return.
3) In the Sharpe-Lintner version of the model, assets whose returns are uncorrelated with the market have expected returns equal to the risk-free rate, and the beta premium is equal to the expected return on the market portfolio minus the risk-free rate (Fama and French, 2004).

However, in testing these implications empirically, researchers face many obstacles. First, the market portfolio is not observable, so adequate testing of the model may be infeasible (Roll, 1977). However, Guermat (2014) clarifies that, if expected returns are observed, the CAPM is testable via a combination of ordinary and generalised least squares methods.

Second, Ferson and Jagannathan (1996) states that if expected returns and market betas are known, a natural way to examine the CAPM would be to estimate the empirical relation between the expected returns and the betas and determine if this relationship is linear. However, the main obstacle is that neither betas nor expected returns are known or observed, and they must therefore be estimated. This, in turn, raises the problem of the "error-in-variable" bias that may jeopardise the results of testing the CAPM empirically.

Specifically, in testing the CAPM empirically, researchers use the following equation which requires estimates of betas (β_i) that are used as the main independent variable:

$$R_i - R_f = \gamma_0 + \gamma_1 \beta_i + \mu_i \quad (2.2)$$

The CAPM implies that the intercept (γ_0) should be equal to zero for every asset tested and the slope (γ_1) applied to the estimates of the betas should be positive and equal to the average market risk premium. However, despite the theoretical purity of the CAPM, earlier tests were inconclusive (Douglas, 1969; Black *et al.*, 1972; Fama and MacBeth, 1973).

These results can be attributed to the fact that any econometric test of the CAPM is a joint hypothesis combining elements of the theory with *ad-hoc* assumptions about unobservable variables (Crotty, 2011). In this regard, Fama and French (2004) argue that one of the reasons behind the failure of the CAPM reported in studies such as Douglas (1969) is that these studies use individual stocks which make them more vulnerable to the "errors-in-variables" bias. Thus, to circumvent this problem, Black *et al.* (1972) work with portfolios rather than individual securities as estimates of betas for diversified portfolios are more precise. However, Ang *et al.* (2010) state that using portfolios as test assets does not lead to smaller standard errors of cross-sectional coefficient estimates as creating portfolios destroys information by shrinking the dispersion of betas and leads to larger standard errors. Hence, the authors claim that using individual stocks permits more efficient tests of whether factors are priced. Therefore, each of the two approaches has its own merits and shortcomings that should be well analysed before choosing any of them.

Despite the above challenges facing testing the CAPM empirically, Fama and Macbeth (1973) provide the most important paper in testing the CAPM and their methodology has been one of the most important methodologies in testing asset pricing models. In testing the model, they use the following extension of the Security Market Line equation:

$$R_{it} = \gamma_{0t} + \gamma_{1t}\beta_i + \gamma_{2t}\beta_i^2 + \gamma_{3t}s_i + \varepsilon_{it} \tag{2.3}$$

They add two additional variables to the cross-sectional regression of returns on market beta to test whether variables other than beta can determine expected asset returns (Ferson and Jagannathan, 1996). The first variable is squared market beta (β_i^2) which is added to test whether the relation between expected return and market beta is linear. The second variable is the standard deviation of the residuals (s_i) which is used to test whether the market beta is a complete measure of the risk needed to explain expected returns. Given Equation 2.3, the following four hypotheses are tested:

1) Linearity suggests that $E(\gamma_{2t}) = 0$, and this implies that there is a linear relation between expected return and risk.
2) No systematic effects of non-β risk, i.e. $E(\gamma_{3t}) = 0$, and this implies that beta is a complete measure of the risk of a stock.
3) A positive expected risk-return trade-off, i.e.$E(\gamma_{1t}) > 0$, and this implies that if investors are risk averse, they should require a positive premium for beta risk.
4) The Sharpe-Lintner hypothesis, i.e. $E(\gamma_{0t}) = R_{ft}$, and this implies that the intercept should be approximately equal to the average risk-free rate.

In order to test the above hypotheses, Fama and Macbeth proposed a different approach that consists of the following steps. First, they divide the total sample period (1926-1968) into nine overlapping analysis periods. Then, each analysis period is divided into three sub-periods which are: a portfolio formation period, a beta estimation period, and a testing period. During the first sub-period, they estimate a time-series regression of individual security returns against a proxy for the market portfolio in order to estimate the betas for individual securities. They then group these securities into portfolios based on their beta coefficients. Then, the betas of these portfolios are re-estimated using the next five years of data in the initial estimation period to ensure that potential measurement error bias is removed. After that, the monthly returns of the portfolios during the testing period are calculated. Then, for every month in the testing period, a cross-sectional regression is run where the monthly returns of the portfolios are regressed against beta, beta squared and unsystematic risk which were estimated based on the preceding five years of data (Schulmerich *et al*., 2015).The factor risk premium and pricing error estimates are then given as simple time-series averages of period by period estimates (Goyal, 2011).

The results of Fama and Macbeth, using all stocks traded on the New York exchange over the time period January 1926 through June 1968, support the testable implications of the two parameter model. The results show that no other measure of risk, in addition to beta, can systematically affect expected returns. Moreover, the coefficient of squared beta proved to be statistically insignificant which supports the linearity assumption. The results also reveal that there is a positive trade-off between risk and return, as the coefficient of the estimated risk premium from the cross-sectional regression is significantly positive, though it is lower than the historical average risk premium. However, there is substantial variability in the coefficient of the risk premium from month-to-month, so this gives evidence of the existence of a time-varying risk premium.

Although the results of Fama and Macbeth provide some support for the CAPM, an enormous body of empirical research starts to accumulate and provide evidence against the validity of the CAPM thereafter. Among these studies is the research of Fama and French (1992) that is considered as one of the most important studies questioning the empirical validity of the CAPM. Studying a sample that includes the stocks of all non-financial firms listed on the NYSE, AMEX and NASDAQ over the time period December 1962 to June 1990, their results indicate that beta does not explain the cross-section of average stock returns. The results are consistent with the results of Reinganum (1981) who claim that the relationship between beta and average returns disappears over the period 1963-1990.

To sum up, it is apparent that although the EMH and the CAPM have shown some success, there are still a lot of puzzles and anomalies that cannot be explained by rational-behaviour based models. On the one hand, the EMH proponents still defend their approach and argue that these anomalies are due to either statistical errors or poor measurements of risk. Thus, they argue that the existence of these anomalies does not necessarily create the need to replace the EMH with an alternative paradigm. On the other hand, behavioural finance proponents argue that there is enough theoretical and empirical evidence that shows that financial markets are not always efficient. Russel and Torbey (2002) argues that in a market consisting of human beings, it is more reasonable to argue that assumptions rooted in human and social psychology play a better role in advancing our understanding of stock market behaviour. Thus, the aim of the next section is to provide an overview about behavioural finance that emerged as an alternative paradigm for the EMH.

2.4 Behavioural Finance

Several decades of research on the EMH, have shown that reality is sometimes at odds with its premises (Shleifer, 2000). This leads to a revolution in academic finance from viewing the EMH as a theory that is beyond doubt to viewing behavioural finance, which is finance from a broader social perspective including sociology and psychology, as the most vital research program in finance literature (Shiller, 2003). Since its emergence, behavioural finance has successfully attempted to challenge standard finance theory and provide a satisfactory explanation for many puzzles in financial markets. Thus, the aim of this section is to provide an overview about behavioural finance and its development as an alternative paradigm for standard finance theories.

Sewell (2010) defines behavioural finance as the study of the effect of psychology on the behaviour of investors and its effect on financial markets. It helps to explain the why and how financial markets can deviate from the rationality assumed by the EMH. This definition of behavioural finance show that it focuses on explaining investors' behaviours, trading patterns in financial market, and the cross-sectional variations in stocks returns from a human perspective.

Despite its appealing and more realistic assumptions, standard finance proponents criticise behavioural finance by being just a collection of stories about investors' cognitive errors and misleading emotions that lacks the solid structure of standard finance (Statman, 2014). However, this criticism is misleading as the empirical evidence about the anomalies that face standard finance makes the whole paradigm no longer solid as before. According to Statman, behavioural finance is now enjoying a solid structure that incorporates part of standard finance, replaces others and provides links between theory, evidence and practice.

In order to get more insights about behavioural finance, it is important to understand the main components and assumptions that differentiate it from standard finance theories. Thus, Table 2.1 highlights the main differences between the two frameworks (Statman, 2014).

The first difference between standard finance and behavioural finance is related to the representative investor. In standard finance, the representative investor is a rational investor who is unaffected by emotions and cognitive errors. In this regard, rationality means two main things (Barberis and Thaler, 2003):

1) When rational investors receive new information, they update their beliefs appropriately based on Bayesian rules.

2) Given these beliefs, investors make choices and decisions that are normatively acceptable, in the sense that they are consistent with the axioms of subjective expected utility.

Shleifer (2000) emphasises that the case that people in general, and investors in particular, are fully rational as hypothesised by standard finance theories is difficult to sustain. Black (1986) shows that, in making their investment decisions, investors tend to trade on irrelevant information or noise. Furthermore, the theoretical and empirical evidence concerning how investors actually trade in financial markets is inconsistent with the claims of the EMH that investors are rational. Specifically, investors tend to follow the advice of financial gurus, fail to diversify, actively trade in the market, and sell winning stocks and hold on losing stocks.

Table 2.1: Comparison between the Building Blocks of Standard Finance and Behavioural Finance

Standard Finance	Behavioural Finance
People are rational	People are normal
Markets are efficient	Market are inefficient, even if they are difficult to beat
Portfolios are designed based on the rules of mean-variance portfolio theory.	Portfolios are designed based one the rules of behavioural portfolio theory.
Expected returns of an investment are determined by conventional asset pricing models such as the CAPM that assume that differences in expected returns are determined only be differences in risk	Expected returns of an investment are determined by behavioural asset pricing models that assume that differences in expected returns are determined by differences in risk and investor sentiment

However, the EMH, as highlighted in Section 2.2, does not rule out the existence of irrational investors. Rather, the EMH shows that although there may be some irrational investors in the market, their actions are random and tend to cancel each other out. Nonetheless, Shleifer (2000) argues that there is sufficient empirical evidence that investors' deviations from economic rationality are highly pervasive and systematic. Shleifer and Summers (1990) emphasise that investors in psychological experiments tend to make similar rather than random mistakes as the judgment biases that affect them while processing information are the same.

Thus, from behavioural finance proponents' point of view, investors in real financial market are "normal" people who are affected by cognitive errors and misleading emotions rather than "rational" people as postulated by standard finance theories. If standard finance theory relies entirely on the rationality of individual investors, then the above psychological evidence by itself may be considered as a serious problem for the theory (Shleifer, 2000). Nonetheless, proponents of standard finance argue that although their theories may fail as descriptive theories of human behaviour, they still succeed as descriptive theories of the equilibrium that result from the interaction of investors in financial markets (Statman, 1995). This leads to the second line of defence of standard finance theories that is based on arbitrage. In this regard, proponents of standard finance theories argue that even if the actions of irrational investors are correlated, any mispricing that they cause will be cancelled out through the actions of rational arbitrageurs, thus the behaviour of irrational investors has no significant impact on prices (Baker and Wurgler, 2006).

However, these claims of the proponents of standard finance theories that their theories succeed as descriptive theories of equilibrium are strongly challenged by the failure of the CAPM, which represents the market equilibrium model by which the relationship between risk and return is determined in standard finance, to explain the cross-sectional variation in stock returns (Statman, 1995). Standard finance proponents argue that the challenges facing the CAPM do not necessarily imply market inefficiency due to the joint hypothesis problem. In contrast, behavioural finance proponents attribute these challenges to market inefficiency that may be attributed to the ineffectiveness of arbitrage. They argue that there is sufficient evidence in finance literature that there are limits to arbitrage that negatively impact the role of arbitrageurs in bringing prices back to fundamentals, leading to persistence in mispricing (Barberis and Thaler, 2003).

One of the main reasons that may deter the effectiveness of arbitrage in real-world financial markets is the absence of close substitutes for mispriced stocks. Arbitrage is defined as the simultaneous sale and purchase of the same or essentially similar security, in two different markets to benefit from different prices (Shleifer and Vishny, 1997). Thus, in the absence of close substitutes, arbitrage is no longer a riskless activity and thus risk-averse arbitrageurs are less willing to engage in arbitrage activities.

Another reason that may deter the effectiveness of arbitrage is fundamental risk. Arbitrageurs, who take bets on relative price movements, bear the risk that some good (bad) information about the securities they sell/sell-short (buy) may be revealed which results in arbitrage losses and puts further constraints on the effectiveness of arbitrage. Finally, noise traders' risk is another reason behind the deterioration of the role of arbitrageurs in driving prices back to fundamentals. De Long *et al*. (1990) define noise traders' risk as the possibility that the mispricing may become even worse before it disappears. This may lead to temporary losses for arbitrageurs. However, if arbitrageurs can maintain their positions through such losses, they still can achieve a positive return from their trades on the long run. Nonetheless, in the real world, arbitrageurs may not be able to maintain their positions through these losses due to the agency problem (Shleifer and Vishny, 1997).

Specifically, Shleifer and Vishny argue that real-world arbitrage is conducted by relatively few professional investors who combine their knowledge with resources of outside investors to take large positions. The fundamental feature of such arbitrage is that the brains and resources are separated by an agency relationship. In this context, since the investors who provide resources to arbitrageurs do not have the knowledge of the rational arbitrageurs, they may withdraw their capital, when they find these temporary losses, and force the arbitrageurs to liquidate their positions and achieve high losses. The fear of such scenario may make arbitrageurs less effective in achieving market efficiency.

After highlighting the main differences between standard finance and behavioural finance, it is apparent that the main area of disagreement between the two paradigms is concerned with the determinants of asset prices in financial markets. On the one hand, proponents of standard finance attribute the failure of the CAPM to explain the cross-sectional variation in stock returns to bad-model problem rather than to market inefficiency. Thus, they emphasise that the focus of researchers should be to search for an asset pricing model that not only can capture the anomalies that challenge the CAPM but that is also consistent with the "rational maximizing behaviour" of all investors (Statman, 1999). This leads to the emergence of many research papers on asset pricing, risk, measurement of risk, and measurement of the relation between expected return and risk as postulated by Fama (2008) in one of his interviews. Nonetheless, despite all of this work, the current state of asset pricing models, that derive their assumptions from standard finance theory, is unsatisfactorily (Statman, 2014).

On the other hand, behavioural finance proponents attribute the failure of conventional asset pricing models such as the CAPM to neglecting the role of value-expressive characteristics in asset pricing models as they are viewed by standard finance proponents as "*unimportant detours from the main road*", namely, asset pricing (Statman, 1999, p.21). Thus, motivated by the failure of conventional asset pricing models along with the theoretical and empirical evidence about investor irrationality and limits to arbitrage, Statman argues that the main focus of researchers should be to develop a behavioural asset pricing model that can incorporate both utilitarian and value-expressive characteristics.

Nonetheless, despite the various attempts of behavioural finance proponents to develop a behavioural asset pricing model that can replace the CAPM and its proliferations, no satisfactory behavioural asset pricing model has emerged to show how both utilitarian and value-expressive factors should be incorporated together in asset pricing models. Zin (2002) points out that the main problem facing behavioural asset pricing models is the lack of structural parameter to incorporate the effect of irrational investors on asset prices. Specifically, researchers face difficulties in quantifying the merely heuristic psychological evidence within the framework of asset pricing models. This, in turn, precludes testing behavioural asset pricing models empirically and it may explain why none of the behavioural models developed so far is commonly accepted as compared to their opponent conventional models (Jackwerth, 2002).

The above discussion implies that the existence of anomalies in financial markets creates the need for either developing alternative asset pricing models that can provide a sufficient explanation for these anomalies, or replacing the EMH assumptions with a new paradigm such as behavioural finance which can potentially better explain these anomalies. Thus, the next section summarizes the most prominent anomalies and the explanations that emerged to justify their existence from the proponents of both standard finance and behavioural finance theories.

2.5 Asset Pricing Anomalies

Jensen (1978) points out that in the finance, accounting and economics literature, the EMH is taken as given, and that any researcher who wishes to model behaviour in a manner that contradicts it faces a challenging task of justification. However, there exists growing empirical evidence of many market anomalies that the EMH cannot explain, including the puzzles of the size effect, the value effect, and the momentum observed in stock returns. Hawawini and Keim (1998) argue that financial market anomalies have created a strong debate in finance literature concerning their interpretation. On the one hand, some researchers interpret the existence of these anomalies as evidence against market efficiency. On the other hand, the results may be due to the failure of the underlying asset pricing model (such as the CAPM) to provide complete description of equilibrium price formation. Therefore, anomalies often provide the most insightful directions for future research (Frankfurter and McGoun, 2001).

2.5.1 The Size Effect

The size effect, which refers to the observation that the stocks of smaller firms have higher returns than the stocks of large ones, is considered one of the most commonly studied anomalies in the finance literature. This, in turn, leads to a wide array of explanations that emerged to justify why stocks of small firms have higher returns than those of large ones (see for example, Vassalou, 2004, Gomes *et al*., 2003). However, to date, there is no consensus on a rational explanation for the size effect. The aim of this section is to review some evidence about the existence of size effect in both developed and emerging markets and highlight that main explanations that emerged to justify this anomaly.

Banz (1981) provides the first systematic evidence of the existence of the size effect in US stock returns. The author empirically examines the relationship between the total market value of the common stock of a firm and its returns using the following generalized asset pricing model which proposes that the expected return of a common stock is a function of risk, β and the market value of equity, Φ.

$$E(R_i) = \gamma_0 + \gamma_1\beta_i + \gamma_2[\frac{\Phi_i - \Phi_m}{\Phi_m}] \quad (2.4)$$

where Φ_i is the market value of stock, i, and Φ_m is the average market portfolio value. However, in contrast to the proposition of the CAPM that beta is a complete measure of risk, the results show that γ_2 is significantly negative which means that the shares of firms with small market values have higher returns, on average, compared to those with large market values.

The size effect observed in the US market is also prevalent in other markets. Rouwenhorst (1999) shows that small stocks tend to outperform large stocks in a sample of 1,705 firms from 20 emerging markets. These results from international markets present a strong argument against data mining concerns (Dijk, 2011). However, another strand of empirical research starts to provide evidence that the size effect has disappeared after its discovery in the 1980s (Horowitz *et al.*, 2000). Horowitz *et al.* suggest that this implies that size is not a systematic risk factor and it is not a proxy for risk in all sample periods. Thus, they question the widespread use of size as one of the explanatory variables for stock returns. However, Hou and Dijk (2008) highlight that the size effect has not disappeared, and this leads to a revival of academic research on the underlying causes of the size effect.

There are currently two explanations to the size anomaly. The first is a rational asset pricing explanation which suggests that the market is efficient, but the CAPM is misspecified. The essence of this explanation is that since differences in average returns are due to differences in risk, then this implies that size is a proxy for unknown risk factors. The second explanation justifies the size effect using advances in human psychology which actually does not receive substantial coverage in behavioural finance literature as compared to other anomalies.

The first set of rational asset pricing explanations attributes the size effect to the inaccuracy of the estimates of the CAPM beta. Roll (1981) argues that the size effect may be the statistical result of imprecise measures of betas resulting from infrequent trading of small stocks. However, Reinganum (1982) conclude that the bias in risk estimates due to non-synchronous trading is not sufficient to explain the observed size effect. Accordingly, the focus of researchers has shifted towards considering the effects of non-market risk factors in order to explain the size effect within rational context.

In this regard, Chan *et al.* (1985) find that the size effect is captured by a multifactor pricing model and the higher average returns of small firms are mainly compensation for the additional risks borne in efficient market. Accordingly, Chan and Chen (1991) attempt to identify why small firms are riskier than big ones. They find that small firms tend to be firms with weak financial performance and, accordingly, they are firms that are not efficiently run and have higher financial leverage. This implies that small firms are riskier than larger firms and this risk cannot be captured by a market index heavily weighted towards large firms.

In the light of previous results, multifactor asset pricing models provide promising insights to explain the size effect. Fama and French (1992) are among those researchers who claim that stock risks are multidimensional where one dimension of risk is proxied by firm size and the other dimension is proxied by the book-to-market ratio. Hence, Fama and French (1993) propose their three factor model that augments the CAPM with two mimicking portfolios formed on size and book-to-market ratio to accommodate the anomalies that the CAPM fails to capture. However, Chou *et al*. (2010) state that despite the popularity of the Fama and French three-factor model, the model fails to fully account for the cross-sectional regularities related to size and the book-to-market ratio as it does not specify precisely the underlying economic rationale behind the inclusion of the two mimicking portfolios formed on size and book-to-market ratio.

Hence, these results create a motive to search for alternative asset pricing models that can better explain the size effect. In this regard, Jagannathan and Wang (1996) show that the failure of the static CAPM to explain the cross-section of average returns on stocks completely is due to the unreasonable assumption that the betas of firms remain constant over time. Thus, they develop a conditional CAPM with human income and time-varying risk aversion, which is captured by introducing an additional beta with a time-varying risk premium, defined as a linear function of the default spread. They find that the explanatory power of firm size can be captured by their conditional model and thus they conclude that the size effect might be a proxy for the risk associated with the return on human capital and beta instability.

In the same spirit, Berk *et al*. (1998) suggest that dynamic evolution of systematic risks is a promising source of explanatory power for understanding different anomalies. Motivated by this argument, Avramov and Chordia (2006) analyse whether conditional asset pricing models can explain the size, book-to-market, turnover, and momentum effects on expected returns, as they are considered the most puzzling anomalies in financial markets.

Their results show that the conditional CAPM, where betas are allowed to vary with firm size, book-to-market ratio and default spread, cannot capture any of the aforementioned anomalies. However, the conditional Fama and French three-factor model provides a major improvement over the conditional CAPM as it is able to explain both the size and book-to-market effects. Avramov and Chordia argue that the success of the conditional Fama and French model to capture the size effect supports risk-based explanations for size effect. If risk is completely unrelated to size and value effects then conditional versions of pricing models will not capture these anomalies.

However, despite the attempts of the proponents of rational asset pricing to explain the size effect, the search for an explanation of this anomaly has been unsuccessful (Berk, 1995). Specifically, the absence of a theoretical underpinning for the relationship between size and expected returns and the disappearance of the size effect after its discovery during certain periods cast doubts on the argument that the previously observed higher returns of small firms are a premium for extra fundamental risk. Thus, our understanding of the economic or statistical causes of the apparently high average returns on small stocks is incomplete.

As a result, behavioural finance proponents attempt to interpret the phenomenon differently (Szyszka, 2013). They attribute the higher returns of small firms to the presence of noise traders whose actions are derived by speculation and emotions rather than rational information analysis. Lemmon and Portniaguina (2006) find that investor sentiment forecasts the returns for small stocks due to the predominant ownership of these stocks by individual investors compared to large stocks. In addition, the higher trading costs and other frictions that are more likely to limit arbitrage in small stocks makes them more vulnerable to variations in investor sentiment. Lee *et al*. (1991) claim that the risk related to the presence of noise traders is systematic and it should be compensated for by an adequate premium. Hence, similar to the proponents of the EMH, behavioural finance justifies the higher returns of small stocks by the higher level of risk common for this group of assets. However, while the EMH proponents relate the extra risk to fundamental factors, behavioural finance proponents relate risk to behavioural factors (Szyszka, 2013). Despite the attempts of behavioural finance proponents to derive reasonable explanations for the size effect, Dijk (2011) argues that there is no direct evidence on whether the size effect is consistent with a mispricing theory.

2.5.2 The Value Effect

Another puzzling anomaly that has strongly challenged the CAPM is the value effect. Lakonishok *et al.* (1994) point out that for many years, scholars and investment practitioners have claimed that value strategies outperform the market. These value strategies are based on buying stocks that have low prices relative to earnings, dividends, book assets or other measures of value. The widespread use of these value strategies among practitioners has motivated academics to test for the existence of the value effect in different markets and different time periods, and to provide reasonable explanations for this anomaly.

The first seminal paper to test the argument that value related variables can explain the cross-sectional variations in expected returns is Basu (1977) who analyses whether the investment performance of common stocks is related to earnings-price (E/P) ratios using US stocks. The results reveal that when dividing stocks over five portfolios according to their E/P ratios, high E/P portfolios earn higher returns compared to the low E/P portfolios. However, contrary to the capital market theory, these higher returns are not associated with higher levels of systematic risk as measured by the CAPM beta.

Basu attributes the above findings to market inefficiency. However, Ball (1978) suggests that such a conclusion is premature as market efficiency tests are joint tests of the EMH, and a particular asset pricing model. Given Ball's argument, the results of Basu may reveal that the CAPM does not completely capture the equilibrium risk-return relationship. Thus, this may indicate that the model is misspecified due to the omission of other relevant factors, and that the E/P ratio seems to be a proxy for these omitted risk factors. Ball claims that E/P is a catch-all proxy for omitted risk factors in expected returns because of the inverse relation between market values and discount rates. Holding book value constant in the numerator, a firm's B/M ratio tends to increase as expected return, and consequently risk, increases (Lewellen, 1999).

Supporting Ball's argument, Fama and French (1992) interpret the empirical results that variables such as firm size, the book-to-market ratio, leverage, and the earnings-price ratio have a significant predictive ability for expected returns as evidence against the CAPM. In this seminal paper, they find that size and the book-to-market equity play a significant role in explaining the cross-section of average stock returns and that they can absorb the explanatory power of other variables such as E/P ratios and leverage. However, they argue that prescriptions for using these results depend on two important aspects: (i) whether these results will persist in the future or are due to chance; and (ii) whether these results are due to rational or irrational asset-pricing.

These two aspects led to a flurry of publications designed to refute or confirm their results. In an attempt to provide out-of-sample evidence about the existence of value effect and refute data mining concerns, Fama and French (1998) test whether there is a significant value premium in 13 major countries for the time period 1975-1995. Their results indicate that there is a strong evidence of a consistent value premium in international returns. In addition, they extend the analysis to include 16 emerging markets and they find that there is a positive value premium in these markets. Thus, they conclude that their results, along with the previous results that support the existence of value effect in the US, provide appealing evidence that the return premium for value stocks is real.

Thus, the focus of researchers has shifted towards providing reasonable explanations for the value effect. Despite the consensus in academic literature about the existence of the value premium, researchers still disagree about the cause of the phenomenon and, thus, they are divided into two camps. The first camp believes that the value effect originates from the relative riskiness of high B/M value stocks and low B/M growth stocks. On the other hand, proponents of the second camp believe that the observed value premium results from the persistent irrational pricing of those stocks.

The main proponents of the first camp are Fama and French (1992) who propose that if assets are priced rationally, then the ability of size and the book-to-market ratio to capture most of the cross-sectional variation in stock returns may imply that these variables act as a proxy for sensitivity to common risk factors in returns. Their results have motivated them to propose their three-factor model that augments the CAPM with two additional factors to mimic risk factors related to size and the B/M ratio.

Lakonishok *et al.* (1994) state that despite the impressive results of the B/M strategy, B/M is not a "clean" variable uniquely related to economically interpretable characteristics of firms. Hence, Fama and French (1995) attempt to fill in this economic void and they identify that, consistent with rational-pricing models, firms with high B/M ratios tend to have persistently low earnings, higher financial leverage, greater earnings uncertainty, and are more likely to cut dividends compared to their low B/M counterparts. Hence, this implies that high B/M stocks are assigned a higher risk premium due to the greater risk of distress (Griffin and Lemmon, 2002).

To provide further evidence concerning whether differences in risk can explain the book-to-market premium, Griffin and Lemmon (2002) test the earnings performance and the likelihood of delisting for both high and low B/M firms. Contrary to Fama and French (1995), their results show that low B/M firms persistently have slightly lower earnings than those of high B/M firms. In addition, firms with low B/M ratio are more likely to be delisted for performance-related reasons than their high B/M counterparts. These results provide evidence against a risk-based explanation for the book-to-market effect.

Further evidence against risk-based explanations is provided by Lakonishok *et al.* (1994) who claim that if value stocks are fundamentally riskier than growth stocks, then they must underperform growth stocks, especially in the states of the economy where the marginal utility of wealth is high. Hence, to test this hypothesis, they analyse the performance of value strategies during bad states of the economy such as extreme down markets and economic recessions. Their results show that over longer horizons, value stocks have consistently outperformed growth stocks and have performed particularly well in bad states of the economy. Hence, this casts doubts on the view that value stocks are fundamentally riskier than growth stocks.

Given the above results, despite the arguments of Fama and French (1993, and 1995) that the ratio of book value to the market value of the firm's equity tends to capture some sort of rationally priced risk, their failure to specify what the risk captured by the B/M ratio might be, or why it is priced, or in what direction casts some doubts on risk-based explanations. This, in turn, leads to the emergence of behavioural explanations for the value premium that are marked by the publication of Lakonishok *et al*. (1994) paper.

Lakonishok *et al*. attribute the predictive power of financial ratios such as the book-to-market ratio to their ability to capture systematic errors in the way investors form expectations about the future returns. Investors expect that future growth rates are strongly tied to past growth rates despite the fact that the growth rates are highly mean-reverting. Hence, they expect growth stocks to continue to grow faster than value stocks. Accordingly, they become overly optimistic (pessimistic) about the recent performance of growth (value) stocks and buy (sell) them, and this causes such stocks to become overpriced (under-priced). However, the actual future growth rate of earnings of growth stocks turns out to be much lower than that expected by investors. Thus, the value premium is merely a result of unravelling the past errors made by investors.

The conflict between risk-based and behavioural explanations of the value effect creates a significant need to discriminate between these two explanations to be able to better understand this anomaly. In this regard, one line of research emphasises the importance of conditional asset pricing models to explain different financial market anomalies within a rational framework (Lewellen, 1999). It hypothesises that the significant relation between predictive variables such as the B/M ratio and the time-series and cross-section of stock returns may be due to their association with risk. Particularly, these variables must contain information about the time variation in risk, and consequently, expected returns. This denotes that the predictive power of these variables should disappear once adequate control for fluctuation in risk is taken into consideration. On the other hand, proponents of the mispricing explanation for the value effect claim that since the B/M ratio contains information about the mispricing of securities, its predictive power will persist even when risk fluctuations are taken into consideration (Bauer *et al.*, 2010). To help distinguishing between these two views, Lewellen tests the predictive power of the B/M ratio within the context of the conditional Fama and French three-factor model. The conditional regressions allow both expected returns and factor loadings to vary with the B/M ratio as in Equation 2.5.

$$R_{it} = \alpha_{i0} + a_{i1}\, B/M_{it-1} + \sum_{k=1}^{3}(\beta_{ik0} + \beta_{ik1} B/M_{it-1}) FF_{kt} + \mathrm{e}_{it} \qquad (2.5)$$

Here, FF_{kt} represents the three Fama-French factors (R_M, SMB and HML). This equation divides the predictive ability of the B/M ratio into risk and non-risk components. The coefficient a_{i1} measures the predictive power of B/M after controlling for its association with the three-factor model. If the three-factor model truly captures the priced risk in the economy, the risk-based view requires a_{i1} to be zero for all stocks. On the other hand, the mispricing view implies that B/M can forecast returns even after controlling for risk and thus this view predicts that a_{i1} should be positive.

The results indicate that the coefficients of interaction terms with B/M reveal interesting insights. First, the results show that B/M captures time-variation in risk, but it does not directly predict expected returns. The results indicate that the B/M is significantly related to loadings on the three Fama-French factors (R_M, SMB and HML). Additionally the results show that after controlling for risk, the B/M ratio contains little additional information about expected returns. These results give support to risk-based explanations for the value effect. However, Lewellen emphasises that, despite the supporting results for risk-based explanations of the value effect, the case for rational pricing is not fully satisfactory as the Fama and French three-factor model does not provide clear identification of the risk factors captured by the size and B/M mimicking portfolios. So the debate between risk-based and behavioural explanations of the value effect is still a heated topic that requires further research.

2.5.3 The Momentum Effect

Momentum in stock returns has become one of the most commonly investigated anomalies in behavioural finance and market efficiency since the publication of Jegadeesh and Titman (1993) paper. In this seminal paper, through employing a sample that includes NYSE and AMEX stocks over the period 1965-1989, Jegadeesh and Titman highlight that a strategy that selects stocks based on their past six-month returns and holds them for six months achieves a compounded excess return of 12.01 percent per year on average. These observations that momentum strategies can generate profits that are statistically and economically large motivates several researchers to test the existence of momentum in stock returns in different markets and different time periods and to investigate whether the existence of momentum is due to market inefficiency or the misspecification of asset pricing models.

Among these studies is Rouwenhorst (1998) who study the profitability of momentum strategies in 12 European countries. The results indicate that a strategy that invests in medium term winners and sells past medium term losers earns around 1 percent per month and that the profit is present in all of the 12 markets investigated during the time period 1980-1995. However, the results for emerging markets are weaker than that for developed markets. Rouwenhorst (1999) finds that there is no evidence of intermediate horizon momentum returns in 14 out of 20 emerging markets studied over the period 1982 to 1997.

From the above evidence, it is obvious that momentum is an anomaly that exists in several markets with different characteristics which rules out data snooping concerns. Thus, the focus of researchers has shifted towards understanding the sources of momentum profits and providing explanations that range from risk-based explanations to behavioural explanations.

The persistence of momentum in stock returns poses strong challenges to the EMH that rules out the possibility that investors can achieve abnormal returns by trading in the markets based on publicly available information (Fama, 1970). However, proponents of market efficiency claim that the impact of security characteristics on stock returns can be captured using appropriate risk factors. For traditional financial theory to be able to explain momentum in stock returns, the winner portfolio should contain more risky stocks compared to the loser portfolio (Sondergaard, 2010).

In this respect, Fama and French (1996) find that, unlike size and value effects, the profitability of a momentum strategy is the main challenge to their three-factor model. As a result Chan *et al*. (1996) consider momentum in stock returns as a major unresolved puzzle in the finance literature.

The failure of the Fama and French three-factor model to explain momentum phenomena motivates Avramov and Chordia (2006) to evaluate the empirical performance of conditional asset pricing models in a framework where factor loadings are allowed to vary with firm size and the book-to-market ratio in addition to business cycle-related variables. However, despite the success of modelling beta variation in improving the pricing abilities of the models[2] tested, the results indicate that none of the models were able to capture the impact of momentum on the cross-section of stock returns.

Griffin *et al*. (2003) find that macroeconomic risk cannot provide a sufficient explanation for the momentum in stock returns using a large sample of international stocks. In addition, in order to provide further evidence about the influence of macroeconomic risk on momentum returns, they analyse the relation between the macroeconomic state and momentum. They find that there are positive momentum returns in both good and bad business cycle states, which is inconsistent with the view that momentum is a reward for priced business cycle risk. However, despite these unfavourable results, Griffin *et al*. argue that momentum may be explained by other forms of risk that are not yet tested, but that the form of this risk and its behaviour remains unclear until now.

Contrary to risk-based models, the behavioural models indicate that momentum profits can be due to the susceptibility of investors to behavioural biases or the

[2] (i) CAPM, (ii) Fama and French (1993) three-factor model, (iii) Fama and French model augmented with Pastor-Stambaugh (2003) liquidity factor, (iv) Fama and French model augmented with winners-minus-losers (WML) portfolio to proxy for momentum, (v) a version of Jagannathan and Wang (1996) that uses excess market return and labour income growth as factors, (vi) a linear version of the consumption CAPM, and (vii) Fama and French model augmented with the liquidity and momentum factors.

interaction between different types of investors which can lead to either under-reaction or overreaction to information.

Among the behavioural models developed to explain momentum is the Daniel *et al.* (1998) model which uses overconfidence and self-attribution bias to generate momentum. Overconfidence refers to the tendency of investors to be overconfident about their private information and this leads to excessive trading which causes prices to deviate from their fundamental values. On the other hand self-attribution bias reflects the investor tendency to relate any success to his stock picking skills and any failure to bad luck and external conditions. Combining self-attribution bias with overconfidence leads prices to move further form their fundamental values if public information is consistent with private information. As a result, the initial overconfidence will be followed by even greater overconfidence generating momentum in stock returns followed by long term reversal as the prices revert to their fundamental values.

Another behavioural model is Barberis *et al.* (1998) model that links conservatism bias, which reflects the tendency of the investors to underweight new information relative to prior information, with representativeness bias, which refers to the judgment of investors based on stereotypes. Following good news (earnings announcements), conservatism bias leads investors to react partly to the new information received and thus prices will increase slightly but under-react to the new information. As good information spreads in the market, representativeness bias means that investors expect that this tendency will continue in the future and hence they push prices up. The logic underlying their action is that they expect that the current situation will persist in the future and thus they will generate momentum in stock prices. As this overreaction gets corrected, prices will revert to their fundamental value leading to a long term reversal in prices.

Hong and Stein (1999) develop another model that is based on the interaction between two groups of investors. The first group is the “news watchers” who make decisions about the prices based on private information only, and they underweight past price information. The second group of investors is “momentum traders” who make their decisions based on the most recent prices. Under this hypothesis, Hong and Stein assume that private information will only be partly reflected in prices as a result of the behaviour of news watchers who are unable to extract any other private information from the prices. This slow diffusion of information will lead to momentum in stock prices. On the other hand, momentum traders will act on the recent price change at the beginning of their actions, and thus they will help prices to move toward their fundamental value, but since they focus on the recent price change as they are trend-chasers, they push prices away from fundamental value and cause an overreaction in the long run. As the overreaction gets corrected, long term reversal will be observed.

Given the wide array of explanations that range from risk-based and behavioural explanations, Griffin *et al.* (2003) propose one way to differentiate between them is based on the dissipation of momentum profits. On the one hand, the behavioural models discussed above allow for initial under-reaction followed by subsequent return reversals. However, these models do not specify a time span for the reversals to occur and thus they possess something of an unfair advantage. On the other hand, if momentum profit is a compensation for risk then momentum strategy should continue to be profitable in post holding periods. However, Jegadeesh and Titman (2001) and Griffin *et al.* find evidence supporting the existence of negative post holding returns. Hence, they conclude that these results are consistent with behavioural explanations. However, they highlight the need for better behavioural models with more specific predictions about the time horizon required for dissipation of momentum profits to fairly evaluate these models in the future.

2.6 Conclusion

This chapter has reviewed three cornerstones of modern asset pricing. The EMH and the CAPM have been influential in modern finance thought. Nevertheless, many anomalies are yet to be explained from a rational point of view. Although Fama (1998) provides a strong defence of the rational investor paradigm, Shiller (2003) argues that although financial markets are not totally "crazy", they still contain substantial noise which is the main reason behind the failure of the EMH to provide a link between stock market fluctuations and subsequent fundamentals. This, in turn, leads to the emergence of several behavioural models. However, most of these models are *ad-hoc* and designed to capture only specific anomalies.

The burden of proof remains with the behavioural finance supporters. Unfortunately none of the available behavioural models has yet been able to fully explain the existing anomalies. Similarly, the attempts of standard finance proponents to attribute the existence of anomalies to the bad-model problem is strongly criticised (Statman, 2014). Statman highlights that this approach leads the asset pricing literature to be dominated by "factor mining" which reflects the attempts of researches to find factors that have a statistically significant association with realized returns without giving due care to understanding the theoretical rationale behind these associations. Statman emphasises, in developing new asset pricing models, researchers should focus on both the theoretical rationales of the new factors as well as their statistical significance in order to have a satisfactorily asset pricing model.

Thus, it is apparent that both standard finance and behavioural finance face serious challenges. The standard finance literature has tackled its problems via a search for relevant state variables that can explain stock returns (Shah *et al.*, 2014; Fama and French, 1993); coupled with careful model specification (Ghysels, 1998).

On the other hand, Shiller (2003) emphasises that future research in finance literature should bear in mind that although standard finance theories can characterize ideal world, they cannot be maintained in their pure form as accurate descriptors of reality. Thus, he recommends that researchers should distance themselves from the assumptions that financial markets always work well and that prices always reflect genuine information if they want to have better understanding of real financial markets.

Chapter 3

The Fama and French Three-Factor Model

3.1 Introduction

The previous chapter covered the CAPM which provides the first coherent framework to determine how the risk of an investment affects its expected returns (Perold, 2004). However, the empirical challenges facing the CAPM necessitate its replacement with another model that can better explain stock returns. Thus, the aim of this chapter is to discuss the Fama and French three factor model (hereafter FF3) that is considered as one of the most important successors of the CAPM.

Upon the emergence of the CAPM, many studies were undertaken to empirically examine its validity. However, most of these studies contradict its central proposition that the market beta is sufficient to describe the cross-section of expected returns. Despite the poor empirical results when testing the model, Fama (1991) argues that without the existence of the CAPM as a benchmark against which to test the cross-section of expected returns, the academic community would not have been able to discover these anomalies which provide a specific roadmap for future research in asset pricing literature in an attempt to understand their potential causes.

Although there are several explanations that have emerged to explain the existence of anomalies in financial markets, this chapter is mainly concerned with the risk-based explanations that are proposed by the proponents of standard finance theories who argue that these anomalies result from sources of risk that are not adequately captured by the CAPM. In this regard, motivated by the theoretical work of Merton (1973) and Ross (1976), researchers add factors beyond market returns to describe the cross-section of expected returns by arguing that these factors are either proxies for underlying state variables that represent changes in the investment opportunity set or proxies for "factor-mimicking" portfolios in an Arbitrage Pricing Theory (APT) setting. The most remarkable asset pricing model here is the FF3 which proposes that most of the well documented empirical anomalies can be captured by sensitivity to three factors which are: (i) the market; (ii) the size factor (SMB); and (iii) a book-to-market (B/M) factor (HML).

The outline of this chapter is as follows. In section 3.2, a brief review of the main foundations and development of the Fama and French three-factor model is provided. Section 3.3 gives an overview of the empirical evidence for the model when applied to both developed and emerging markets. Section 3.4 summarises the main schools of thought that have emerged to justify the empirical success of the model. Section 3.5 summarises the salient discussion from the chapter.

3.2 Multifactor Asset Pricing Models

The most obvious candidate that has been developed to capture the CAPM anomalies is the seminal three-factor model developed by Fama and French in 1993. Since its development, the model has been considered as a benchmark model for risk adjustment in the empirical asset pricing literature (Hahn and Lee, 2006). The aim of this section is to discuss and analyse the development of the FF3.

3.2.1 The Need for Alternative Asset Pricing Models

Recent empirical evidence has shown that much of the variation in expected stock returns is unrelated to the market beta (Fama and French, 2004). Researchers have identified a number of empirical challenges in asset prices that have come to be considered as anomalies. It has been documented that variables such as the size of the firms (Banz, 1981), the ratio of the book value of equity to the market value of equity (Lewellen, 1999), and earnings-price ratios (Basu, 1977) have some power in explaining the cross-sectional variation in average stock returns.

In their seminal paper, Fama and French (1992) assess the ability of market betas, size, the earnings/price (E/P) ratio, leverage, and the book-to-market (B/M) ratio in explaining the cross-sectional variation in expected returns. They use the Fama-

Macbeth cross-sectional regression to test which of these explanatory variables have, on average, a non-zero expected premium. Their most striking result is the failure of the market beta to explain average stock returns that represents "*a shot straight at the heart*" of the CAPM (Fama and French, 1992, p.438). In addition, the results show that there are strong univariate relations between average returns and each of size, leverage, the B/M ratio, and the E/P ratio independently. Finally, by using multivariate tests to investigate the joint roles of these variables in explaining the cross-sectional variation in average returns, they find that the combination of size and the B/M ratio tends to subsume the roles of leverage and the E/P ratio in explaining average returns.

Fama and French summarize the main results of their paper as follows: (i) beta does not seem to help to explain the cross-sectional variation in expected returns, which contrasts with the key prediction of the CAPM that there is a positive relation between average returns and market betas; and (ii) the combination of two empirically motivated variables, size and book-to-market equity, captures the cross-sectional variation of average returns well. These results have led Fama and French to argue that the CAPM does not explain average stock returns, at least during their sample period, thereby shifting the focus of academics to search for explanations for the model's empirical problems. In this regard, three main schools of thought have emerged. The first school argues that the size and book-to-market effects may be attributed to the behavioural biases of investors and inefficiencies in the market, as proposed by Daniel and Titman (1997) and Lakonishok *et al*. (1994).

The second school argues that most of the empirical studies that have documented empirical results which contrast with the CAPM involve an errors-in-variables (EIV) bias, since the true betas are unobservable, and thus estimated betas are used as a proxy for the true unobservable beta (Kim, 1997). Kim (1995) highlights that the EIV bias leads to an underestimation of the price of beta risk and an overestimation of the other cross-sectional regression coefficients associated with idiosyncratic variables that can be observed without error such as firm size and book-to-market equity. However, Kim (1997) shows that the EIV bias cannot save the CAPM as the book-to-market ratio retains its significant explanatory power even after correcting for the bias.

The third school proposes that the failure of the CAPM is due to its unrealistic assumptions. For example, it is unreasonable to assume that investors care only about the mean and the variance of their one-period portfolio returns as they will also care about how their portfolio returns covary with labour income and future investment opportunities (Fama and French, 2004). The argument here is that a portfolio's return variance tends to miss important dimensions of risk. Thus, market beta may not represent the only source of risk that investors should be rewarded for bearing, and differences in expected return may not be completely explained by differences in beta. This, in turn, reinforces the need for further development of asset pricing models that can better explain average returns.

3.2.2 The Development of the Fama and French Three-Factor Model

Motivated by the argument of the proponents of the third school of thought, many asset pricing models have emerged to provide a better explanation for average returns. One of these models is the Merton (1973) Intertemporal Capital Asset Pricing Model (ICAPM). Contrary to the simple CAPM which assumes that investors care only about the wealth produced by their portfolio at the end of the current period, in the ICAPM, investors are concerned with the relationship between current returns and the returns that will be available in the future. This leads to the emergence of additional sources of risk that an investor has to hedge against. Thus, similar to the CAPM, in the ICAPM, investors tend to prefer higher expected returns and lower return variances. However, they tend also to be concerned with the covariances of their portfolio returns with changes in the investment opportunity set (Fama and French, 2004). According to Cochrane (2001), the cross-sectional equilibrium relation between expected return and risk in the context of the ICAPM is as follows:

$$E_t(R_{i,t+1}) - R_{f,t} = \lambda Cov_t(R_{i,t+1}, R_{m,t+1}) + \lambda_z Cov_t(R_{i,t+1}, \Delta z_{t+1}) \tag{3.1}$$

where R_i represents the expected return on asset i, R_f represents the risk-free rate of return, R_m is the return on the market portfolio, λ represents the market price of covariance risk (which corresponds to the coefficient of the relative risk aversion of the representative investor), λ_z is the intertemporal price of covariance risk, and Δz represents the innovation in the state variables that captures the uncertainty about the future investment opportunities.

The second term in Equation 3.1 represents the expected return component that emerges as compensation for unexpected changes in the investment opportunity set. These changes in the investment opportunity set are captured by the state variables z which are essentially the variables that characterise the conditional distribution of returns that will be available in the future. Fama and French (2004) argue that an ideal implementation of the ICAPM requires specification of the state variables that affect expected returns. However, the ICAPM does not specify these state variables, and this has encouraged Fama (1991) to label it as a "fishing license" as it allows researchers to choose from a wide spectrum of potential factors and use the model as a theoretical underpinning for the relatively *ad-hoc* factors used in their models (Maio and Santa-Clara, 2012).

Another model that has emerged to respond to the failures of the CAPM is the Arbitrage Pricing Theory of Ross (1976). Ross (1978) argues that the APT appears to offer practitioners and academics an alternative model which maintains the simplicity of the CAPM, while avoiding many of the theoretical challenges and empirical problems of that model. Although the CAPM and the APT both propose that in a well-diversified portfolio, investors should only care about systematic risk that represents pervasive factors that affect the whole stock market, they differ in how to measure this systematic risk. The CAPM assumes that only market risk affects expected returns, while the APT states that stock returns are driven by a number of factors that reflect basic economic forces. This aspect of the APT constitutes one of its main advantages over the CAPM as it allows a larger number of factors to affect stock returns and this, in return, makes the model more operational and with better explanatory power than the CAPM (Paavola, 2006). Within the context of the APT, the equilibrium expected return on asset i must be equal to a linear combination of the beta coefficients:

$$E(R_{it}) = \lambda_{0t} + \sum_{k=1}^{K} b_{ik}\lambda_k \tag{3.2}$$

where λ_{0t} represents the expected return on an asset with zero systematic risk. Further, λ_k represents the risk premium associated with the kth factor, f_k, and the betas represent the factors' loadings (Reinganum, 1981). However, similar to the ICAPM, the APT does not offer any theoretical or empirical grounds for identifying the economic nature of the factors (Bishop *et al.*, 2001).

Driven by the failure of the CAPM to explain patterns in average stock returns, as summarised in Fama and French (1992), and the theoretical underpinnings of Merton's (1973) ICAPM and Ross's (1976) APT, Fama and French (1993) proposed their three-factor model as an alternative asset pricing model to the CAPM. The model postulates that the expected return on a portfolio in excess of the risk-free rate can be explained by the sensitivity of returns to three main factors: (i) the excess return on the broad market portfolio; (ii) the difference between the returns on a portfolio of small stocks and a portfolio of large stocks (SMB); and (iii) the difference between the returns on a portfolio of high-book-to-market stocks and a portfolio of low-book-to-market stocks (HML) (Fama and French, 1996). Specifically, the model can be represented by the following Equation:

$$E(R_{it}^{e}) = \beta_{iM}E(R_{M,t}^{e}) + \beta_{is}E(R_{SMB,t}) + \beta_{ih}E(R_{HML,t}) \tag{3.3}$$

Here $E(R_{it}^e)$ is the expected excess return on stock i for month t. $E(R_{M,t}^e)$, $E(R_{SMB,t})$ and $E(R_{HML,t})$ are, respectively, the expected risk premia on the aggregate market index (excess returns), the expected return of small stock portfolios minus the return of large stock portfolios, and the expected return of high book-to-market ratio portfolios minus the return of low book to market ratio portfolios.

Fama and French (1993) argue that the empirical success of their three-factor model implies that the model is an equilibrium asset pricing model that can be considered as a three-factor version of Ross's (1976) APT or Merton's (1973) ICAPM. In this regard, the SMB and the HML factors can be viewed as mimicking portfolios for two underlying risk factors or state variables that are of special hedging concern to investors (Fama and French, 1996). However, the model generated considerable scepticism centred on explaining why the SMB and the HML are considered as risk factors. Before discussing the competing explanations that have emerged regarding why both factors require risk premia, the results of the model for both developed and emerging markets are discussed in order to provide evidence against factor dredging as one explanation for the results of Fama and French (1993).

3.3 Empirical Tests of the Fama and French Three-Factor Model

Reinganum (1981) emphasises that a minimum requirement for any alternative asset pricing model should be that it can accommodate the empirical anomalies that the CAPM fails to explain. Consequently, Bishop *et al.* (2001) argue that the FF3 requires more time and more empirical verification before it can be recognized as a credible theory-based model that can replace the CAPM. The aim of this section is to discuss the empirical evidence of the FF3.

3.3.1 Empirical Tests of the FF3 Using Size and BM Portfolios

The first seminal paper to test the FF3 is Fama and French (1993). They use 25 portfolios sorted on size and the book-to-market equity as the main test assets due to the following reasons. First, size and the book-to-market equity are among the most important anomalies facing the CAPM. Second, these portfolios produce a wide range of average returns which represent an interesting challenge to be explained by competing asset pricing models. In testing the model, they use a time-series regression as it provides a convenient way for testing two important asset-pricing issues:

(i) By focusing on the slopes and R^2 statistics of the time-series regression, researchers can determine whether mimicking portfolios for risk factors related to size and the book-to-market equity can capture common variation in stock returns that is not explained by other variables.

(ii) By focusing on the values of the estimated intercepts of time-series regressions, researchers can determine how well different combinations of the common factors can capture the cross-sectional variation in stock returns.

In the light of the above advantages of using time-series regressions, Fama and French assess whether the market, the SMB, and the HML factors can capture common variation in stock returns. The results show that the three risk factors tend to capture strong common variation in stock returns by recording a high R^2 statistics of more than 90% for almost all of the portfolios tested, which represents a significant improvement over the CAPM where R^2 statistics of 80% or 70% are the norm.

The estimates of the slopes of the three factors also show interesting patterns. First, although the market betas are significantly positive, they are close to one for all of the portfolios tested, which implies that they can only explain the return differences between stocks and bonds but not across stocks. Second, the slopes of the SMB factor tend to be significant and related to firm size. In particular, in every book-to-market quintile, the slopes of the SMB factor decrease as we move from the smallest to the biggest portfolio. Finally, the slopes of the HML factor also prove to be significant and related to the B/M ratio. Specifically, in every size quintile, the slopes of the HML factor increase monotonically from strong negative values for the lowest B/M portfolio to strong positive values for the highest B/M portfolio. The significance of all of the three slopes implies that each of these risk factors captures common variation in stock returns that is missed by the other two factors.

Fama and French also test how well the average premiums for the three risk factors explain the cross-sectional variation of average stock returns by analysing the intercepts of the time-series regressions. Their results show that using all the three factors together results in intercepts that are close to zero which implies that the model can capture the cross-sectional variation in stock returns. However, using the F-statistic of Gibbons, Ross, and Shanken (1989) to formally test whether the three-factor model produces regression intercepts that are all equal to zero reveal that the joint test of whether all the intercepts of the 25 portfolios are equal zero is rejected at the 5% level. The rejection of the model is mainly caused by the stocks in the lowest B/M quintile. Within this quintile, relative to the predictions of the model, the smallest stocks achieve average returns that are too low, while large stocks achieve returns that are too high. This implies that the size effect is absent in this quintile. However, Fama and French argue that in spite of the marginal rejection of their model in the F-tests, it still does a good job capturing the cross-sectional variation of the average stock returns. This argument of Fama and French implies that they do not take the small-growth puzzle as a major challenge for their model. However, Cochrane (2008) argues that this puzzle should be given more due care, and asset pricing models that aim to achieve a better improvement over the FF3 can do so by better pricing the small-growth puzzle.

Despite the empirical success of the model documented in Fama and French (1993), it is essential to test the model in other markets in order to provide out-of-sample tests before concluding that the model provides good description of average returns. In this regard, Drew and Veeraraghavan (2002) highlight the importance of analysing whether the FF3 can explain the cross-sectional variation in stock returns in emerging markets. In particular, they emphasise that the results for developed markets may be sample-specific and driven by the economic, institutional and regulatory characteristics of these markets. Thus, they underscore testing the model in emerging markets context to provide out-of-sample evidence.

Motivated by this argument, Drew and Veeraraghavan study whether the FF3 can capture the cross-sectional variation in stock returns in the Malaysian stock market using six portfolios sorted on size and the book-to-market equity over the time period December 1992 to December 1999. The results show that the intercept of their model is not significantly different from zero for each of the six portfolios. Thus, they argue that since their results are consistent with those of Fama and French (1993), then this implies that the model is robust and is able to explain the expected returns in an economically meaningful way. However, the results of this paper are limited by the small sample it uses. Thus, more recent empirical evidence from other emerging markets is required before forming final conclusions about the performance of the model in emerging markets context.

The above results for different markets support the argument that the FF3 provides a good description of average returns. However, the results face strong criticism that they may be spurious as the SMB and the HML factors are formed from the intersection of the size and B/M sorted portfolios and thus it is not surprising that they can predict the returns of these portfolios. Thus, this implies that the empirical successes of the model are restricted to the set of portfolios used as test assets and that the model may fail in tests on other assets.

In addition, Daniel and Titman (2012) argue that the previous empirical results that support asset pricing models do not necessarily imply that these models are supported by the data, but these results may be due to a flawed or biased methodology. In particular, they argue that using size and book-to-market portfolios as test assets is potentially problematic as grouping all of the assets with similar size and book-to-market ratios together in one portfolio results in eliminating any variation in factor loadings that is independent of size and the book-to-market ratio. Consequently, this grouping results in a set of test portfolios that exhibit a strong relationship between loadings on the proposed factor and expected return, even if the true loadings on the factors are only loosely correlated with the expected returns of the individual assets in the economy. One way to avoid this problem and develop more powerful tests of asset pricing models is to expand the set of test assets to include portfolios sorted in other ways (Lewellen *et al.*, 2010).

3.3.2 Tests of the FF3 Using Different Test Assets

Given the argument of Daniel and Titman (2012), the focus of researchers has shifted towards using different sets of test assets in evaluating the validity of different asset pricing models. In this regard, Lewellen *et al.* (2010) suggest that industry portfolios or individual stocks may be reasonable choices. Thus, Fama and French (1997) use industry portfolios to test how well their model can capture the cross-sectional variation in returns by using all stocks listed on the NYSE, AMEX, and NASDAQ for the time period July 1963 to December 1994. The Gibbons, Ross, and Shanken (1989) test rejects the hypothesis that the intercepts of the time-series regressions are equal to zero for all the industries. They attribute the rejection of the model to its failure to account for the time-varying risk loadings. Consequently, these results motivate the application of conditional models to provide a better explanation of stock returns.

Fama and French (1996) provide further attempts to test the model using an expanded set of test assets such as portfolios sorted on the E/P ratio, the cash-flow to price (C/P) ratio, and sales growth. Their results show that the model can reliably explain the returns on these portfolios, providing broader support for the model as it uses a wider range of test assets compared to their earlier paper in 1993. Specifically, the success of the model to describe the returns on portfolios formed on sales growth warrants special attention as sales growth is the only portfolio-formation variable that is not a transformed version of stock price. Thus, this provides some evidence to counter the claims that the model can only explain the returns on portfolios sorted on size and the B/M ratio.

In addition, Fama and French find that the model can capture the reversal of long-term returns of DeBondt and Thaler (1985) which is a significant improvement over the CAPM. Since long-term losers tend to load more on the SMB and the HML factors, the model predicts that the long-term past losers will earn higher average returns. However, the model fails to accommodate the momentum in stock returns of Jegadeesh and Titman (1993). Similar to long-term losers, short-term losers appear to have high loadings on the SMB and the HML factors compared to winners which predict reversal rather than continuation in stock returns. Therefore, Fama and French find that momentum in stock returns represents the main challenge for their model.

Fama and French propose that there are three main competing explanations for the failure of their model to capture the momentum in stock returns. First, they argue that momentum in stock returns is mainly due to data snooping. However, the significant amount of empirical evidence suggesting the existence of momentum in both developed and emerging markets rules out their argument about data snooping concerns. Second, they argue that momentum can be due to investor irrationality. On the one hand, investors underreact to short-term past information, which results in a continuation of stock returns, but they overreact to long-term past information which leads to the observed return reversal. However, this requires behavioural finance proponents to explain why investors tend to underreact to some news and overreact to others. Unfortunately, until now behavioural finance has not provided a coherent framework that can explain this.

Third, asset pricing is rational, but the three-factor model is just a model that represents a mere approximation of the reality and thus it should not be expected to fully represent the real world. In this context, momentum in stock returns can be thought of as one of the model's shortcomings. This motivates researchers to search for richer models that can accommodate this puzzling anomaly by including additional risk factors. However, despite the failure of the model to encompass the momentum in stock returns, Fama and French conclude that the model can capture much of the variation in the cross-section of average stock returns and it is able to explain most of the anomalies that have long challenged the CAPM, and thus the FF3 has become the standard model replacing the CAPM for risk adjusting returns (Cochrane, 2008).

The shared feature of all of the above studies is that they use portfolios as test assets. However, recent empirical research suggests that portfolio-based asset pricing tests suffer from data-snooping biases and lead to a loss of information. This criticism has inspired researchers to use individual stocks in empirical tests of asset pricing models to guard against the sensitivity of asset pricing tests to the portfolio grouping procedure. A comprehensive study that responds to this criticism is Avramov and Chordia (2006) that tests the ability of various asset pricing models to explain the anomalies that plague the CAPM using a sample of common stocks of NYSE, AMEX, and NASDAQ-listed firms over the time period July 1964 to December 2001. They run a regression of excess stock returns on the three risk-factors of Fama and French model. Next, they run cross-sectional regressions of risk adjusted returns, obtained from the first regression, on size, the book-to-market ratio, turnover and prior return variables as they represent the main anomalies facing the CAPM, as shown in Equation 3.4. If the asset pricing model used in the first regression can explain the predictive power of such firm characteristics, then the coefficients of these characteristics in the second-pass cross-sectional regression should be statistically insignificant.

$$R_{jt} - [R_{Ft} + \beta F_t] = c_{0t} + c_t Z_{jt-1} + \varepsilon_{jt} \quad (3.4)$$

where F_t represents the vector of Fama and French three risk-factors, and Z_{jt-1} represents the vector of firm characteristics known to have strong predictive power for stock returns (size, the book-to-market ratio, turnover, and prior return variables).

Their results show that the unconditional FF3 fails to explain the financial market anomalies (size, book-to-market, turnover and momentum). These results contrast with the results of Fama and French (1996) that show that the model can capture both the size and value effects on portfolio returns. However, Avramov and Chordia find that the conditional FF3, where factor loadings are conditioned on size, the book-to-market ratio and default spread, can capture the size and value effects, while it fails to accommodate both the momentum and turnover effects. These results, along with the results of Fama and French (1997), emphasise the importance of modelling the time-variation of factor loadings in order to better characterize risk and motivate the extension of the model to conditional specifications.

The overall conclusion of the above studies is that the methodology applied to testing asset pricing models may strongly affect the results. This, in turn, emphasises the argument of Daniel and Titman (2012) that the failure of empirical tests to reject an asset pricing model does not guarantee that the model is actually correct as a fundamental issue in applications of the FF3 is that different results may be obtained when different approaches of portfolio formation are adopted. Thus, checking the robustness of the model requires testing its performance using a wide set of tests for different markets and for different time periods.

In this regard, Dolinar (2013) analyses the performance of the FF3 for the Croatian stock market using a sample of 37 listed stocks over the period 2007-2013 to determine whether the model can explain the cross-sectional variation in stock returns in emerging markets context. Their results reveal that the SMB and the HML factors are not always significant, and only add marginal explanatory power. The R^2 values are relatively low, indicating that substantial common variation in stock returns is left unexplained. Dolinar attributes the poor performance of the model to the special nature of emerging capital markets as represented be their lower liquidity, the lower level of knowledge and experience of the investors, the smaller number of institutional investors in these markets, the absence of a simple registry for dividend payments, and the non-correction of the time-series of stock prices for stock splits. These factors highlight the major differences between emerging markets and developed markets and they may negatively impact the performance of the model and may suggest that the model should be augmented by other risk factors in order to account for the special nature of emerging markets.

To sum up, despite the promising results of the FF3 that have resulted in viewing it as a benchmark in both academia and the finance industry (Hahn and Yoon, 2016), subsequent tests of the model result in mixed empirical evidence concerning its performance. However, despite the challenges facing the model, Hahn and Yoon emphasise that it has succeeded in providing a comprehensive description of most of the anomalies that have challenged empirical research in a parsimonious three-factor framework for the US and other major stock markets. This, in turn, justifies why the model is still widely used as a benchmark asset pricing model for risk-adjustment.

3.4 Criticisms of the Fama and French Three-Factor Model

Despite the argument of Hahn and Yoon (2016) that the FF3 is still widely used as a benchmark asset pricing model, it is apparent that the model suffers from several empirical shortcomings that represent stylized facts to be explained by alternative models. Specifically, the empirical shortcomings of the model can be summarized as follows.

(i) The failure of the model to explain the small-growth puzzle (Cochrane, 2008);
(ii) The failure of the model to accommodate momentum in stock returns (Fama and French, 1996);

(iii) The failure of the model to explain the returns for industry portfolios. In this regard, Fama and French (1997) and Avramov and Chordia (2006) motivate the extension of the model to conditional specifications.

(iv) The poor empirical results of the model when applied to emerging stock markets as compared to developed ones.

Apart from these empirical challenges of the model, Fama and French (1993) argue that the main criticism facing the model is that the selection of size and the book-to-market factors is empirically motivated. In this regard, Cochrane (1999) argues that there is an inverse relationship between the empirical success of the FF3 and its theoretical purity. Fama and French (1996) postulate that there are three main schools of thinking that have emerged to provide an economic interpretation of the empirical successes of the model.

The first school proposes that the results of Fama and French (1993, 1996) are consistent with a rational asset pricing story that conforms to a three-factor ICAPM, or APT that does not collapse to the standard CAPM. The second school argues that investor irrationality is the main reason that prevents the three-factor model from collapsing to the standard CAPM (Lakonishok *et al.*, 1994). Finally, the third school proposes that the CAPM holds but it is mistakenly rejected due to: (i) survivorship bias in the returns employed in the tests of the model (Kothari *et al.*, 1995); (ii) data snooping (Lo and Mackinlay, 1990); or (iii) the use of bad market proxies in the CAPM tests. Distinguishing between these three schools of thought is an issue that created significant debate in the finance literature and is considered as the main challenge facing asset pricing literature (Campbell, 2000).

3.4.1 Rational Asset Pricing to Explain the SMB and the HML Factors

Fama and French (1993, 1996) argue that since their three-factor model can capture the cross-sectional variation in average stock returns, then the rational pricing story implies that the SMB and the HML factors must be proxies for sensitivity to common risk factors in returns. However, returns tests do not provide a complete economic story as both the SMB and the HML factors remain arbitrary factors that, for unknown economic reasons, are associated with risk factors in returns. In an attempt to respond to this criticism and rationalize their model, Fama and French argue that the SMB and the HML factors are proxies for multifactor-minimum variance portfolios in a two-state ICAPM that may be related to relative distress. Nevertheless, in order to attain a complete rational explanation for the model, Lewellen (1999) emphasises that the underlying risk factors behind the size and book-to-market portfolios must be specified precisely. Thus, this has been one of the main challenges in asset pricing literature and it has been the focus of many researchers.

Liew and Vassalou (2000) show that the SMB and the HML factors contain significant information about future GDP growth. However, they do not address the asset pricing implications of their results. Thus, in a follow up paper, Vassalou (2003) shows that news regarding future GDP growth is an important factor in capturing the cross-sectional variation in average returns. Vassalou also reports that much of the explanatory power of the SMB and the HML factors diminishes once a GDP news-related factor is included in the model. Thus, these results support the claims of Fama and French that the SMB and the HML factors are state variables that predict future changes in the investment opportunity set in the context of Merton's ICAPM.

Overall, despite all of the above and other attempts (Vassalou and Xing, 2004; Hahn and Lee, 2006), there is still no a clear agreement among academics on the economic interpretation of the SMB and the HML factors. Lewellen (1999) summarizes the state of the debate over the economic interpretation of size and the book-to-market effects by highlighting that the rational pricing view will remain imperfect until the academic community provides more direct evidence on the underlying risks.

3.4.2 Behavioural Explanations for the SMB and the HML Factors

Proponents of the second school favour behavioural justifications for the ability of the model to capture the cross-sectional variation in stock returns. They attribute this ability to investors' irrationality rather than to risk-based explanations. Lakonishok *et al.* (1994) argue that value firms tend to earn higher returns than growth firms as investors erroneously extrapolate past earnings growth of these firms too far into the future. Nevertheless, they do not refute the proposition that there may be priced factors related to value (growth) stocks. Rather, they propose that the large return premia related to these factor portfolios and their low covariances with macro factors cannot be fully justified within the context of a rational pricing model.

In response to these arguments, Fama and French (1996) argue that investor overreaction cannot justify why the value premium persists for at least five years after portfolio formation while investors can notice the mean reversion of earnings growth much earlier than this. Thus, they argue that the overreaction hypothesis is not a complete story behind the value premium. In addition, Fama and French dispute the argument of Lakonishok *et al.* that the value premium must be irrational as periods of low returns on value stocks are not typically periods of low GNP growth or low overall market returns as explained in Chapter 2. Although this argument seems appealing, it does not contradict Merton's ICAPM or Ross's APT that propose that the market return is an insufficient measure risk and that there should be other priced factors that are orthogonal to the market and yet affect future investment opportunities (Daniel and Titman, 1997). Thus, it is not surprising that variations in the return of the HML factor are not significantly associated with GNP or with the market return itself. Despite these arguments against the overreaction hypothesis, this cannot rule out the plausibility of behavioural explanations for the empirical successes of the model.

The most rigorous criticism for risk-based explanations is provided by Daniel and Titman (1997) who argue that the ability of the FF3 to capture the cross-sectional variations in stock returns can be explained within the context of a characteristic-based model rather than a risk-based model, as argued by Fama and French (1993, 1996). Daniel and Titman propose that the book-to-market and size effects are a manifestation of investor preferences for certain firm characteristics. In particular, investors tend to prefer growth and large stocks and dislike value and small stocks. Thus, the characteristic-based model suggests that a stock's expected return is determined more by its characteristics (small versus big or high versus low book-to-market ratio) rather than by the covariance structure of the returns.

Daniel and Titman argue that there are several explanations for their proposition that characteristics such as size and the B/M ratio are the main determinants of returns rather than risk. First, they refer to Lakonishok *et al.* (1994) who advocate that investor overreaction to the firm's past performance may be the reason behind the explanatory power of firm characteristics. Second, they argue that this explanatory power may be justified by an agency explanation, as suggested by Lakonishok *et al.* (1992) who claim that although institutional investors are aware of the high expected returns associated with value stocks, they still prefer growth stocks as they are easier to justify to their sponsors. Finally, they highlight that investors may consistently believe that size and the B/M ratio are proxies for systematic risk and thus they assign higher discount rates for stocks with these characteristics given the ample evidence that stocks with these characteristics are more sensitive to aggregate economic and credit conditions.

In contrast to other behavioural models, Daniel and Titman provide a clear empirical approach to differentiate between the characteristic-based model and the FF3 which is the main reason behind the severity of their criticism. Specifically, to differentiate between the two models, Daniel and Titman form portfolios that have a low correlation between their factor loadings and their characteristics (for example, high book-to-market ratios but low loadings on the HML factor). In order to construct these portfolios, they sort stocks into portfolios based on their characteristics (size and the book-to-market ratio), then sort each of these portfolios based on the firm preformation loadings, which represent the loadings formed using data up to 5 years before the portfolio formation period, on each of the Fama and French factors.

Given the above approach, if the factor model is correct, then a portfolio that includes stocks with high book-to-market ratio but low loadings on the HML factor should exhibit low returns. But, if the characteristic-based model is correct, then a portfolio with high book-to-market stocks should have high returns regardless of its factor loadings. Using data for US stock returns over the time period 1973 to 1993, they show that the characteristics rather than the factor loadings explain expected returns. Thus, they reject the FF3 in favour of their characteristic-based model.

However, their results are questionable as they refute a model that can capture the main intuition of traditional asset pricing models in favour of a model that is almost entirely *ad-hoc* (Daniel *et al*., 2001). Davis *et al.* (2000) argue that the FF3 should only be rejected in favour of a better model, and this cannot be settled unless more tests are undertaken on the robustness of the characteristic-based model. In this regard, Davis *et al.* use an extended sample compared to that of Daniel and Titman (1997) by analysing US data over the time period July 1929 to June 1997. Their tests reveal that the results of Daniel and Titman in favour of the characteristic-based model are specific to their short sample period. In contrast to Davis *et al.*, by using Japanese data over the time period 1975-1997, Daniel and Titman (2001) clearly reject the FF3 in favour of the characteristic-based model. However, they point out that these results may be due to the inappropriateness of the FF3 rather than the superiority of the characteristic-based model.

Given the above results, several points should be noted. First, since the international evidence on the performance of the two models yields contrasting results, there is no definitive answer concerning whether a factor or a characteristics model provides a superior explanation of how the FF3 actually works, and thus further studies should focus on testing both models using data from other developed markets as well as emerging markets. Second, all of the above studies agree that the FF3 cannot provide a complete description of stock returns and that it should be replaced by a better model. Until a better model is found, the FF3 should be used with caution.

3.4.3 The Argument that the CAPM is Erroneously Rejected

Proponents of the third school attribute the success of the model to either survivorship bias or data snooping concerns, but many researchers have provided evidence to counter these two concerns such as Fama and French (1996). Additionally, others argue that the CAPM actually holds but it is erroneously rejected as a result of using bad market proxies for the true market portfolio. Among the researchers who tackle this issue are Ferguson and Shockley (2003). They hypothesise that one of the central problems in the CAPM tests is the use of an equity-only proxy for the true market portfolio which ignores the economy's debt claims. They argue that equity betas calculated using this inefficient proxy will be understated, with the error escalating with the firm's leverage and distress risk. Hence, firm specific variables such as size and the book-to-market equity that are strongly correlated with leverage and distress risk will be able to explain the cross-sectional variation in average returns, even after controlling for proxy betas as they adjust for the downward bias in estimated equity betas.

Ferguson and Shockley highlight that the above argument provides a theoretical justification for the FF3. They argue that although Fama and French (1996) suggest that the SMB and the HML factors represent priced risk factors of relative distress risk, they do not provide an explanation as to why relative distress risk can be considered as a separately priced risk. The results of Ferguson and Shockley imply that the cross-sectional relationship between distress, as represented by the SMB and the HML factors, and many anomalies emerge only as a result of the underestimation of the market betas of distressed firms and the loadings on the SMB and the HML factors represent appropriate corrections for this error.

In order to test the above theoretical argument empirically, Ferguson and Shockley create two portfolios based on relative distress risk (Altman's Z-score) and relative leverage (the debt-to-equity ratio), in the same way that Fama and French create the SMB and the HML factors. Then, as shown in Equation 3.5, they examine whether a model that includes these portfolios along with a proxy for the market portfolio can explain the cross-sectional variation in stock returns using 25 portfolios sorted on size and book-to-market equity as test assets over the time period July 1964 to December 2000.

$$R_{p_{i,t}} - R_{F_t} = \gamma_0 + \gamma_{MKT}\hat{\beta}_t^{MKT} + \gamma_{D/E}\hat{\beta}_t^{D/E} + \gamma_Z\hat{\beta}_t^{Z} + \varepsilon_{i,t} \qquad (3.5)$$

Using a Fama-Macbeth regression to test the above model reveals that it beats the FF3 in capturing the cross-sectional variation of returns. In addition, they find that when the SMB and the HML factors are orthogonalised with respect to the distress and leverage portfolios, their explanatory power diminishes. Thus, they conclude that their results support the proposition that a model that uses more direct proxies for financial leverage and financial distress can compensate for the underestimated equity betas and may capture the cross-sectional variation in stock returns better than the FF3.

To summarise, there is a major argument in the asset pricing literature concerning whether the explanatory power of the SMB and the HML factors is: (i) compensation for common risk factors in returns; (ii) due to a mispricing story that emerges as a result of investor irrationality; or (iii) spurious and sample specific (De Pena *et al.*, 2010). Despite the various attempts of researchers to distinguish between these three schools of thought, understanding of the underlying economic forces behind the SMB and the HML factors is far from perfect and many exciting research opportunities remain.

3.5 Conclusion

The aim of this chapter is to discuss the development of the FF3 which is considered as the most popular multifactor asset pricing model that emerged to respond to the challenges facing the CAPM (Culp and Cochrane, 2003). The popularity of the model arises mainly from its ability to capture most of the variations of average returns (Fama and French, 1996). Culp and Cochrane argue that this good performance represents the hallmark of an empirically valuable asset pricing model. However, despite this empirical success, the model does not provide any clue to determine the additional sources of risk that investors are concerned about. Identifying the additional sources of risk properly has a fundamental role in asset pricing literature as it helps to answer one of the central questions in finance literature which is whether financial markets are efficient and rational or not (Cochrane, 2008).

However, the failure of the model to determine precisely the underling risk factors behind the explanatory power of the SMB and the HML factors is not the only shortcoming of the model. An empirical counterpart to this theoretical shortcoming is the failure of the model to accommodate momentum in stock returns that has been considered as the main challenge to the model. Cochrane (2008) argues that one way to respond to this shortcoming is by augmenting the model with a momentum factor (Carhart, 1997). However, this solution is mainly *ad-hoc* and Cochrane strongly criticises it as it is unreasonable to add a new factor for every anomaly. Thus, rather than adding *ad-hoc* factors, researchers should try to find a factor model that can capture the cross-sectional variation in stock returns better than the FF3.

Two strands of literature have emerged to provide better explanation of the cross-sectional variation in stock returns. The first strand of literature that responds to this need proposes that the failure of the unconditional CAPM to accommodate asset pricing anomalies may be due to the unrealistic assumption about the constancy of expected returns, betas and risk premia. As a result, the focus of this approach is to incorporate conditioning information available to investors. This will be the purpose of the first part of Chapter 4.

The second strand of literature argues that if the conventional finance model is undermined by many anomalies, then restructuring the conventional asset pricing models seems to be warranted. Given this argument, behavioural finance proponents have been working to supplement the conventional model with an alternative behavioural model to provide reasonable explanations for such anomalies (Statman, 1999). This is the aim of the second part of Chapter 4.

Chapter 4

Conditional versus Behavioural Asset Pricing Models

4.1 Introduction

Up to this point, the main focus of this thesis has been on the ability of asset pricing models to explain the cross-sectional variation in stock returns. Such models should explain the patterns by which expected returns vary both over time and across assets (Cochrane, 2008). Fama (1991) argues that researchers should search for a coherent story that links the cross-sectional variation in expected returns with the variation in expected returns over time. Thus, this chapter focuses on the literature that concerns the predictability of stock returns over time.

Cochrane (2008) argues that the consensus among researchers about the predictability of stock returns over time makes predictability an economically significant phenomenon that cannot be ignored. There are two competing schools of thought that have emerged to explain the strong predictability of stock returns (Fama and French, 1998). The first school argues that the predictability does not necessarily imply market inefficiency, and may arise from changes in the required rates of return over time and thus may be explained within the context of rational asset pricing models in an efficient market (Ferson and Harvey, 1991). In contrast, the second school argues that the predictability can be explained within the context of common models which assume that stock prices deviate irrationally from their fundamental values.

The first part of this chapter considers the first explanation. Rational asset pricing models suggest that the expected returns of stocks can be explained by their sensitivity to changes in the state of the economy. Within this context, since sensitivity is measured by the beta coefficients of the stocks, and there is a market-wide price of risk for each relevant state variable measured as the increment to the expected return per unit of beta risk, then predictable variations in stock returns may arise due to changes in beta, changes in the price of beta (risk premium) or both (Ferson and Harvey, 1991).

The second part of this chapter considers the second explanation. The proponents of behavioural finance argue that the predictability of stock returns may be attributed to the failure of conventional asset pricing models to account for the effect of mass psychology on the movements in aggregate stock market which is one of the most remarkable mistakes in the history of economic thought (Shiller, 1984).

The structure of the remainder of this chapter is as follows. Section 4.2 provides a brief review of the predictability of stock returns. Section 4.3 provides an overview of conditional asset pricing models and the various approaches that emerged to capture the time-variation in risk and in risk premia. Section 4.4 discusses the empirical results of studies that test conditional asset pricing models in both developed and emerging market settings. Section 4.5 provides a brief overview on the relationship between sentiment and stock prices and provides a summary of previous studies that test the predictive ability of investor sentiment. Section 4.6 highlights the various attempts emerged to behaviouralize asset pricing models. Finally, Section 4.7 concludes.

4.2 The Predictability of Stock Returns

The economic explanation of the predictability of stock returns is highly controversial and far from settled (Cochrane, 1999). This is mainly due to the fact that all asset pricing tests involve a joint hypothesis that stock markets are efficient and expected returns can be explained by a pre-specified equilibrium model such as the CAPM or the FF3. Cochrane argues that the predictability of stock returns does not necessarily contradict market efficiency. Predictability simply enhances our view of what activities provide rewards for risk bearing and it improves our understanding of those risk premia.

In the pre-1970 literature, the common view was in an efficient market, changes in stock prices must be unpredictable (Lo, 2004). However, researchers have identified a number of variables that can forecast securities returns such as past returns, dividend yields, earnings/price ratios, term-structure variables, size, and the book-to-market ratio (Fama and French, 1989; Chen, 1991; Gomes *et al.*, 2003).

Hawawini and Keim (1995) argue that the simple fact that the empirical evidence about the predictability of returns persists for decades implies that the benchmark asset pricing models commonly used in the finance literature provide an incomplete explanation of returns. Other researchers argue that the mounting evidence about the predictability of stock returns is due to market inefficiency. Therefore, the focus of research shifts towards analysing these two competing explanations to resolve this puzzling issue. Fama (1991) argues that distinguishing between the two explanations is a daunting task as all of the theoretical attempts to differentiate between them are model-dependent (Pesaran and Timmermann, 1995). Nonetheless, many researchers attempt to distinguish between the two explanations through rationalizing the predictive ability of different state variables by investigating the relationship between these variables and business and economic conditions.

4.2.1 State Variables and Economic Conditions

Dividend yield is considered one of the most commonly used variables in predictability tests. However, there is an ongoing debate concerning whether this predictive ability is rational or irrational. Dividend yield is widely believed to vary with expected returns (see for example, Shiller, 1984; Fama and French, 1988). In particular, during stable economic conditions, expected returns are more likely to decrease, resulting in an increase in stock prices as future dividends are discounted at a lower rates, and vice versa. Thus, since a low (high) price may imply a market expectation of a high (low) expected return, then a high (low) dividend yield may signal times when the market as a whole expects high (low) average returns. Thus, the most natural explanation for the predictive ability of the dividend yield is that it can track the market's expectations of returns.

Furthermore, Chen (1991) argues that the dividend yield is considered one of the indicators of the current health of the economy as it tracks variations in expected returns related to long-term and persistent business and economic conditions. Nevertheless, Fama and French (1989) argue that although the relation between dividend yield and economic conditions seems comforting, there are some arguments that show that the dividend yield and expected returns may be high when prices are temporarily irrationally low, and thus this implies that variations in dividend yields are due to irrational bubbles.

Default spread is another commonly used variable in predictability tests. Along with the significant empirical evidence concerning its predictive ability for stock and bond returns, it is also considered a useful factor for forecasting economic conditions. Chen *et al.* (1986) argue that the default spread can be viewed as a direct measure of the degree of risk aversion implicit in pricing securities which is closely tied to economic conditions. In particular, Fischer (2012) finds that during economic booms, investors tend to be less risk averse, while their risk aversion tends to increase substantially during periods of economic instability as they are more likely to face income uncertainty and liquidity problems during these periods.

Fama and French (1989) find that the default spread tends to take its highest values during periods of unstable economic conditions when investors are more likely to be more risk averse, while it tends to be lower during periods of stable economic conditions when risk aversion tends to be low. Thus, these empirical results imply that the link between the default spread and economic conditions supports the rational pricing story.

The term spread is also commonly used in forecasting bond and stock returns. It is measured as the difference between the yield on long-term and short-term bonds (Chen, 1991; Campbell, 1987). Fama and French (1989) divide term spread into its components (the difference between the yields on long-term Treasury bonds and Treasury bills) to arrive at a better insight concerning its relationship with business conditions. They argue that the term spread is tied to short-term business cycles.

In particular, the term spread tends to be low near business-cycle peaks and high near troughs. During business-cycle troughs, the demand for treasury bills increases dramatically, leading to an accompanying decrease in their yields. Noeth and Sengupta (2010) argue that "*the flight to safety*" is the main reason underlying the increased demand for treasury bills during troughs. Furthermore, during these periods, investors are more reluctant to hold long term assets due to their greater need for liquidity. This, in turn, explains why the yields on long-term bonds fall less than the yields on treasury bills during these periods, leading to the observed large term spread as argued by Fama and French (1989). All of these arguments support the predictive ability of the term spread within a rational context.

Another line of research reports striking evidence about the predictive ability of some firm-specific characteristics such as size and the book-to-market ratio. In addition to the considerable empirical evidence about the ability of these two variables to capture the cross-sectional variation in stock returns (Fama and French, 1993), Lewellen (1999) finds that these characteristics can also predict the time-variation in expected returns. This evidence, in turn, gave rise to studies seeking to determine whether this predictive ability reflects changes in risk or mispricing over time.

Proponents of behavioural finance argue that the absence of a precise economic rationale for the predictive ability of these variables implies that it is due to irrationality and behavioural biases (DeBondt and Thaler, 1985). Zhang (2005) emphasises that researchers should attempt to provide a coherent framework that can link the behaviour of expected returns to the real economy rather than focusing on behavioural explanations. Since measuring the real economy is much easier than measuring investor sentiment, any predictions derived from rational models will be more robust and easier to justify than alternative behavioural models. Thus, many researchers attempt to provide models that can explicitly link such firm-specific characteristics to risks and risk premia.

Berk *et al.* (1998) argue that one way to reconcile the empirical evidence of the predictive ability of size and the book-to-market ratio is to develop models that relate these variables to changes in risk. A common feature of such models is that they start by emphasising that firm value is equal to the output from existing projects (assets in place) and the present value of dividends from future projects (growth options). Over time, firms make optimal investment decisions that result in variations in their assets in place and growth options. These variations in the components of the firm's value results in variations in its risk and expected returns over time. Further, these models link size and the book-to-market ratio to these changes in systematic risk in order to justify their predictive ability within a rational context. In this regard, Gomes *et al.* (2003) argue that size may be considered a proxy for growth options while the book-to-market ratio may be considered a proxy for the productivity and systematic risk of the firm's assets in place.

Zhang (2005) provides a coherent model to justify the predictive ability of the book-to-market ratio through relating it to cost reversibility and the countercyclical price of risk. During unstable economic conditions, value firms are more loaded with unproductive capital than growth firms. Since cost reversibility implies that firms suffer from higher costs in cutting than in expanding capital, the dividends and the returns of value firms will covary more with bad economic conditions. In contrast, during stable economic conditions, growth firms tend to invest more and benefit from the economic boom, while value firms are less eager to expand their capital as their previously unproductive capital tends to be more productive. Since expanding capital is easier than cutting capital, the covariation of the returns of growth firms with economic booms is low. This difference in productivity between value and growth stocks results in differences in their risk and expected returns. Thus, this model rationalizes the predictive ability of the book-to-market ratio.

To justify the predictive ability of firm size, Perez-Quiros and Timmermann (2000) establish a link between firm size and changes in risk via imperfect capital market theories that hypothesise that changing credit market conditions have different effects on the risk of small and large firms. To understand this asymmetry between large and small firms, they argue that since the collateral held by small firms is much lower than that of large firms, small firms have lower ability to raise external funds. Consequently, small firms are strongly adversely affected by lower liquidity and higher short-term interest rates. Furthermore, they argue that the impact of tighter credit market conditions on small firms is not symmetric in all economic conditions as it is stronger during recessions when the net worth of small firms and their collateral decline sharply. In contrast, large firms do not suffer from these strong asymmetries over time as they have greater collateral across varying economic conditions. Thus, this model establishes a link between risk, expected return and firm size. Furthermore, it shows that the risk and expected returns of small firms tend to vary considerably over the business cycle.

To sum up, As far as asset pricing models are concerned, predictability of stock returns leads to an increased interest in testing conditional asset pricing models. Thus, the next section covers the development of conditional asset pricing models along with the main approaches developed to capture time-variation in risk and risk premia.

4.3 Conditional Asset Pricing Models

The CAPM was initially developed in a theoretical model where investors are expected to live for only one period. However, in real life, investors typically live for more than one period. Thus, when testing the CAPM empirically using real data, certain assumptions are required (Jagannathan and Wang, 1996). One of these assumptions is that expected returns and betas are constant over time.

Both theoretical arguments and empirical results cast doubt on the validity of this assumption (see for example, Ferson and Harvey, 1991; Ghysels, 1998). Thus, this leads to an increased interest in testing conditional asset pricing models that allow for time-variations in risk and risk premia as they are more interesting and realistic than static models that assume a stable and linear relation between risk and returns. However, conditional asset pricing models have their own shortcomings as they suffer from difficulty in modelling the time-variation in the parameters. Thus, the aim of the next sections is to highlight the relative merits of the different approaches employed to capture time-variation in risk and risk premia.

4.3.1 Time-Varying Betas

Accurate estimates of beta provide a crucial input to many financial decisions and applications such as asset pricing, corporate finance and risk management (Nieto *et al*., 2014). In asset pricing applications, betas were initially assumed to be constant over time. However, Jagannathan and Wang (1996) and Lettau and Ludvigson (2001) find that the betas of assets with different characteristics exhibit significant time-variation over the business cycle. Moreover, Ferson and Harvey (1999) and Fama and French (1997) find that time-variation in beta plays a considerable role in capturing many asset pricing anomalies. Nonetheless, Lewellen and Nagel (2006) criticise these studies and argue that the observed pricing errors in previous tests of the static CAPM are too large to be explained by time-variation in betas alone. Nieto *et al.* (2014) argue that the main reason behind these contradicting results is that capturing beta dynamics requires the determination of investor information sets which are unobservable. Thus, the best that the econometrician can do is to test the model based on the observed information set (Cochrane, 2001). Thus, the results of the model will be dependent on the chosen set of information variables. In order to address this problem of capturing beta dynamics, a variety of approaches have emerged in the literature to model the time-variation of betas.

Nieto *et al.* (2014) argue that there are two main approaches to modelling beta dynamics. The first one is to make assumptions regarding the dynamics of beta, while the second approach is concerned with making assumptions regarding the conditional covariance matrix of stock returns. The aim of this section is to review the different methods that have emerged under each of these two approaches, along with highlighting their relative merits.

One of the simplest approaches to capturing beta dynamics is the short-window regression approach such as the 60-month rolling regression of Fama and Macbeth (1973) or the shorter window rolling regression of Lewellen and Nagel (2006). Lewellen and Nagel argue that as long as betas are relatively stable within short periods, this simple short-window regression can provide good estimates of conditional betas. The main advantage of this approach is that there is no need to determine the set of information variables that investors use in their investment decisions. The only thing that researchers are required to determine is the window length. Lewellen and Nagel recommend using short windows when estimating betas. In addition, Bollerslev and Zhang (2003) argue that high frequency data should be used in estimating betas as this results in better estimates compared to the commonly used monthly returns. However, using high frequency data may lead to non-synchronicity effects on beta estimates especially in markets that suffer from thin trading.

Despite its simplicity, Ang and Chen (2007) criticise this approach by arguing that it may result in incorrect inferences about the validity of conditional models as it ignores the variation in betas in each window, and thus it understates the variation of the true conditional betas.

Another simple approach commonly employed in literature is the use of macroeconomic and microeconomic variables to model the time-variation in betas (Lettau and Ludvigson, 2001). The rationale underlying this approach is as follows. Since investors use a set of information variables in their investments decisions, it sensible to model the coefficients of conditional factor models as a function of investors' information sets. However, investors' information sets are unobservable and thus researchers should assume that they can be well summarized by a few variables that they can measure and observe. This, in turn, makes the performance of conditional models dependent on the choice of the set of conditioning information (Cochrane, 2001).

To defend this approach, Cochrane argues that if researchers can find a small set of conditioning information that can characterize the conditional distribution of returns, then there is no need to add more instruments. However, although this approach may result in the exclusion of potential instruments, Cochrane highlights that such practice is common in asset pricing tests which makes this omission less severe. Nonetheless, researchers should give due care to the choice of the appropriate set of conditioning information to use in tests of conditional asset pricing models.

Chen *et al.* (2011) criticise scaled factor model approach as it results in estimating highly volatile betas due to assuming that betas literally change value with every new data point and thus it overestimates the time variation in betas. In addition, Ghysels (1998) proposes that continuous time-varying models do not capture risk dynamics appropriately as betas change more slowly and discretely than these models suggest. The argument here is that these problems in modelling beta dynamics may outweigh the benefits of conditional models. Thus, researchers should either focus on providing more sophisticated approaches to model beta dynamics or they should stick to using constant beta models until they can capture beta dynamics appropriately (Akdeniz *et al.*, 2003).

This leads to the emergence of new approaches to allow betas to change discretely over time. One of the seminal papers in this regard is Akdeniz *et al.* (2003) who employ the threshold regression framework of Hansen (2000) to better capture beta dynamics. The threshold regression framework allows betas to vary slowly over time by responding to changes in economic conditions. In this regard, market risk is modelled as a function of an underlying economic variable called the threshold variable. Betas are allowed to change when this threshold variable hits a specific threshold level. Nonetheless, one of the criticisms of this framework is that allowing for only two extreme regime with an abrupt transition between them is a restrictive assumption that may lead to beta misspecification (Jawadi *et al.*, 2018). To circumvent this criticism, Chen *et al.* (2011) propose a multiple-regime CAPM threshold GARCH model that allows for more than two discrete values of market beta as well as heteroscedasticity and nonlinearity in the mean and volatility equations. However, since such models are very complicated and requires intensive computational power, and since they require large data sets to ensure that there is sufficient data in each regime to make valid inferences, the empirical application of these models is somehow limited.

Engle (2016) argues that the criticisms facing the above approaches induce researchers to propose an alternative method for modelling the time variation of betas by making assumptions regarding the conditional covariance matrix of stock returns. Proponents of this approach argue that since the CAPM beta is defined as the ratio of the conditional covariance between asset returns and the market return and the conditional variance of the market return, then one way to incorporate conditioning information in asset pricing models is to model the time variation in these two components of the assets' betas (Bodurtha and Nelson, 1991).

One of the most important methods for modelling time varying variances and covariances of stock returns is the Multivariate Generalized Autoregressive Conditional Heteroscedasticity (GARCH). However, mulitvariate GARCH suffers from the curse of dimensionality as it requires estimating a large number of free parameters which is obviously infeasible in terms of data availability and in numerical terms. To circumvent this problem, the focus of researchers has shifted towards developing a multivariate GARCH model that enjoys the flexibility of univariate GARCH but is still parsimonious. One of the seminal approaches is to decompose the conditional covariance matrix into conditional standard deviations and a conditional correlation matrix (Orskaug, 2009). The first type of models here is the constant conditional correlation (CCC) model developed by Bollerslev (1990). In this model, the conditional correlation is assumed to be constant over time and any variation in the conditional covariance is derived from variations in the conditional standard deviations. However, the assumption of constant conditional correlation is very restrictive in most empirical applications. Therefore, Engle (2002) develops the Dynamic Conditional Correlation (hereafter DCC) GARCH which is an extension of the CCC-GARCH model, for which the conditional correlation is allowed to vary over time. One of the advantages of DCC-GARCH is that, unlike other multivariate GARCH models, it enjoys a degree of flexibility and parsimony that makes it one of the most successful econometric methods to model conditional variances and covariances in financial data (Maurer and Tang, 2016).

To sum up this section, despite the wide range of methods available to model the time-variation in beta, there is no consensus about which method is better. Thus, researchers facing this wide array of methods have to choose among them based on researcher skills and data availability. This may, in turn, lead to imperfect choices that may jeopardise the results of conditional asset pricing models.

4.3.2 Time-Varying Risk Premia

Despite the focus of researchers on modelling time-variation in betas, Ferson and Harvey (1991) argue that a constant beta model might be a good approximation of reality as long as the time-variation of risk premia is taken into consideration.

However, modelling time-variation in risk premia does not receive substantial empirical coverage in asset pricing literature.

Cohn *et al.* (2015) argue that the time-variation in risk premia is one of the main puzzles in the finance literature. They argue that the equity risk premium tends to be higher during recessions, while it tends to be lower at peaks. Many researchers attribute this evidence about time-varying risk premium to countercyclical risk aversion which is considered a conventional wisdom in the literature (Campbell and Cochrane, 1999). However, despite this, most asset pricing models assume that investor risk aversion, and consequently risk premia, are constant over time. The strong empirical evidence on the time-variation in risk premia and the rejection of static asset pricing models give rise to the need to provide theoretical and empirical justifications for the time-variation in risk premia through models that assume countercyclical risk aversion.

Campbell and Cochrane (1999) develop a habit formation model that shows that investors derive utility from consumption relative to a specific habit level, and they become more risk averse when consumption falls below this habit level during bad economic conditions. However, despite the theoretical appeal of the model, Cohn *et al*. (2015) argue that models that assume countercyclical risk aversion need more empirical support before being used to justify the time-variation in risk premia. Thus, they run an experiment for finance professionals who are primed with a scenario of either a financial boom or bust to determine how their risk aversion will differ under these two scenarios. They find that the willingness of finance professionals to take risk decreases substantially when they are primed with a financial bust as opposed to financial boom. This provides support for the conventional wisdom of countercyclical risk aversion and implies that investors demand higher (lower) risk premia when their risk aversion is higher (lower) during bad (good) economic conditions.

In an attempt to provide direct empirical evidence about the time-variation in risk premia and its role in capturing predictability in stock returns, Ferson and Harvey (1991) run a time-series regression of the fitted risk premium (obtained from cross-sectional regression of returns on estimated betas) on a set of predetermined information variables. They find that the adjusted R^2 in this predictive regression is almost 10% which implies that expected risk premium is higher at some times and lower at other times depending on the prevailing macroeconomic conditions. Specifically, they find that the expected risk premium increases during periods of economic contractions and peaks near business troughs, while it decreases near business peaks. Furthermore, they find that this time-variation in risk premia captures most of the predictability in stock returns. Thus, these results, along with the previous results of Cohn *et al.* (2015) highlight the importance of modelling the time-variation in risk premia.

One of the simple ways to model the time-variation in risk premia that has received increased interest in recent years is regime switching techniques (see for example, Vendrame *et al*., 2018). In this regard, Vendrame *et al.* test a conditional version of the CAPM that models time-variation in risk using the DCC-GARCH model and time-variation in risk premia using a Markov switching model and they find that their model can explain some of the prominent anomalies that challenge the unconditional CAPM. Thus, they highlight the importance of modelling time-variation in risk and risk premia.

4.4 Previous Studies of Conditional Asset Pricing Models

The aim of this section is to summarize the empirical evidence on the performance of conditional asset pricing models that employ different techniques to capture time-variation in risk and risk premia.

Among the most prominent conditional asset pricing models developed is the Jagannathan and Wang (1996) model. Jagannathan and Wang argue that the poor empirical results of the CAPM are due to model misspecification resulting from poor identification of the market portfolio and the unrealistic assumption of constant betas that is applied in all previous tests of the CAPM.

Thus, to account for these criticisms facing the unconditional CAPM, Jagannathan and Wang provide a simple way to test conditional models by deriving a two-factor unconditional model that is implied by the conditional CAPM. Furthermore, they include a measure of human capital in forming a proxy for the market portfolio to provide better identification of the market portfolio. Their conditional CAPM is as follows:

$$E(R_{it}) = a_0 + a_1\beta_i + a_2\beta_i^{\gamma} + a_3\beta_i^{labour} \tag{4.1}$$

Equation 4.1 implies that the unconditional expected return of asset i is a linear function of market beta (β_i), the premium beta (time-varying beta) (β_i^{γ}) which measures the beta-instability risk, and the labour beta (covariance with labour income return) (β_i^{labour}). In this regard, the premium beta is calculated as follows:

$$\beta_i^{\gamma} = Cov(R_{it}, R_{t-1}^{Prem})/Var(R_{t-1}^{Prem}) \tag{4.2}$$

where R_{t-1}^{Prem} is the default spread measured as the difference between BAA- and AAA-rated bonds. Furthermore, labour-beta is defined as follows:

$$\beta_i^{Labour} = Cov(R_{it}, R_t^{labour})/Var(R_t^{labour}) \tag{4.3}$$

where R_t^{Labour} is a measure of human capital calculated as the growth rate in the per capita labour income as follows:

$$R_t^{Labour} = (L_t - L_{t-1})/L_{t-1} \tag{4.4}$$

Equation 4.1 implies that any asset should yield a higher expected return if it has a higher market beta, which is consistent with the general premises of the static CAPM, and if its beta is more prone to vary with the market risk premia and hence is less stable during the business cycle.

To test their model, they use 100 stock portfolios first sorted on size and then on pre-ranking betas as the main test assets. The results show that the static CAPM, in which the market beta (β_i), in Equation 4.1, is assumed to be the only explanatory variable, explains only 1.35% of the cross-sectional variation in average returns. Furthermore, when firm size is added as an additional factor with market beta, it turns to be strongly significant. This strongly contradicts one of the premises of the CAPM that no variable other than beta can explain the cross-sectional variation in stock returns. In contrast, the conditional CAPM without human capital, shows that when the premium beta (β_i^{γ}) is added to the static CAPM, the R^2 rises to 29% and that the coefficient of time-varying risk (a_2) is positive and significant, which is a significant improvement over the static CAPM. Nonetheless, when firm size is added as an additional factor to this version of the model, it remains significant but its significance level decreases substantially when compared to the static the CAPM. This implies that part of the size effect is due to the time-variation in betas.

Finally, they test the conditional model with human capital, as in Equation 4.1, and the results show that the R^2 of this model is around 56% which is a significant improvement over the other two models. In addition, the premium associated with labour beta is significantly positive, while the coefficient of firm size is insignificant when it is added to this version of the model. This implies that the model captures the size effect well within a rational context. Nonetheless, despite these favourable results, there are some challenges facing the model. First, the premium associated with the value-weighted market beta (a_1) is negative which is a severe contradiction to the general premises of the CAPM that propose that the market risk premia should be positive. Second, the intercept of the model is positive and significant which means that there are other important factors that are not captured by the model.

Overall, although the model developed by Jagannathan and Wang provides a simple way to model the time-variation of betas, their results show that the conditional CAPM plays a considerable role in capturing the cross-sectional variation in stock returns. Thus, these results led to a proliferation of conditional models that aim to provide better ways to model the time-variation in betas and risk premia.

4.4.1 Scaled Factor Models

Cochrane (2001) argues that an alternative approach to capture time-variation in betas and risk premia is to explicitly model the conditional distribution of asset payoffs and discount factor variables. However, this approach is cumbersome as it requires the econometrician to know all of the information used by investors in decision making. Unfortunately, the set of information variables used by investors is unobservable and this may imply that conditional asset pricing models are not testable (Hansen and Richard, 1987). To circumvent this problem, researchers choose an arbitrary set of information variables that is expected to capture the conditional distribution of returns. Nonetheless, the results of such conditional models should be interpreted with caution as they are dependent on the chosen set of information variables.

One of the attempts to test scaled factor models is Lettau and Ludvigson (2001). In order to capture variations in conditional moments, Lettau and Ludvigson develop a conditional asset pricing model by explicitly modelling the dependence of the parameters in the discount factor on the current period information set. The dependence is modelled by interacting or scaling factors with information variables that the researchers believe to have a role in summarizing the variation in conditional moments. In this approach, the conditional linear factor model can be expressed as an unconditional multifactor model where the factors are the original factors, information variables, and the scaled version of the original factors obtained by multiplying each factor by each information variable.

Lettau and Ludvigson use the consumption to aggregate wealth ratio, cay, as the main instrumental variable due to its ability to describe the state of the economy and forecast future returns of the market portfolio.

They derive their model in the stochastic discount factor approach where the general theory states that in the absence of arbitrage there exists a stochastic discount factor, M_{t+1}, such that, for an asset with a net return of R_{it+1}, the following equation holds:

$$1 = E_t[M_{t+1}(1 + R_{it+1})] \qquad (4.5)$$

where E_t represents the mathematical expectation operator conditional on time t information. M_{t+1} is the stochastic discount factor that is assumed to be a linear function of the risk factor (such as the market portfolio return in the CAPM) as shown in the following equation:

$$M_{t+1} = a_t + b_t R^M_{t+1} \qquad (4.6)$$

To model the time-variation in a_t and b_t, Lettau and Ludvigson assume that they can be expressed as linear functions of a set of information variables (z_t) available at time t as follows:

$$a_t = a_0 + a_1 z_t \text{ and } b_t = b_0 + b_1 z_t \qquad (4.7)$$

Therefore the conditional asset pricing model in Equation 4.5 can be expressed as an unconditional multifactor model as follows:

$$1 = E[(a_0 + a_1 z_t + b_0 R^M_{t+1} + b_1(z_t R^M_{t+1}))(1 + R_{it+1})] \qquad (4.8)$$

The above representation of the stochastic discount factor M_{t+1} implies an unconditional beta representation for an asset i as follows:

$$E(R_{it+1}) = E(R_{0t}) + \beta_{zi}\lambda_z + \beta_{Mi}\lambda_M + \beta_{Mzi}\lambda_{Mz} \qquad (4.9)$$

where $\lambda_M = E(R^M_{t+1})$ and the instrumental variable $z_t = \widehat{cay_t}$. The implication of Equation 4.9 is as follows. Stocks should yield higher expected returns not only if their returns are simply unconditionally correlated with the market return, but also if their returns are more highly correlated with the market return during bad economic conditions when risk/risk aversion are high (cay is high) than when risk/risk aversion are low (cay is low). Following this intuition, Lettau and Ludvigson find that value stocks have higher betas in bad economic conditions when cay is high. This justifies the value premium within a rational context as value stocks are more correlated with the market return during bad economic conditions when investors least want them to be which makes them riskier than growth stocks and justifies their higher returns.

After developing the rationale for their model, Lettau and Ludvigson test the static and scaled versions of the CAPM, the CAPM with human capital, and the consumption CAPM using 25 stock portfolios sorted on size and the B/M ratio. The results show that the static CAPM can only explain 1% of the cross-sectional variation in returns, and the estimated risk premium associated with the beta is insignificant and negative. However, the conditional CAPM produces a significant improvement over the static CAPM, explaining around 31% of the cross-sectional variation in returns. Furthermore, the coefficient on β_{Mzi} is strongly significant which supports the importance of the time-varying beta in explaining the cross-sectional variation in returns. In addition, the coefficients on β_{Mi} and β_{Mzi} are significant when jointly considered. When human capital is added to the model, the performance of the model improved significantly, with the R^2 increasing to reach 75% which is as high as the R^2 of the FF3.

Finally, Lettau and Ludvigson test the performance of consumption CAPM using the following model:

$$E(R_{it+1}) = E(R_{0t}) + \beta_{zi}\lambda_z + \beta_{\Delta ci}\lambda_{\Delta c} + \beta_{\Delta czi}\lambda_{\Delta cz} \tag{4.10}$$

where Δc represents the log difference in consumption. Their results can be summarized as follows. First, the static version of the consumption CAPM performs better than the static CAPM, explaining 16% of the cross-sectional variation in returns. Second, the conditional consumption CAPM explains around 70% of the cross-sectional variation in stock returns. Third, the explanatory power of size and the B/M ratio diminishes only when they are included in the conditional consumption

CAPM. Thus, Lettau and Ludvigson conclude that, relative to other models tested in their paper, the conditional consumption CAPM is considered the best.

Lewellen and Nagel (2006) criticise the results of both Lettau and Ludvigson (2001) and Jagannathan and Wang (1996) by arguing that the conditional CAPM cannot explain the large pricing errors resulting from the unconditional CAPM. To support their argument empirically, they provide a simple test of the conditional CAPM by modelling the time-variation in betas using a short-window regression. They estimate the conditional CAPM using a time-series regression for size, B/M and momentum portfolios for the period 1964 to 2001and they test the hypothesis that the average conditional alphas estimated from these regressions are equal to zero. The results reveal that the conditional alphas are large and significant for B/M and momentum portfolios. Thus, they reject the hypothesis that the conditional CAPM holds. In particular, they argue that although the betas vary considerably over time, this time-variation in betas is not enough to explain the observed anomalies.

Lewellen and Nagel attribute this difference in results to the methodology used in testing conditional asset pricing models. Jagannathan and Wang and Lettau and Ludvigson employ cross-sectional regressions and they ignore important restrictions on the cross-sectional slopes, while Lewellen and Nagel use time-series regression to test the implications of conditional asset pricing models. Thus, they argue that previous cross-sectional regression does not provide a full test of the conditional CAPM.

Another seminal paper that use a scaled factor model as the main method to account for the time-variation in risk and risk premia is Avramov and Chordia (2006). In contrast to Lettau and Ludvigson who use cay as the only conditioning variable and use portfolios as the main test assets, Avramov and Chordia use a wider set of instrumental variables which are firm size, the B/M ratio, and the default spread. In addition, they use individual stocks as the main test assets rather than portfolios in order to circumvent the data snooping bias inherent in portfolio-based asset pricing tests. Furthermore, they test the impact of modelling the time-variation in risk on a rich set of asset pricing models which are: (i) the CAPM; (ii) the Fama and French three-factor model; (iii) the Fama and French model augmented with a Pastor and Stambaugh (2003) liquidity factor; (iv) the Carhart four factor model; (v) the CAPM augmented with human capital; (vi) the consumption CAPM; and (vii) the Fama and French model augmented with momentum and liquidity factors. Avramov and Chordia also contribute towards the debate concerning whether the existence of anomalies are attributed to risk or behavioural explanations by directly testing the ability of conditional asset pricing models to explain size, value, turnover and momentum effects.

They extend the framework of Brennan *et al.* (1998) by first running a time-series regression of excess stock returns on risk factors where the loadings are allowed to vary both cross-sectionally and over time with firm size, the B/M ratio, and the default spread. Then, they run cross-sectional regression of risk-adjusted return, rather than gross return, on a set of equity characteristics which are size, the B/M ratio, turnover, and variables related to past returns. If the asset pricing model used in the time-series regression is appropriately determined and the time-variation in betas has been adequately captured, then all of these equity characteristics should be insignificant in the cross-sectional regression.

The framework employed by Avramov and Chordia to test the conditional asset pricing models begins by assuming that the returns are generated by a conditional version of K-factor model:

$$R_{it} = E_{t-1}(R_{it}) + \sum_{k=1}^{K} \beta_{ikt-1} f_{kt} + \varepsilon_{it} \tag{4.11}$$

where E_{t-1} is the conditional expectations operator, β_{ikt-1} is the conditional beta corresponding to the kth factor, and f_{kt} represents the risk factors at time t.

The expected return can be modelled as follows using the exact pricing specification:

$$E_{t-1}(R_{it}) = R_{ft} + \sum_{k=1}^{K} \beta_{ikt-1}\lambda_{kt-1} \quad (4.12)$$

where λ_{kt-1} is the risk premium associated with factor k. Consequently, the risk-adjusted return is given by the following equation:

$$R_{it}^{*} = R_{it} - R_{ft} - \sum_{k=1}^{K} \hat{\beta}_{ikt-1}F_{kt} \quad (4.13)$$

where beta has been estimated from the first-pass time-series regression of excess returns on the risk factors, and F_{kt} is the sum of the factor innovation and its corresponding risk premium ($F_{kt} = \lambda_{kt-1} + f_{kt}$).

The next step is to run a cross-sectional regression of the risk-adjusted return on a set of equity characteristics as follows:

$$R_{it}^{*} = c_{0t} + \sum_{m=1}^{M} c_{mt}Z_{mit-1} + \varepsilon_{it} \quad (4.14)$$

where Z_{mit-1} represents the value of characteristic m of security i at time $t-1$. Under an exact pricing specification, the coefficient c_{mt} should be zero as equity characteristics should have no power to explain risk-adjusted returns. This proposition is tested using a Fama-Macbeth cross-sectional regression where the standard errors are corrected using the approaches of Shanken (1992) and Jagannathan and Wang (1998).

The results of Avarmov and Chordia show that both the static and the conditional versions of the CAPM and the consumption CAPM fail to capture size, value, turnover and momentum effects. These results contradict the results of Lettau and Ludvigson (2001) who show that the consumption CAPM scaled by cay can capture both size and value effects. Avramov and Chordia attribute this difference in the results to the fact that Lettau and Ludvigson use portfolios rather than individual stocks as the main test assets. These results highlight that using individual stocks rather than portfolio as test assets may yield significantly different results.

The results of testing the static and conditional versions of the FF3 show a significant improvement over the CAPM. Although the static FF3 fails to explain any of the prominent anomalies tested, the conditional version of the model captures both the size and value effects, while it fails to capture the turnover and momentum effects. Thus, Avramov and Chordia test whether the FF3 augmented with momentum and liquidity factors can explain these two anomalies. However, their results show that none of the models tested can capture momentum and turnover.

Given the results of Avramov and Chordia, several points should be noted. One problem related to scaled factor models is that, as the number of conditioning variables increases, the number of parameters to be estimated will increase and this gives rise to the problem of over-fitting. Furthermore, although there is significant empirical evidence supporting the modelling of the time-variation in betas, Ghysels (1998) argues that if this time-variation in betas is not appropriately modelled, this may result in significant pricing errors that may even exceed the pricing errors associated with static models. Avramov and Chordia argue that the type of modelling they use in their paper significantly improves the pricing abilities of all models tested, and this supports that they are able to capture the time-variation in betas well.

Given that the empirical evidence above is based mainly on US data, more tests of conditional asset pricing models are required for other markets in order to provide out-of-sample evidence on their performance. Bauer *et al*. (2010) test whether conditional asset pricing models can explain the time variation and cross-sectional variation in returns of 25 size-B/M portfolios formed using data from 16 European markets. Similar to Avramov and Chordia (2006), Bauer *et al.* model the time variation in betas as a linear function of a set of predetermined instrumental variables (Z_{it}) which are size, the B/M ratio, the default spread and the interaction between these variables. Thus, the conditional FF3 can be expressed as follows:

$$R_{it+1} = \alpha_{i0} + \alpha_{i1} W_{it} + \sum_{k=1}^{3} (\gamma_{i0} + \gamma_{i1} Z_{it}) FF_{kt+1} + \varepsilon_{it+1} \quad (4.15)$$

where W_{it} represent the set of instrumental variables that are believed to capture the time-variation in alphas. FF_{kt+1} are the Fama and French three factors.

Their results show that the intercepts of the static FF3 are significantly different from zero which implies the failure of the model to explain portfolio returns. However, the results of the conditional model show that the R^2 increases significantly when the time-variation in betas is taken into consideration. In addition, the coefficients of the interaction term between the factors and the instrumental variables are significant which implies that the instrumental variables can capture the significant time-variation in betas.

However, despite these favourable results, the tests of whether the pricing errors are equal to zero and whether the alphas are constant over time (α_{i1}=0) are rejected which implies that the model does not fully capture the conditional expected returns on the 25 portfolios. Finally, to identify the sources of the pricing errors detected in the time-series regression, Bauer *et al.* run a cross-sectional regression of risk-adjusted return on size, book-to-market and momentum variables, similar to that employed by Avramov and Chordia (2006). The results show that the conditional model fails to capture momentum effect.

Since most of the results above employ scaled factor models as a way to incorporate the impact of conditioning information, they are highly sensitive to the set of conditioning variables used. Thus, the following section aims to provide an overview of models that employ dynamic conditional correlation to capture the time-variation in betas.

4.4.2 Conditional Asset Pricing models and Dynamic Conditional Correlations

One of the seminal papers, that models time-variation in betas by allowing the conditional covariance matrix of returns to vary over time following a GARCH process, is Bollerslev *et al.* (1988). In this respect, investors update their estimates of the means and covariances of returns each period based on newly revealed shocks in the returns of the last period as follows:

$$y_{it} = b_i + \delta \sum_j \omega_{jt} h_{ijt} + \varepsilon_{it}, \tag{4.16}$$

$$h_{ijt} = \gamma_{ij} + \alpha_{ij}\varepsilon_{it-1}\varepsilon_{it-1} + \beta_{ij}h_{ijt-1} \text{ for } i, j = 1, \ldots, N \tag{4.17}$$

They estimate the above model using the quarterly returns of T-bills, bonds and stocks for the period 1959 to 1984. Estimating the CAPM with time-varying covariances using a multivariate GARCH reveals that the covariance matrix of returns is time-varying and this invalidates the use of unconditional covariance in estimating betas. Furthermore, the coefficient of the conditional covariance (δ) is positive and strongly significant which supports the argument that conditional covariance provides a better description of risk compared to the unconditional covariance. However, one criticism of this approach of modelling time-varying covariance is that it is computationally difficult and is tractable only for a small number of assets (Hedegaard and Hodrick, 2014).

Thus, Bali and Engle (2010) estimate the conditional covariance matrix using a dynamic conditional correlation (DCC) model which is tractable for a large number of assets. They test both the CAPM and the ICAPM to determine whether modelling time-varying covariance can lead to better results compared to the previous studies that assume that the covariance matrix of returns is constant over time. They analyse the two models using 10 value-weighted size, B/M, momentum, industry, investment-to-assets and return-on-assets portfolios for the period January 1972 to June 2009. Furthermore, they test the models using Dow 30 stocks for the period July 1986 to June 2009. According to their arguments, the conditional CAPM states that the expected return on an asset depends on its conditional time-varying covariance with the market portfolio excess return as follows:

$$R_{it+1} = C_i + A * \sigma_{imt+1} + \varepsilon_{it+1} \tag{4.18}$$

The above model implies that all the intercepts C_i should be jointly equal to zero and the coefficient on the conditional covariance A should be significantly positive and constant for all test assets. Testing these two hypotheses shows that the coefficient of the conditional covariance is positive and strongly significant. In addition, it is stable across the test assets ranging between 1.59 and 3.32. These estimates of relative risk aversion are also economically reasonable giving further support for the model.

The tests that the intercepts are jointly equal to zero show that their conditional CAPM can explain cross-sectional and time-series expected returns for individual stocks, size, B/M and industry portfolios. These results contradict the results of Avarmov and Chordia that the conditional CAPM in which betas are allowed to vary with size, B/M and the default spread cannot explain any of the prominent anomalies in the finance literature. This implies that different approaches to modelling time-variation in betas can lead to different results. However, the conditional CAPM with a time-varying covariance fails to capture the cross-sectional and time-series variation in returns of momentum, investment-to-assets and return-on-assets portfolios.

All the previous studies presented so far focus mainly on developed markets and there is a significant paucity in research studies that focus on emerging markets. Nonetheless, testing the performance of conditional asset pricing models in emerging markets is interesting for the following reasons. First, Harvey (1995) argues that predictability of stock returns is more significant in emerging markets compared to developed markets. This, in turn, raises the need to test conditional asset pricing models in emerging markets to determine whether this predictability is due to market inefficiency or time-variation in risk and risk premia. Second, Iqbal *et al.* (2010) argue that if the assumption of constant betas and risk premia is questioned in developed markets, then it is more questioned in emerging markets due to the unstable macroeconomic and political conditions prevalent in these markets which may result in a considerable variation in risk and expected returns. Thus, the aim of the next section is to summarize the results of conditional asset pricing models for emerging markets.

4.4.3 Conditional Asset Pricing Models for Emerging Markets

Iqbal *et al.* (2010) test the performance of both the static and conditional versions of the CAPM and the FF3 for the Pakistan stock market using 16 size-B/M portfolios for the period October 1992 to March 2006. In order to model the time-variation in risk and risk premia, they use the scaled factor model approach. Their results show that conditional models do not result in significant improvement in the explanatory power of asset pricing models in the Pakistan stock market.

Garcia and Bonomo (1997) test and compare the performance of unconditional and conditional versions of the CAPM and the arbitrage pricing theory for the Brazilian stock market following the approach of Bodurtha and Nelson (1991). In this approach, betas are defined as the conditional covariance between the forecast error of the asset return and the forecast error of the market return, divided by the conditional variance of the forecast error of the market return. To model the time-variation in betas, these beta components are modelled as ARCH processes. In addition, the market risk premium is modelled as an autoregressive process. Garcia and Bonomo argue that this approach of modelling beta dynamics provides estimates that are more robust to structural changes and thus it overcomes the problems of parameter instability that is apparent in scaled factor models as argued by Garcia and Ghysels (1998).

Garcia and Bonomo then test both the conditional CAPM and the conditional APT using only three size portfolios for the period January 1976 to December 1992. Their results indicate that although the assumptions of constant betas and constant market risk premia are strongly rejected by the data, the conditional CAPM misses important dimensions of risk and it underestimates the returns of the three test portfolios. However, the results of the conditional APT, that includes an additional risk factor to capture the effect of inflation, are more favourable as the predicted mean returns from the model are more consistent with the actual returns compared to the conditional CAPM.

Overall there is a limited evidence on the performance of conditional asset pricing models in emerging markets. Thus, future research should focus on testing and evaluating conditional asset pricing models in emerging markets given the challenges that these markets pose to the asset pricing theory.

4.4.4 Regime Switching and Conditional Asset Pricing Models

Vendrame *et al*. (2018) emphasise that in the real world, it should be expected that investors' marginal utility of consumption, and hence the risk premia, vary over the business cycle as postulated by Campbell and Cochrane (1999). However, modelling time-variation in risk premia has received limited coverage in asset pricing literature.

Thus, given this gap, Vendrame *et al.* (2018) introduce a simple conditional CAPM that takes time-variations in betas and risk premia into consideration. Specifically, they use the DCC-GARCH to model time-variation in betas and the Markov regime switching model of Hamilton (1989) to model time variation in risk premia. The main motive behind their approach to model time-variation in risk premia is the results of Pettengill *et al*. (1995) who develop one of the seminal approaches to test the conditional CAPM. Pettengill *et al.* argue that the general premises of the CAPM assert that the expected return of an asset should be a positive function of only three variables which are: beta, the risk-free rate, and the expected return of the market portfolio. However, although the theory is stated in terms of expected or ex-ante returns, it must be linked to ex-post or realized returns in order to be tested which is one of the main obstacle's facing testing asset pricing models. Pettengill *et al.* highlight that the failure of researchers to recognize this shift from ex-ante universe to ex-post universe is the main reason behind the failure of previous tests of the CAPM to find a systematic relationship between beta and returns. Specifically, they argue that although the CAPM asserts that there is a positive relationship between beta and expected returns, the relation between beta and realized returns is conditional on the sign of excess market returns. Specifically, there should be a positive (negative) relationship between beta and realized returns during periods of positive (negative) excess market return.

The rationale behind this relationship is as follows. Although high betas stocks/portfolios should earn higher expected returns to compensate investors for bearing high risk, there must be some periods in which the realized returns of these stocks/portfolios are lower than that of low beta stocks/portfolios or otherwise no investor will be inclined to hold the low beta stocks/portfolios. These time periods should correspond to periods when excess market return is negative to justify the high risk of these stocks/portfolios. To test for this conditional relationship, Equation 4.19 is proposed:

$$R_{it} = \hat{\gamma}_{0t} + \hat{\gamma}_{1t} * D_{bull} * \beta_i + \hat{\gamma}_{2t} * (1 - D_{bull}) * \beta_i + \varepsilon_t \qquad (4.19)$$

where $D_{bull} = 1$ if market excess return is positive (bull regime), and zero otherwise. Equation 4.19 is tested each month and an estimate of either $\hat{\gamma}_{1t}$ or $\hat{\gamma}_{2t}$ is obtained based on the sign of excess market return. If the proposed conditional relationship holds, then $\bar{\gamma}_1$ ($\bar{\gamma}_2$) should be positive (negative) as it is estimated in periods when market excess return is positive (negative).

The main proposition derived from Pettengill *et al.* is that there are two risk premia: one for bull market and one for bear market. In this regard, they define bull (bear) markets as periods in which market excess return is positive (negative). However, this definition of bull and bear markets is strongly criticized as the true market regime is unobservable (Vendrame *et al.*, 2018). To overcome this problem, Vendrame *et al.* propose that the market's bull and bear regimes are random variables that can only be inferred using a certain probability estimated using a Markov switching model.

They use a three-pass methodology to test their conditional CAPM and determine whether it can explain the cross-sectional variation in stock returns better than the static CAPM. Specifically, in the first step, they estimate the probabilities of the bull and bear market regimes using a Markov switching model on market returns. Then, they estimate the conditional betas using the DCC-GARCH. Finally, they estimate the bull and bear risk premia. However, in contrast to previous asset pricing tests, they do not use the conventional cross-sectional regression approach to estimate the risk premia. They argue that since there is only one beta but two risk premia that should be estimated, a time-series of risk premia as in Fama-Macbeth cross-sectional regression cannot be obtained. Thus, to circumvent this problem, they use panel data regression as follows:

$$R_{it} - R_{ft} = \gamma_0 + \gamma_{12} p_t \beta_{it} + \gamma_2 \beta_{it} + \varepsilon_{it} \qquad (4.20)$$

where $\gamma_{12} = \gamma_1 - \gamma_2$ is the difference between the bull risk premia (γ_1) and the bear risk premia (γ_2). p_t is the probability of the bull market estimated using a Markov switching process. β_{it} represent the betas estimated using the DCC-GARCH model.

Their results show that, consistent with the theoretical proposition highlighted by Pettengill *et al.* (1995), they find that bull risk premia is significantly positive, whereas the bear risk premia is significantly negative. Furthermore, their results strongly criticises the unconditional CAPM as they show that the bull and bear risk premia are significantly different from each other. In addition, given the proposition that investors are inclined to hold risky assets only if they know that they are well compensated for bearing this risk, they find that the weighted average of the risk premia calculated as $(\Gamma_t = p_t \hat{\gamma}_1 + (1 - p_t)\hat{\gamma}_2)$ is positive and significant which provides further support for the conditional CAPM. Finally, they find that, compared to the static model, their conditional model has lower pricing errors and it can explain the size anomaly but it is still weakened by the value and momentum anomalies.

To sum up, the failure of conditional asset pricing models proposed so far to provide a coherent framework that can link the cross-sectional variation of expected returns to the variation of expected returns over time may imply the importance of incorporating the impact of noise traders on stock prices in order to provide better explanation of the cross-sectional variation in stock returns as proposed by behavioural finance proponents.

4.5 Investor sentiment and Stock Prices

Behavioural finance proponents argue that the overwhelming empirical evidence about the existence of anomalies that standard finance theories cannot accommodate leads to the emergence of models that use psychological biases to explain the observed anomalies in the market and provide better explanations of the cross-sectional variations in stock returns.

One of these models is Shleifer and Summers (1990) model that introduces an alternative model to the EMH that resides on two main assumptions. First, some investors are not fully rational and they make investment decisions without the use of fundamental information, exhibit poor market timing, follow trends and overreact or underreact to good and bad news. Second, arbitrage which is defined as trading by rational investors is risky and therefore limited and not effective in driving prices back to fundamentals.

Shleifer and Summers defend their approach against the EMH for two main reasons. First, their approach assumes that investors are normal people, who are subject to human errors and cognitive biases, and that arbitrage is limited provides more accurate description of financial markets compared to the traditional paradigm. Second, their approach provides new and testable implications about asset prices that are consistent with the real data derived from financial markets.

Although standard finance proponents argue that uniformed shifts in demand should not matter in price determination as they are random and uncorrelated and thus they should cancel each other out or they are eliminated by rational arbitrageurs, there is growing empirical evidence that news is not the only reason behind the movement in stock prices which supports the claims of behavioural finance proponents that prices may change due to uniformed shifts in demand resulting from changes in investor sentiment. This observation can help explain several anomalies in asset pricing literature.

For example, in a market where arbitrage is limited and prices respond to changes in fundamentals and uniformed shifts in investors' demand, prices vary more than is warranted by changes in fundamentals which may explain the excess volatility puzzle documented by Shiller (1981). In addition, since changes in investor sentiment is somehow unpredictable, this unpredictability contributes towards increasing noise traders' risk. If noise traders are pessimistic today, they will on average be less pessimistic in the future. Nonetheless, rational arbitrageurs cannot determine when exactly they will be less pessimistic and there is always a chance they will become even more pessimistic before they correct their beliefs. Since investor sentiment affects a wide range of stocks in the same way, this means that noise traders' risk is a systematic risk that should be rewarded in equilibrium. Thus, stocks that are more affected by the unpredictable swings in investor sentiment should yield higher returns compared to those that are less subject to shifts in sentiment.

This argument may play a considerable role in explaining the cross-sectional variations in stock returns. Specifically, since stocks of small firms are mainly held by individual investors who are more likely to trade on noise, then these firms will be more affected by noise traders' risk than stocks of big firms and thus they should yield higher returns. This, in turn, explains the size effect that is considered as one of the anomalies that challenges traditional finance theory. Finally, the overwhelming empirical evidence about the predictability of stock returns using simple valuation ratios or past return variables may be explained by the correction of sentiment-induced mispricing.

Despite the appeal of the alternative approach of Shleifer and Summers, standard finance proponents argue that behavioural finance cannot replace standard finance as a dominant paradigm as it lacks the solid structure of standard finance. This, in turn, leads to the emergence of a new strand of literature that tries to document the predictive ability of investor sentiment as well as determine how it can be incorporated in asset pricing models in order to provide a solid structure that is favoured by standard finance proponents.

4.5.1 Predictive Ability of Investor sentiment

Baker and Wurgler (2007) accentuate that in an attempt to provide direct evidence about the effect of investor sentiment on stock prices, three critical aspects should be considered. The first aspect is providing a well-stated and measureable definition of investor sentiment. Shefrin (2008) argues that the absence of such definition is one of the main obstacles facing developing a coherent behavioural approach to asset pricing. This, in turn, leads researchers to develop clear and concise definitions of investor sentiment.

Baker and Wurgler (2007) define sentiment as a belief about future cash flows and investment risks that cannot be explained by the facts at hand. Brown and Cliff (2004) define sentiment as the expectations of market participants relative to a norm such as the true fundamental value of the underlying asset. In this respect, an investor is considered as a bullish (bearish) investor if he expects returns to be above (below) this norm. From these definitions, it is apparent that sentiment is tied to the concept of investors’ erroneous beliefs that may occur because they either use noisy signals in updating their beliefs or because they do not use Bayesian techniques to reach valid statistical judgements from the fundamental information they receive.

The second critical aspect that may preclude researchers from providing a direct evidence about the effect of sentiment on stock prices is concerned with determining an appropriate proxy for investor sentiment. Baker and Wurgler (2007) argue that there is no a straightforward way to measure investor sentiment. Nonetheless, they point out that researchers can still find some imperfect proxies for sentiment that can be useful over time. In this regard, they argue that an exogenous shock in investor sentiment can result in a chain of events, and the shock itself could in principle be observed at any or every part of this chain. It might be observed in investors' beliefs which could be achieved through surveys. These beliefs might then be translated to observable trading patterns which could be recorded. In addition, limited arbitrage implies that these demand shocks might lead to mispricing which could be observed using benchmarks for fundamental values. Furthermore, this mispricing might stimulate an informed response by insiders, such as corporate executives, who may have both superior information and the incentive to take advantage of it.

Nonetheless, despite the variety of proxies that can be used to measure sentiment, Baker and Wurgler argue that each of the above proxies has some shortcomings that may preclude using it as a proxy for sentiment. Thus, there is no consensus in the literature regarding a definitive or uncontroversial measure of investor sentiment. However, the most commonly used proxies for investor sentiment are survey-based measures and market-based measures. Survey-based investor sentiment indices are obtained by collecting the opinions or perceptions of household investors and finance experts on a regular basis to identify their beliefs concerning the prospects for the economy, personal financial situations, or the future movement of the stock market.

Market-based measures seek to combine several imperfect financial proxies of investor sentiment in order to mitigate the shortcoming of individual proxies. The most commonly used market-based proxy for investor sentiment is Baker and Wurgler (2006) index. This composite index is based on the common variation in six underlying proxies for sentiment which are: (i) the close-end fund discount; (ii) NYSE share turnover; (iii) the number of IPOs; (iv) the average first-day returns on IPOs; (v) the equity share in new issues; and (vi) the dividend premium.

Finally, the last critical aspect is concerned with providing empirical evidence about the aggregate and the cross-sectional predictive ability of investor sentiment in order to provide support for behavioural finance theories. Baker and Wurgler (2007) underscore the importance of such evidence as return predictability tests imply the existence of profitable trading strategies that cannot exist in efficient markets in which prices are determined correctly. However, Baker and Wurgler (2006) are aware that this predictability patterns may reflect compensation for systematic risk rather than mispricing. Nonetheless, in their follow up paper in 2007, they emphasise that, in contrast to standard finance theories that hypothesise that high beta stocks should yield higher expected returns, hard-to-value and hard-to-arbitrage stocks, that have high betas, yield lower future returns on average compared to safe stocks when sentiment is high. They argue that these results support the sentiment-driven mispricing view as they imply that these stocks were overvalued. Nonetheless, the results of Vendrame *et al.* (2018) show that these results can be explained within the context of conditional asset pricing models as they show that investors may tolerate negative risk premia during down markets if they know that they are well compensated during bull markets with positive premia. Thus, this raises an interesting research question of whether the periods in which hard-to-value and hard-to-arbitrage stocks underperform safe stocks correspond to periods of market downturns in which investors tolerate negative risk premia.

Before presenting the empirical results of the studies that attempt to document the aggregate and the cross-sectional predictive ability of investor sentiment, it is important to review the main theoretical propositions upon which these studies are based. In this regard, Baker and Wurgler (2006) provide two distinct channels through which investor sentiment might affect the cross-section of stock returns which are: (i) uninformed demand shocks caused by irrational investors; and (ii) limits to arbitrage that prevent rational arbitrageurs from driving prices back to fundamentals. According to Baker and Wurgler, these two channels vary across stocks. Specifically, given that sentiment can be defined as the propensity of investors' to speculate, it is reasonable to assume that some stocks, such as stocks of young, small, and unprofitable firms, are more vulnerable to uninformed demand shocks by irrational investors than others as they are characterized by the difficulty and subjectivity of determining their true values which may allow investors to defend a wide variety of valuations that range from too low to much too high based on their sentiment. In the same spirit, limits to arbitrage also tend to vary across stocks. Baker and Wurgler (2006) argue that there is sufficient empirical evidence that arbitrage tends to be more risky and costly for small, young, unprofitable, and extreme growth stocks as they are more costly to buy and to sell short (D'Avolio, 2002), have higher variability (Shleifer and Vishny, 1997) and have high idiosyncratic risk.

The main implication derived from the above theoretical proposition of Baker and Wurgler is that the same stocks that are more vulnerable to investors' uninformed demand shocks are also more vulnerable to limits to arbitrage. Thus, the testable hypothesis derived from this theoretical positions is that: *stocks of small, more volatile, unprofitable, and distressed or extreme growth firms are more sensitive to investor sentiment than stocks of large, stable, profitable firms.*

Schmeling (2009) argues that it is also important to test the predictive ability of sentiment on the aggregate returns as stock markets at the aggregate country level are both difficult to value and difficult to arbitrage. In testing the relationship between sentiment and aggregate stock returns, the general hypothesis is that: *there is a negative relationship between sentiment and aggregate stock returns*.

The theoretical rationale behind this hypothesis is derived from the theoretical work of Barberis *et al.* (1998) who argue that since sentiment-prone investors extrapolate the current trend too far into the future due to having the representative bias, they make erroneous bets on future prices and they push prices away from fundamental values. As sentiment wanes in the long run, and rational arbitrageurs start to engage in price-stabilizing activities to drive prices back to fundamentals, a negative relationship between sentiment and subsequent aggregate returns should be observed.

However, a major criticism of the above hypothesis is that it does not provide firm guidelines concerning the appropriate time frame to be used in testing it (Warther, 1995). Thus, Han and Li (2017) provide some useful caveats to identify the relationship between sentiment and subsequent returns over different horizons. Specifically, in contrast to previous studies that propose a negative relationship between sentiment and subsequent returns, Han and Li argue that this negative relationship may be valid only in the long run, while in the short run, a positive relationship between sentiment and subsequent returns should be observed. The negative relationship between sentiment and subsequent stock returns depends greatly on the effectiveness of rational arbitrageur in driving prices back to fundamentals by bucking the trend induced by sentiment. Nonetheless, as is elaborated in Chapter 2, there is a number of frictions in real financial markets that may limit the effectiveness of arbitrage. Thus, the mispricing induced by irrational investors may persist for extended periods of time leading to a positive relationship between sentiment and subsequent stock returns in the short run. Then, as sentiment wanes over the long run, this positive relationship is expected to reverse leading to the well-documented negative relationship between sentiment and subsequent returns.

4.5.1.1 Empirical Evidence on the Predictive Ability of Investor sentiment

Behavioural finance theory suggests that investor sentiment has a significant effect on the cross-section of stock prices (Baker and Wurgler, 2006). These authors test for this effect using two main approaches.

In the first approach, using monthly stock returns from 1963 to 2001, they sort stocks into equal-weighted decile portfolios based on several firm characteristics that are related to how vulnerable stocks are to uniformed demands shocks and limits to arbitrage. Then, they investigate the patterns in the average monthly returns of these portfolios conditional on the level of sentiment at the end of the previous calendar year. Consistent with the theoretical propositions, they find that when sentiment is low (below average), portfolios that include small, young, unprofitable, high volatility, and non-dividend-paying stocks earn higher subsequent returns than portfolios that include big, old, low volatility, and dividend payers stocks, whereas this pattern is completely reversed when sentiment is high (above average).

Second, they use predictive regressions to provide more formal tests on the cross-sectional predictive ability of sentiment. In this approach, they examine whether sentiment can forecast the returns of various long-short portfolios constructed using the aforementioned firm characteristics as follows:

$$R_{X_{it=High,t}} - R_{X_{it=Low,t}} = c + dSentiment_{t-1} + \varepsilon_{it} \tag{4.21}$$

where $R_{X_{it=High,t}} - R_{X_{it=Low,t}}$ is the monthly return on a long-short portfolio such as the SMB. The monthly returns from January till December of year t are regressed on the sentiment index that prevailed at the end of year $t-1$. Furthermore, they test whether the predictive ability of sentiment remains significant even after adjusting for the Fama and French three risk factors augmented with the momentum risk factor of Carhart (1997) to rule out risk-based explanations. The results of the above predictive regression show that when sentiment is high, returns on small, young, unprofitable, non-dividend paying, high volatility, high growth and distressed stocks are relatively low over the coming year and vice versa. This significant predictive ability of sentiment remains even after adjusting for risk.

However, these results do not necessarily imply market inefficiency. The debate in Section 4.2 shows that predictability in stock returns may be due to rational variation in expected returns over time or to market inefficiency. Thus, to contribute towards this debate, Baker and Wurgler test whether systematic risk can accommodate the predictive ability of sentiment through two main channels. The first channel is concerned with whether systematic risks (beta loadings) of stocks with certain characteristics vary with investor sentiment. To test this possibility, they estimate the following scaled factor model:

$$R_{X_{it=High,t}} - R_{X_{it=Low,t}} = c + dSentiment_{t-1} + \beta(1 + fSentiment_{t-1})R_{MKT,t} + \varepsilon_{it} \quad (4.22)$$

The main prediction of this first channel is that the composite coefficient βf should have the same sign as the estimate of d in Equation 4.21. However, the results show that the coefficient βf is mostly insignificant for all long-short portfolios tested and when it is significant, it has the wrong sign. They take these results as an evidence against risk-based story. Nonetheless, these results should be interpreted with caution, as these results are dependent on the approach followed to model time-variation in betas. Furthermore, Baker and Wurgler do not report whether the predictive ability of sentiment disappears after capturing time-variation in betas.

The second channel through which systematic risk can accommodate the predictive ability of sentiment is through allowing for time-variation in risk premium. This channel requires stocks of older, less volatile, profitable, and/or dividend-paying firms to earn a risk premium over stocks of young, highly volatile, unprofitable, and/or non-dividend-paying firms when sentiment is low and vice versa. However, they argue that this is counterintuitive and thus they refute risk-based explanations for their results. Nonetheless, Vendrame *et al.* (2018) show that, by modelling time-variation in risk premia using a Markov switching process, risk premia may change sign and magnitude over different economic conditions. However, no clear empirical evidence is available on whether the predictive ability of sentiment can be accounted for using time-variation in risk and risk premia.

In this regard, Shen *et al.* (2017) show that time-variation in risk premia cannot fully account for the predictive ability of investor sentiment. Specifically, they argue that if sentiment captures time-variation in risk premia, then, the market price of risk for the market factor should be lower following high sentiment than low sentiment. Nonetheless, they find that the market excess return is positive following both high- and low-sentiment periods. Furthermore, they show that high-sentiment periods are not mechanically followed by down markets. Thus, these results emphasise the argument of behavioural finance proponents that sentiment plays a crucial role in developing accurate models for stock prices and expected returns.

Consequently, these results give rise to several papers that attempt to use investor sentiment to explain the anomalies that challenge standard finance theories. One of these papers is Stambaugh *et al.* (2012) who investigate whether sentiment-related mispricing can provide partial explanation for 11 prominent anomalies[3] that challenge standard finance theories. Their main theoretical proposition is that when market-wide sentiment is high, many investments are expected to be overvalued. In contrast, when market-wide sentiment is low, the short-sale constraints may hinder pessimistic investors from causing substantial mispricing. Thus, this implies that financial markets tend to be more rational and efficient during low-sentiment periods. In contrast, during high-sentiment periods, sentiment-induced mispricing and market inefficiency are likely to be more prevalent (Shen *et al*., 2017). Given this theoretical proposition, they argue that if mispricing is prevalent only when sentiment is high, then the anomalies under investigation should be stronger only following high sentiment. Consistent with this argument, they find that each of the anomalies tested achieves higher average returns following high sentiment.

Following the same argument, Chung *et al.* (2012) find that investor sentiment has a significant predictive ability only during bullish regimes, whereas during bearish regimes the predictive ability of sentiment is generally insignificant. Furthermore,

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[3] These anomalies reflect sorts on variables such as financial distress, net stock issues, composite equity issues, total accruals, net operating assets, momentum, gross profit-to-assets, asset growth, return-on-assets (ROA), and investment-to-assets. Chen *et al.* (2010) find that these anomalies cannot be captured using conventional asset pricing models such as the CAPM and the Fama and French three-factor model.

they use the monthly sentiment index in order to provide some useful caveats regarding the short-term predictive ability of sentiment. Their results show that even in the short-term, sentiment is a contrarian predictor of stock returns which contradicts the argument of Han and Li (2017) that sentiment is a momentum predictor of short-term stock returns. The differences between these two papers may be attributed to the effectiveness of arbitrage in eliminating the mispricing caused by irrational investors. Specifically, since Chung *et al.* focus on the US market which is one of the most efficient markets, it is reasonable to assume that arbitrage is effective in correcting the sentiment-induced mispricing quickly. This, in turn, can justify the negative relation between sentiment and subsequent returns even in the short-run.

Another strand of literature provides evidence on the relationship between investor sentiment and aggregate stock returns. Initially, this strand of literature focuses on testing the relationship between sentiment and short-run market returns. Nonetheless, the empirical evidence from these studies show that sentiment has little predictive power for subsequent near-term returns (see for example, Brown and Cliff, 2004). However, Brown and Cliff (2005) argue that the results of these studies should not be taken as an evidence against the theoretical propositions that sentiment affect stock prices due to the following reasons. First, they argue that since sentiment is a persistent variable, it is reasonable to assume that the importance of sentiment tends to increase over time. Specifically, investors tend to be more optimistic as they are supported by others joining on the bandwagon. Second, although arbitrage can eliminate short-run mispricing, it normally breaks down at longer horizons due to the limits to arbitrage prevalent in financial markets. These reasons imply that researchers should focus on the relationship between sentiment and long-run rather than short-run returns.

Motivated by the above reasons, Brown and Cliff test whether high sentiment leads to low cumulative long-run returns as the market prices revert back to their fundamental values. To achieve this aim, they regress the future k-period log returns on sentiment (S_t). However, since sentiment partially contains rational expectations based on risk factors and other variables that can predict future performance, they include a set of control variables (z_t)[4] to disentangle the rational and irrational parts of investor sentiment.

$$(r_{t+1} + \cdots + r_{t+k})/k = \alpha(k) + \beta_1(k)z_t + \beta_2(k)S_t + \varepsilon_t^k \tag{4.23}$$

Their results show that $\beta_2(k)$, which shows the sensitivity of expected monthly returns over different horizons to sentiment, is significantly negative for all portfolios tested[5] which implies that sentiment is a contrarian predictor of long-run returns.

In order to provide an out-of-sample evidence on the predictive ability of sentiment and determine whether the sentiment-return relationship is prevalent in different countries with different cultures and different stages of institutional development, Schmeling (2009) investigates whether sentiment affects stock returns internationally in 18 industrialized countries. The results indicate that the predictive ability of investor sentiment shows quite heterogeneity across countries. Specifically, the effect of sentiment on stock returns is stronger in countries that are more vulnerable to herd-like behaviour and overreaction as well as countries that have lower market integrity as they are less efficient.

The main implication from these results is that empirical evidence from the US market cannot be directly transferred to other markets by assuming that irrational noise traders affect stock market in general. Rather, researchers should test the relationship between sentiment and stock returns in different countries as this relationship is dependent on institutional quality and cultural factors prevalent in each country. This, in turn, necessitates testing the relationship between sentiment and

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[4] The control variables include: the stochastically detrended 1-month U.S Treasury bill return, the difference between the monthly returns on 3-month and 1-month T-bills, the term spread, the default spread, the dividend yield for the market index over the past twelve month, and the rate of inflation.

[5] The portfolios include the 25 Fama and French (1993) portfolios double sorted on size and the book-to-market ratio, the 5 portfolios sorted on size only, the 5 portfolios sorted on the book-to-market ratio only, and the market portfolio.

stock returns in different countries and use these results to determine whether developing a behavioural asset pricing model for this country is warranted.

In this regard, Han and Li (2017) contribute to the evolving literature on the relationship between sentiment and subsequent stock returns in a number of distinctive aspects. First, in contrast to previous studies that test the predictive ability of sentiment in developed markets, they focus on the Chinese stock market as one of the growing emerging markets. They argue that this evidence is important as emerging markets are mainly characterized by speculative trading and binding arbitrage constraints such as stronger short-sale constraints and less openness to international investors. Thus, this implies that the sentiment-return relationship in these markets may show different patterns compared to that in developed markets. Second, since there is a lot of controversy regarding the short-run predictive ability of sentiment, Han and Li argue that, given the characteristics of emerging markets, it is expected that there is a positive relationship between sentiment and short-run returns, whereas the well-documented negative relationship between sentiment and subsequent stock returns is more likely to prevail in the long-run.

In pursing their aim to test the sentiment-return relationship, they construct a market-based sentiment index for the Chinese stock market. They defend this index over the consumer confidence index as a proxy for sentiment for the following reasons. First, they argue that the consumer confidence index focuses on consumers' general expectations about the overall prospects of the economy rather than the stock market. Second, since the consumer confidence index is a survey-based measure, it is subject to the criticism that the survey respondents may not really act in the way they described in the survey.

To test their theoretical proposition empirically, they use the following predictive regression for return horizons that range from 1 month to 60 months:

$$r_{t+h} = \alpha + \beta sentiment_t + \varphi z_t + \varepsilon_{t+h} \quad (4.24)$$

where r_{t+h} is the market excess return in the period $t + h$, $sentiment_t$ is the h-period lagged sentiment index at the end of month t. The results show that sentiment is a strong momentum predictor of stock returns in the short-run as the coefficient of sentiment remains positive for the first eight consecutive months. Then, as the horizon increases and the coefficient of sentiment turns to be negative and significant from the ninth month onwards. This, in turn, supports the proposition that sentiment is a contrarian predictor of long-run returns.

Given that failure of conventional asset pricing models to explain the cross-sectional variation in stock returns in emerging markets, the results of Han and Li may motivate researchers to develop and test behavioural asset pricing models within emerging markets.

4.6 Behavioural Asset Pricing Models

Until this point, the literature review of this thesis has shown that the rational asset pricing theory is still challenged by its failure to explain the cross-sectional variations in stock returns. Nevertheless, the discussion in Sections 4.3 and 4.4 shows that conditional asset pricing models play an important role in capturing the cross-sectional variation in stock returns within a rational context (see for example, Vendrame *et al*., 2018; Lettau and Ludvigson, 2001). However, Potì and Shefrin (2014) show that analysing the results of conditional asset pricing models reveal a puzzling contrast between the high cross-sectional explanatory power of the models and the inconsistency between the parameter estimates and the fundamental assumptions underlying these models. For example the estimates of the risk premia of the conditional (C)CAPM of Lettau and Ludvigson (2001) imply that the representative investor's conditional relative risk-aversion takes negative values for certain sample realizations of the conditioning variable, which is inconsistent with the general premises of the CAPM that assumes that investors are risk averse. Furthermore, these estimates imply a stochastic discount factor that takes negative values over a range of the values that consumption growth may take which implies the existence of arbitrage opportunities that contradicts one of the main building blocks of standard finance theories.

The above challenges facing conventional asset pricing models may cast some doubts on the assumptions upon which these models are built (Chandra and Thenmozhi, 2017). Specifically, contrary to the assumptions of conventional asset pricing theory, behavioural finance proponents argue that investors are affected by psychological biases and limits to arbitrage prevent rational investors from driving prices back to fundamentals. This, in turn, implies that investor sentiment should have an effect on asset prices which is supported empirically by the wide array of papers that documents the aggregate and the cross-sectional predictive ability of investor sentiment (Baker and Wurgler, 2006).

This theoretical and empirical evidence leads behavioural finance proponents to emphasise the importance of behaviouralizing asset pricing theory. However, Shefrin (2005) argues that behavioural asset pricing models that emerged so far are mainly *ad-hoc* models that aim to provide behavioural explanations for particular anomalies which is one of the main shortcoming of behavioural asset pricing models. Nonetheless, Shefrin emphasises that the future of asset pricing theory should lie in bringing together the powerful SDF-based tool adopted by neoclassical asset pricing theorists and the more realistic assumptions adopted by behavioural asset pricing theorists.

One of the attempts to augment conventional asset pricing models with behavioural factors is Potì and Shefrin (2014). This paper has two main contributions. First, this paper tests whether augmenting the 2 and 3 moment versions of the (C)CAPM with a sentiment factor can improve the ability of the models to explain the cross-sectional variation in stock returns and provide estimates of the risk premia that are consistent with the underlying economic theory. Second, Potì and Shefrin attempt to overcome the criticism facing most behavioural asset pricing models that they lack the general SDF-based approach favoured by standard finance proponents by proposing a model that is based on both behavioural assumptions and the use of SDF-based tools. In this regard, they base their model on the results of Shefrin (2005) who argues that the stochastic discount factor (SDF), $M(x_i)$, can be decomposed into two components: a behavioural component that depends on investor sentiment and a rational component that depends on economic fundamentals as follows:

$$M(x_i) = \frac{U'(C(x_i))}{U'(C_0)} + ln\Lambda(x_i)\frac{U'(C(x_i))}{U'(C_0)} = M_R + M_s \tag{4.25}$$

where $\Lambda(x_i) = \frac{P_R(x_i)}{\Pi(x_i)}$

Equation 4.25 shows that the SDF has a rational component, M_R , which represents the aggregate marginal utility growth, and a behavioural component, M_s which is the product of the marginal utility growth and the log of the ratio of representative investor's probabilities and the correct probabilities ($ln\Lambda(x_i)$).

In order to estimate Equation 4.25 empirically, several points should be highlighted. First, investors' utility functions should display non satiation (NS), risk aversion (RA) and non-increasing absolute risk aversion (NIARA). With utility function defined over wealth, NS requires positive marginal utility of wealth, i.e. $U'(W) > 0$, RA implies decreasing marginal utility, i.e. $U''(W) < 0$, and NIARA implies that the rate of decrease of marginal utility does not increase with wealth, i.e. $U'''(W) > 0$. Thus, NIARA means that investors are averse to negative skewness. These specifications are important to assess the results and determine whether they are consistent with economic fundamentals. Second, Potì and Shefrin argue that with the marginal utility growth of the representative investor approximated with preferences defined over aggregate consumption, the rational component of the SDF can be defined as follows:

$$M_{R,t+1} = 1 + b_{1t}R_{ct+1} + b_{2t}R_{ct+1}^2 \tag{4.26}$$

where R_{ct+1} is the aggregate consumption growth. In order to ensure that investors' utility functions display non satiation, risk aversion, and non-increasing absolute risk aversion, b_{1t} should be negative, whereas b_{2t} should be positive. Third, since the behavioural component of the SDF, M_s, is the cross-product of M_R and the log-likelihood ratio $ln\Lambda(x_i)$. Thus, the SDF function can be defined as follows:

$$M_{t+1} \cong 1 + b_{1t}R_{ct+1} + b_{2t}R_{ct+1}^2 + b_{3t}s_{t+1}R_{ct+1} \tag{4.27}$$

where $s(x_i) = ln\Lambda(x_i)$. s_{t+1} is calculated as the first difference of Baker and Wurgler (2006) sentiment index. Equation 4.27 provides a simple way to incorporate behavioural factors within conventional asset pricing models.

The results of the (C)CAPM show that, inconsistent with the theoretical propositions of investors' utility functions, both the SDF and b_{1t} have the wrong signs for prolonged portions of the sample period. Specifically, the estimated SDF often has negative values which indicates the existence of arbitrage opportunities and the violation of the assumption that investors' preferences display non satiation. Furthermore, the estimates of b_{1t} are not always negative which violates the assumption of risk aversion. The results of the 3 moment (C)CAPM also face the same problems concerning the signs of the SDF and b_{1t}. In addition, the negative values of b_{2t} also violate the assumption of non-increasing absolute risk aversion.

However, when both models are augmented with sentiment, a significant improvement in the results is witnessed. Specifically, Potì and Shefrin argue that by taking the behavioural component of the SDF into consideration, the results show a significant improvement in the ability of the SDF to fit the cross-sectional variation in stock returns while allowing the parameters of the rational component of the SDF to be consistent with the tenets of rational optimizing behaviour.

Another attempt to behaviouralize asset pricing models is Ho and Hung (2009). Motivated by the increased interest in testing conditional asset pricing models, they test whether using investor sentiment as a conditioning variable within the context of scaled factor model approach can provide better explanation of financial market anomalies. By using the two-pass regression framework of Avramov and Chordia (2006), they show that using investor sentiment as conditioning information enhances the overall performance of different asset pricing models. Specifically, they show that conditional models that use investor sentiment as conditioning information can explain the size, value, liquidity and momentum effects on individual stock returns, despite the failure of conditional models that use a set of macroeconomic and microeconomic variables as conditioning information in explaining the liquidity and momentum effects.

Despite the favourable results of Potì and Shefrin (2014) and Ho and Hung (2009), the empirical coverage of behavioural asset pricing is very limited which may explain why these models are not as popular as conventional models. Thus, to fill in this gap, Dash (2016) tests whether conditional asset pricing models that use investor sentiment as conditioning information can explain the cross-sectional variation in stock returns in the Indian stock market as one of the growing emerging markets. The results show that using sentiment as a conditioning variables improves the performance of the different asset pricing models[6] tested. However, inconsistent with Ho and Hung (2009), Dash finds that using investor sentiment as the only conditioning variable can only capture momentum in stock returns, whereas it fails to explain size, value, and turnover effects. This implies that the results obtained from developed markets cannot be applied directly to emerging markets.

Berger and Turtle (2012) and Ho and Hung (2012) attempt to investigate the role of sentiment as a risk factor. In this regard, Berger and Turtle argue that identifying whether sentiment risk is diversifiable is one of the critical questions in behavioural asset pricing models literature. Specifically, they highlight that if sentiment cannot be

[6] The CAPM, the Fama and French three-factor model, the Carhart four-factor model, and the Fama and French model augmented with liquidity and momentum factors.

diversified, then investors and practitioners should focus on modelling sentiment risk and determining whether it is priced in equilibrium, whereas if sentiment is an idiosyncratic risk that affects stock prices only through its effect on systematic risk sensitivities, then it should not be a major concern for researchers and investors.

In order to answer this question, Berger and Turtle follow the same theoretical proposition of Baker and Wurgler (2006). They argue that if information about certain stocks (opaque stocks) is difficult to interpret, then investors find it challenging to determine the value of these stocks. Furthermore, arbitrageurs may find it difficult to correct any mispricing in these stocks as the veracity of available information may be difficult to resolve. Berger and Turtle argue that if these stocks are prevalent in the market and if this risk is difficult to diversify, then these stocks are expected to be more sensitive to overall measures of sentiment. In contrast, if this risk is largely diversifiable, then observed premiums on these opaque stocks should be comparable to those offered by translucent stocks with similar risk profiles. Their results show that there is a significant relation between stock opacity and sentiment sensitivities. Specifically, they find that stocks that are more sensitive to sentiment (have high sentiment betas) display volatile returns, a small equity base, low-earnings, low dividends, high distress risk, and have more intangible assets. Furthermore, they find that both simple and multifactor asset pricing models fail to capture the variability in these stocks' returns over time. This, in turn, supports the claims that sentiment risk is not diversifiable and it should be rewarded in equilibrium.

Motivated by this evidence, Ho and Hung (2012) contribute to behavioural asset pricing models in several aspects. First, they construct a sentiment risk factor in the spirit of the SMB and HML factors constructed by Fama and French (1993). Specifically, they first estimate the sentiment betas of individual stocks using monthly rolling regressions to capture the sensitivity of each stock to the shift in the market-wide sentiment measured using the orthogonalised sentiment index of Baker and Wurgler (2006) as in the following equation.

$R_{i,\tau} - R_{f,\tau} = \alpha_i + \beta_{iM}(R_{M,\tau} - R_{f,\tau}) + \beta_{i,sent}\Delta sent_\tau \quad \tau = t-23, t-22, \ldots, t$ for each $t = 24 \ldots., T$ (4.28)

where $R_{i,\tau} - R_{f,\tau}$ is the excess return of individual stocks, $(R_{M,\tau} - R_{f,\tau})$ is the excess return on the market portfolio, $\Delta sent$ is the monthly change in the sentiment index, and $\beta_{i,sent}$ measures the sensitivity of each stock to changes in the market-wide sentiment index.

Then, they rank all stocks each month in ascending order based on their sentiment betas and divide them into equally-weighted decile portfolios. Stocks in the highest decile portfolio have the highest positive sentiment betas, whereas stocks in the lowest decile portfolio have the lowest (most negative) sentiment betas. Stocks in the middle deciles have sentiment betas close to zero and thus they are the least sensitive to swings in sentiment. They, then, construct three measures of sentiment risk factor using these deciles. The first measure, SMN*Plus*, is the difference between the returns of the portfolios with the highest and lowest positive sentiment betas. The second measure, SMN*Minus*, is the difference between the returns of the portfolios with the most and least negative sentiment betas. Finally, SMN*AVG*, is the arithmetic average of SMN*Plus* and SMN*Minus*. The last measure of sentiment risk factor is constructed based on ranking stocks into quintiles based on their absolute betas rather than raw betas. This measure, SMN*Abs*, is the difference between the returns of portfolios with the highest and lowest absolute sentiment betas.

Having these measure of sentiment risk factor, Ho and Hung then investigate whether they are significantly priced in equilibrium using the Fama-Macbeth cross-sectional regression approach. The results reveal that all measures of sentiment risk factor except SMN*Minus* are significantly priced even after controlling for market risk. This implies that investors require higher expected returns as compensation for bearing the exposure to the SMN factor. These results support the argument of De Long *et al*.

(1990), Berger and Turtle (2012) that sentiment is a risk factor that warrants additional risk premium.

4.7 Conclusion

This chapter discusses two major breakthroughs in asset pricing literature which are conditional asset pricing models and behavioural asset pricing models. The first part of this chapter deals with the main milestones of conditional asset pricing models. This review reveals important aspects concerning developing and testing conditional asset pricing models that are worth highlighting as they represent the basis upon which the empirical analysis of this thesis is based.

Although there is sufficient theoretical and empirical evidence that conditional models may do a better job than static models in explaining stock returns within a rational framework (Wang, 2003), there is no a clear-cut approach to model time-variation in risk and risk premia. This, in turn, makes the performance of conditional asset pricing models dependent on the chosen approach to capture time-variation in risk and risk premia.

Reviewing the relative merits of the different approaches that are used to model time-variation in risk (betas) reveals that the most commonly used approaches are the simple rolling regression approach, the scaled factor model approach, and the DCC-GARCH model. These three approaches provide simple ways to capture time-variation in betas. Furthermore, empirical tests of conditional models that use these approaches show that these model can provide better explanations of the cross-sectional variation in stock returns compared to their static counterparts which implies the appropriateness of these approaches to model time-variation in betas (Avramov and Chordia, 2006; Vendrame *et al.*, 2018).

Despite the variety of approaches available to capture time-variation in betas, there is a paucity in studies that attempt to model time-variation in risk premia. However, recent empirical evidence shows that regime switching techniques provide a simple way to model time-variation in risk premia (Vendrame *et al*., 2018).

The above aspects concerning developing and testing conditional asset pricing models provide useful avenues for future research. First, conditional asset pricing models presented in this chapter focus mainly on modelling time-variation in risk and risk premia within the context of the CAPM. Thus, one of the explanations that may justify the challenges facing these models is the omitted variable bias. This, in turn, necessitates testing whether modelling time-variation in risk and risk premia within the context of multifactor asset pricing models can provide better explanation of the cross-sectional variation in stock returns. Second, in testing conditional asset pricing models, researchers mainly focus on developed markets and there is a significant lack in studies that test these models using emerging market data which is counterintuitive given the unstable macroeconomic and political conditions prevalent in these markets which may result in a considerable variation in risk and expected returns. Thus, it is of interest to test whether conditional asset pricing models can explain the cross-sectional variation in stock returns in emerging markets.

The second part of this chapter deals the development of behavioural asset pricing models and their empirical evidence from both developed and emerging markets. Although Shefrin (2005) emphasises the importance of behaviouralizing asset pricing models, no satisfactory behavioural asset pricing model has emerged to show how both utilitarian and value-expressive factors should be incorporated together in asset pricing models. However, the empirical evidence on the relationship between sentiment and stock prices and the role of sentiment in asset pricing models either as a conditioning variable or as a risk factor provide support for the claims of behavioural finance proponents that a paradigm shift from the fully rational paradigm to a broader psychological paradigm should be warranted (Hirshleifer, 2001).

To sum up, the two opponent views of standard finance proponents and behavioural finance proponents and the continuous attempts of both groups to provide a satisfactorily explanation of the cross-sectional variations in stock returns make asset pricing an important ongoing topic of debate (Xu, 2010).

Chapter 5

Research Methodology

5.1 Introduction

The aim of this chapter is to highlight the main approaches employed to estimate the parameters of asset pricing models and to test whether the models can explain the cross-sectional variation in stock returns.

The outline of this chapter is as follows. Section 5.2 discusses the definition of the main variables used in this thesis. Section 5.3 presents an overview of the main the research methods employed. Finally, Section 5.4 concludes.

5.2 Construction and Definition of Variables

5.2.1 Construction of the Fama-French Factors for the Egyptian Stock Market

Following the discussion in Chapter 1, in attempting to determine the relevant state variables that can explain stock returns in the Egyptian stock market, this thesis uses the Egyptian version of the Fama and French three factors as the main risk factors. However, since the Fama and French factors are not readily available for the Egyptian stock market, these factors are constructed by the author following Fama and French (1993).

The market factor, which is the excess return on the market portfolio, is formulated as the difference between the value-weighted average return of all of the stocks listed in the Egyptian stock market (excluding financial firms) and the three-month Treasury bill rate.

The SMB and the HML factors are constructed from portfolios formed based on 2x3 sorts on size and the B/M ratio. The choice of the 2x3 sort is supported by the argument of Fama and French (1992) that the B/M ratio has a stronger role in average stock returns than firm size. For a stock to be included in the factor construction process, it must have a stock price for December of year $t-1$ and June of year t, and book equity for year $t-1$. In order to construct the SMB and HML factors, two steps are required. First, at the end of June of year t, stocks are sorted based on market capitalization, calculated as stock price times the number of outstanding shares, and then stocks whose market capitalization constitutes 90% of the total market capitalization of all of the stocks used in this thesis are classified as big stocks “B” while all the remaining stocks are classified as small stocks “S” (Cakici *et al.*, 2013).

The rationale behind this approach is that when choosing the appropriate size breakpoints for developed markets, Fama and French (2012) emphasize that it should roughly correspond to the median value of NYSE stocks which is the breakpoint used in their original paper in 1993. However, when replicating this approach for the Egyptian stock market, given its small market capitalization, the NYSE size breakpoint is simply too large, resulting in leaving only a very limited number of firms in the big portfolio. Thus, to avoid this problem, Cakici *et al.* (2013) recommend using a market share based approach to determine the appropriate size breakpoint for emerging markets. They argue that this approach ensures that the small and big portfolios include the same shares of the total market capitalization as the US (NYSE, AMEX, and NASDAQ stocks) small and big portfolios with respect to the NYSE breakpoint. Specifically, Fama and French (1993) show that although the small stock portfolio includes a large number of stocks, it covers only around 8% of the combined value of their two size portfolios (small and big). Following the same logic, the small stocks portfolio for the Egyptian stock market includes 91 stocks out of 131 stocks in the year 2014, while it represents only 10% of the total market value.

The second step in constructing the SMB and HML factors is to sort stocks independently into three portfolios (Value “H”, Neutral “N”, and Growth “L”) based on the B/M ratio. The B/M ratio is calculated as the ratio of the book value of stockholders’ equity for the fiscal year ending in calendar year $t-1$, to the market equity at the end of December $t-1$. Regardless of the fiscal year end of the firms, the market capitalization at the end of December is used to calculate the firm B/M ratios to neutralize the impact of market conditions on the ratio. Firms that have negative B/M ratios are excluded when determining the B/M ratio breakpoint.

To determine the B/M ratio breakpoint, stocks in the big "B" portfolio are classified based on their B/M ratio to determine the usual bottom 30% (growth), middle 40% (neutral) and top 30% (value) breakpoints for the B/M ratio, and then these breakpoints are applied to all big and small stocks. Determining the breakpoints using stocks in the big portfolios is intended to ensure that the factors are not dominated by less important illiquid small and tiny stocks which may jeopardize the results of testing asset pricing models (Fama and French, 2012; Gregory *et al*., 2013). By the end of this step, three portfolios are formed which are the value "H" portfolio, which includes stocks whose B/M ratios are in the top 30% group, the neutral portfolio "N", which includes stocks whose B/M ratios are in the middle 40% group, and the growth "L" portfolio, which includes stocks whose B/M ratios are in the bottom 30% group. Then, from the intersection of the two market capitalization and the three B/M groups, six portfolios will be formed which are (S/H, S/N, S/L, B/H, B/N, B/L). For example, the S/H portfolio, includes stocks that are in the small market capitalization portfolio and that are also in the high B/M ratio portfolio.

Then, the monthly value-weighted return for each of these portfolios from July of year t to June of year $t + 1$ is calculated. Returns are calculated starting from July to ensure that the book equity for year $t - 1$ has been announced to the public. The use of value-weighting rather than equal weighting is justified by the following. First, to ensure that the variance of firm specific factors is minimized as return variance is negatively correlated with firm size. Second, to ensure constructing mimicking portfolios that capture the different return behaviours of small and big stocks, or value and growth stocks, in a manner that corresponds to real investment strategies followed by investors.

The last step is to calculate the SMB each month as the difference between the simple average of the returns on the three portfolios of small stocks (S/H, S/N and S/L) and the simple average of the returns on the three portfolios of big stocks (B/H, B/N and B/L). Constructing the SMB factor as the difference between small and big portfolios with about the same weighted-average book-to-market equity (Fama and French, 1993) is intended to disentangle between the size and B/M effects.

$$SMB = \frac{(SH+SN+SL)}{3} - \frac{(BH+BN+BL)}{3} \tag{5.1}$$

Similarly, the HML factor is calculated monthly as the difference between the simple average returns on the two portfolios of stocks with high book-to-market ratios (SH and BH) and the simple average returns on the two portfolios of stocks with low book-to-market ratios (SL and BL). Similar to the SMB factor, this way of constructing the HML factor ensures that the size and B/M effects are disentangled.

$$HML = \frac{(SH+BH)}{2} - \frac{(SL+BL)}{2} \tag{5.2}$$

5.2.2 Appropriate Proxy for Conditional Betas

In asset pricing applications, betas were traditionally assumed to be constant over time. Specifically, researchers, initially, run time-series regression over the entire sample period to estimate full sample constant betas. The time-series regression is as follows:

$$R_{it}^e = \alpha_i + \sum_{k=1}^{K} \beta_{ik} F_{kt} \tag{5.3}$$

where $R_{it}^e = R_{it} - R_{ft}$ and F_{kt} represent the risk factors under consideration such as the Fama and French three factors and the sentiment risk factor. However, given the well documented challenges of static asset pricing models, researchers start to model time-variation in both risk and risk premia. Following the discussion in Chapter 4 concerning the relative merits of the different approaches employed in the literature to capture time-variation in betas, the following three approaches are used in this thesis.

5.2.2.1 Rolling Regression

The rolling regression is one of the simplest approaches that can provide good estimates of conditional betas. The main obstacle in this approach is to determine the appropriate window length. Lewellen and Nagel (2006) recommend using short windows in estimating betas. Thus, in this thesis, rolling regression of 24 months are employed to estimate betas due to the following reasons. First, the short sample period of this thesis that starts only from July 2004. Second, the highly volatile nature of the Egyptian stock market implies that it is more reasonable to assume that betas remain constant over only short periods.

Although Bollerslev and Zhang (2003) recommend using high frequency data in estimating betas, this approach is not followed in this thesis as the Egyptian stock market suffers from thin trading and thus using high frequency data may lead to non-synchronicity effects on beta estimates. Thus, monthly data is used in estimating betas.

The estimation of betas using a rolling regression approach involves running time-series regressions of individual/portfolio stock returns on the Fama and French three factors. Specifically, for each stock/portfolio, there will be $t-24$ time-series regressions as follows:

$$R_{i\tau}^{e} = \alpha_i + \beta_{iM} R_{M\tau}^{e} + \beta_{i,SMB} SMB_\tau + \beta_{i,HML} HML_\tau \qquad (5.4)$$

$$\tau = t-23, t-22, \dots, t \quad \text{for each } t = 24 \dots., T$$

where $R_{i\tau}^{e} = R_{i\tau} - R_{f\tau}$ and $R_{M\tau}^{e} = R_{M\tau} - R_{f\tau}$.

5.2.2.2 Scaled Factor Models

The scaled factor model approach defines beta as a linear function of the investor information set. However, since investors' information set is unobservable, the performance of scaled factor models is dependent on the choice of the set of conditioning information (Cochrane, 2001). Therefore, one of the crucial steps in a scaled factor model approach is to determine the appropriate set of conditioning variables with due care. Rather than determining *a priori* the set of conditioning variables based on the results of previous literature, the predictive power of different instrumental variables is evaluated to choose the most appropriate set to use in this thesis.

Then, the following time-series regression is estimated in which monthly stock returns are regressed on the Fama and French three factors, while allowing the factor loadings in that model to vary with conditioning variables as in Equation 5.5:

$$R_{it} - R_{ft} = \alpha_{i0} + \sum_{k=1}^{3}(\beta_{ik0} + \beta_{ik1} Z_{it-1}) FF_{kt} + \varepsilon_{it} \quad (5.5)$$

where Z_{it-1} represents a vector of N conditioning variables, while FF_{kt} represents the three Fama-French factors (R_M, SMB and HML). The set of conditioning variables includes macroeconomic variables, firm-specific variables and investor sentiment. Each of these variables is used on its own and with other variables to determine which combination of conditioning variable provides the best explanation for the well-documented financial market anomalies.

Unlike the betas estimated from the rolling regression approach and the DCC-GARCH approach, there is one main challenge in estimating the risk premia for the betas estimated using a scaled factor model approach. The main idea of a scaled factor model is to scale the risk factors in the FF3 using the set of predetermined conditioning variables. The new model can be treated as an unconditional model whose factors are the original factors, conditioning variables and the scaled version of the original factors obtained by multiplying each factor by each conditioning variable. However, Avramov and Chordia (2006) argue that since the conditioning variables include firm-specific variables, the resulting factors that are obtained from multiplying the Fama and French factors with these variables cannot be interpreted as risk factors in the unconditional representation. Thus, estimating risk premia for these variables may not be feasible.

To avoid this problem as well as the problem of the errors-in-variables bias resulting from using betas as regressors in the second pass cross-sectional regression, in the cross-sectional regression, the risk adjusted return, which is calculated as the sum of the pricing errors and the residuals from the first pass regression in Equation 5.5, is regressed on equity characteristics (size, value, liquidity and momentum variables) as proxies for the most commonly reported anomalies in financial markets to determine whether the asset pricing model used in the time-series regression is capable of explaining these anomalies (Avramov and Chordia, 2006). The second-pass cross-sectional regression can be summarized as follows:

$$r_{it}^{*} = c_{0t} + c_t Y_{it-1} + e_{jt} \tag{5.6}$$

Where r_{it}^{*} is the risk adjusted return on stock i at time t. Y_{it-1} is the vector of anomalies that traditional asset pricing models fail to explain (size, value, liquidity and momentum effects) and c_t represents the vector of characteristic rewards. Jagannathan and Wang (1998) support the use of firm characteristics in cross-sectional regressions as a way to detect model misspecification. Specifically, they show that if the beta pricing model employed in the first-pass time-series regression is mis-specified, then the t-statistics for the coefficients on the firm characteristics generally converge to infinity in probability. However, if the model is well specified, then, c_t should be insignificantly different from zero.

5.2.2.3 Multivariate GARCH Models with Dynamic Conditional Correlations

The DCC-GARCH model represents an alternative approach to model time-variation in betas through making assumptions regarding the conditional covariance matrix of stock returns. It provides estimates of conditional betas in two steps: (i) the conditional variances are estimated using univariate GARCH; and (ii) the conditional correlations are estimated using a multivariate model. Since the estimates are obtained using pairs, the DCC for two variables is explained briefly below.

The DCC proposed by Engle (2002) can be summarized by the following equations

$$r_t = \mu_t + a_t \tag{5.7}$$

$$a_t = H_t^{1/2}\varepsilon_t \tag{5.8}$$

$$H_t = D_t R_t D_t \tag{5.9}$$

$$D_t = diag(\sigma_{11,t}^{\frac{1}{2}} \ldots\ldots \sigma_{nn,t}^{\frac{1}{2}}) \tag{5.10}$$

where the elements in the diagonal matrix D_t represent the standard deviations obtained from univariate GARCH models as follows:

$$\sigma_{it} = \alpha_0 + \alpha_1 a^2{}_{it-1} + \beta\sigma_{it-1} \tag{5.11}$$

Equation 5.11 shows that the estimated variance is a function of the long-term average value captured by α_0, the past volatility lag a_{it-1} and the fitted variance from the previous period σ_{it-1}.

The second step in the DCC-GARCH is concerned with calculating the conditional correlation matrix R_t. Specifically, R_t represents the conditional correlation matrix of the standardized residuals (ε_t) at time t calculated as follows:

$$\varepsilon_t = D_t^{-1} a_t \tag{5.12}$$

$$R_t = \begin{bmatrix} 1 & \rho_{12,t} & \cdots & \rho_{1n,t} \\ \vdots & 1 & \ddots & \vdots \\ \rho_{1n,t} & \rho_{2n,t} & \cdots & 1 \end{bmatrix} \tag{5.13}$$

In estimating R_t two conditions are required: (i) R_t must be positive definite to ensure that H_t, the covariance matrix, is also positive definite; and (ii) since R_t is a correlation matrix, then all its elements must be equal to or less than one by definition ($|\rho_{ij}| \le 1$).To ensure these requirements, the estimation of R_t is decomposed into:

$$R_t = (diagQ_t)^{-1/2} Q_t (diagQ_t)^{-1/2} \quad (5.14)$$

$$Q_t = (1 - a - b)\bar{Q} + a\varepsilon_{t-1}\varepsilon_{t-1}^T + bQ_{t-1} \quad (5.15)$$

where $\bar{Q}$ represent the unconditional covariance matrix of the standardized residuals $\varepsilon_t = (\varepsilon_{1t} \dots \varepsilon_{nt})'$ and $diagQ$ represents a diagonal matrix with the square root of the diagonal elements of Q_t.

A typical element of Q_t can be represented as follows:

$$q_{ij,t} = \bar{\rho}_{ij}(1 - \alpha_1 - \alpha_2) + \alpha_1 q_{ij,t-1} + \alpha_2 \varepsilon_{i,t-1}\varepsilon_{j,t-1} \quad (5.16)$$

where $\bar{\rho}_{ij}$ is the unconditional covariance (correlation) between $\varepsilon_{i,t-1}$ and $\varepsilon_{j,t-1}$.

A typical element of the correlation matrix R_t is:

$$\rho_{ij} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \quad (5.17)$$

Given the estimates of the conditional variances and conditional correlations obtained from the DCC-GARCH, estimates of conditional betas are obtained to be used in the estimation of risk premia.

5.2.3 Appropriate Proxy for Investor Sentiment

The behavioural pricing literature suggests different proxies for sentiment indicators, though there are no definitive or uncontroversial measures (Baker and Wurgler, 2006). The choice of a proxy of investor sentiment to be used in this thesis depends on data availability. Thus, given the unavailability of data about many of the market-based proxies of investor sentiment, and the widespread use of consumer confidence indices as a proxy for sentiment, this thesis employs the Egyptian Consumer Confidence Index as the main proxy for investor sentiment.

The Egyptian Consumer Confidence Index (CCI) is a simple monthly measure that is published by the Egyptian Cabinet's Information and Decision Support Centre (IDSC) to gauge how consumers feel about the economy, and, based on this, how short-term consumer spending might be affected. The methodology of the Egyptian CCI is similar to the Conference Board methodology of Michigan University, which represents the longest-running confidence survey, with minor modifications and changes (IDSC, 2014).

The sample size for the Egyptian CCI is 1,000 respondents who are individuals over 18 years old and selected from all of the country's Governorates. The opinions of the respondents are collected via telephone on three sub-indices (standard of living, confidence in current economic policies, and expectations about improvements in general economic conditions and standard of living).

Similar to the University of Michigan Index, the Egyptian CCI combines questions on current conditions with questions measuring expectations for the future. In addition, the questions include both personal and national economic conditions questions. The opinions are gauged by means of the following set of questions as shown in Table 5.1.

Table 5.1: The Egyptian Consumer Confidence Index Questions

1.	Would you say that you and your family are better off or worse off financially than you were a year ago?
2.	Do you think that now is a good time for people to buy major household items (furniture, refrigerators, etc.)?
3.	Do you think that the overall economic situation in the country (prices, investment, production, financial position) is better off or worse off than it was a year ago?
4.	You know that the Government modify laws and decisions from time to time, do you think these modifications would affect you and your family positively or negatively, or they will not affect you at all?
5.	As for job availability, do you think jobs are available, or available to some extent, or not available at all?
6.	Looking ahead, do you think that a year from now, you and your family will be better off financially or worse off, or just about the same as now?
7.	Looking ahead, do you think that one year from now, the economic situation in the country as a whole will be better off, or worse off, or just about the same as now?
8.	Looking ahead, do you think that one year from now the number of available jobs will increase, or decrease, or stay the same?

For each sub-index, a diffusion measure is calculated as the difference between the percentage of favourable and unfavourable replies. Then 100 points are added to the result to guarantee that the index will not take a negative value if the percentage of unfavourable responses is higher. The overall CCI is then calculated as a simple average of the three sub-indices. The monthly index value ranges from 0-200, where the index reaches the value of 200 if all the responses were favourable, while if the index value is below 100 this means that overall consumer opinion is pessimistic.

Lemmon and Portniaguina (2006) state that, in general, consumer confidence indices include both rational and emotional components. Thus, to separate these two components and have a cleaner measure of investor sentiment, the Egyptian CCI is regressed on the dividend yield, the Treasury bill rate, growth in industrial production index, the inflation rate, the exchange rate and the three Fama and French factors to isolate the impact of the business cycle component and the sentiment component. The residual from this regression is used as the main proxy for investor sentiment.

This proxy of investor sentiment is then used to construct a sentiment risk factor. Following the same approach as Fama and French (1993), investor sentiment risk factor is the return difference between portfolios of stocks with high sensitivity and low sensitivity to investor sentiment (Sentiment beta), as in Ho and Hung (2012). To calculate the sensitivity of stocks to investor sentiment (the sentiment beta), the excess return of each individual stock is regressed on the changes in investor sentiment as in Equation 5.18:

$$R_{it} = \alpha_i + \beta_{is}\,\Delta sent_t + \beta_{iM}\,(R_{Mt} - R_{ft}) + \beta_{iSMB}\,SMB_t + \beta_{iHML}\,HML_t + \varepsilon_{it} \quad (5.18)$$

To estimate these betas, an estimation window of 24 months on a rolling basis is used. Based on these estimated sentiment betas, stocks are ranked at the beginning of each month and divided into five equally weighted portfolios where the first portfolio includes stocks that have the most negative sentiment betas, while the fifth portfolio includes stocks that have the most positive sentiment betas. The other portfolios include stocks that are least sensitive to investor sentiment. Having these five portfolios, the sentiment risk factor (SMN) is calculated as the difference between the returns of the fifth portfolio (the most positive sentiment betas) and the third portfolio (the least sensitive) (Ho and Hung, 2012). Excess market returns, the SMB and the HML factors are included in the model to ensure that the beta of investor sentiment is not affected by any of these factors, and hence the results are more accurate and robust.

5.2.4 Sampling and Data Collection

The basic data for this thesis includes monthly returns, size, the book-to-market ratio, turnover, and lagged returns for a sample of 134 stocks listed in the Egyptian stock market. The sample spans the period July 2004 to June 2016. All of the data employed in this thesis are collected from the Egypt for Information Dissemination (EGID) Company, DataStream, and Thomson's Reuters (EIKON). However, before describing the variables employed in this thesis, a brief introduction about the Egyptian stock market is given and a justification for the choice of only 134 companies to be the main sample used in this thesis is provided.

The Egyptian stock market is one of the oldest stock markets that traces its origins to1883 when the Alexandria Stock Exchange was established, followed by the Cairo Stock Exchange in 1903. Since its inception, the Egyptian stock market has witnessed several development phases. Specifically, prior to its demise due to the wave of nationalizations during 1950s-1960s, the Egyptian stock market was considered the fifth largest exchange in the world. However, this wave of nationalizations led to a severe reduction in the number of listed firms from 275 to 55 in 1958-1975. Consequently, the Egyptian stock market remained inactive until the passage of the Capital Market Law 95 in 1992 which introduced a number of changes into primary and secondary markets such as encouraging private investments and improving investors' protection in order to restore capital market infrastructure and to allow the

Egyptian stock market to play its role as a viable venue for attracting local and foreign investments. Following the enactment of the Capital Market Law and motivated by the improvement witnessed in the regulatory environment in Egypt, the Egyptian stock market started to grow rapidly especially after the introduction of the Asset management Program in 1994 that led to an increase in the number of listed firms to be 1100 firms by the end of 2001. However, despite having 1100 firms listed in the market, the market remained illiquid as is shown in Table 5.2 that highlights the gap between the number of listed firms and the number of traded ones.

Table 5.2: Summary about the Egyptian Stock Market

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Number of Listed Firms	795	744	595	435	373	306	212	213	213	212	214	221	222
Number of Traded Firms	503	441	407	337	322	289	211	204	204	206	206	217	213

Source: EGX Annual Reports (2004-2016)

In order to bring liquidity to the market and remove inactive firms, many companies were delisted from the exchange by 2005 due to their failure to meet the liquidity and transparency requirements (Sourial and Amico, 2015). This wave of delisting continued as a result of the effective policy followed by the Egyptian stock market to enforce listing, disclosure, and corporate governance rules on issuers. Consequently, the number of listed firms decreased to be only 222 firms in 2016 (EGX Report, 2016). Thus, this observation that many of the listed firms in the Egyptian stock market are inactive provides the first justification of choosing a sample of 134 stocks despite the fact that the number of listed firms in the market is greater than this.

The second justification of having a sample of 134 stocks is related to the main sectors in the Egyptian stock market. Specifically, following Fama and French (1993), banks and financial service companies are excluded from the sample due to their special nature. This exclusion leads to a reduction in the number of firms that are eligible for use in this thesis. In this regard, although there are 17 main sectors in the Egyptian stock market, Figure 5.1 shows that banks and financial services account for around

36% of the total market capitalization in 2016 which implies the importance of these two sectors in the market. Thus, the omission of these two major sectors from the sample may, in turn, provide further justification of why the sample contains only 134 stocks.

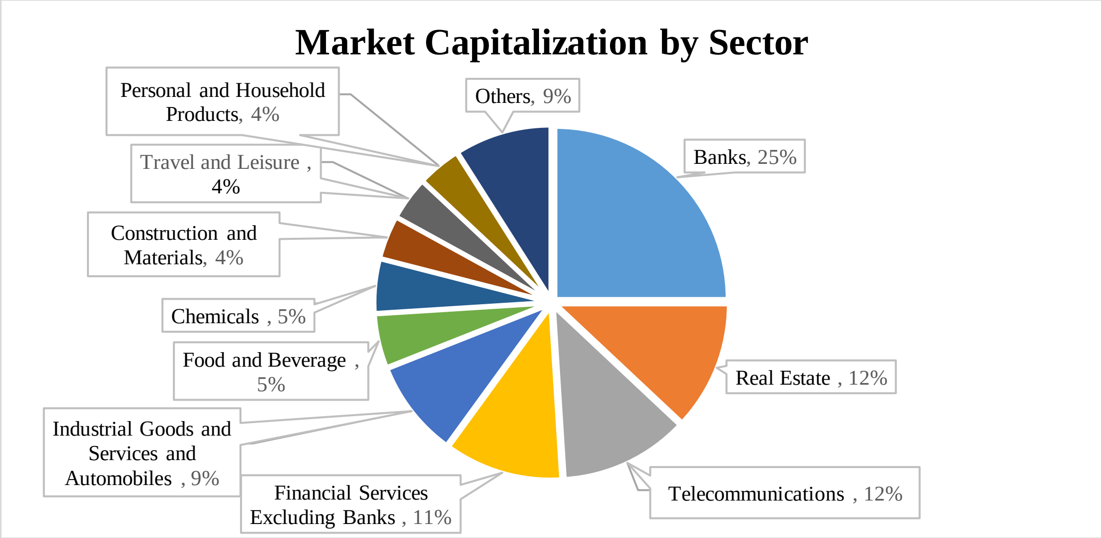


Figure 5.1: Market Capitalization by Sector in 2016 (Source: EGX Annual Report, 2016)

After providing a brief historical overview about the Egyptian stock market and understanding the main reasons behind the choice of the sample, Table 5.3 shows the variables employed in this thesis along with their calculations.

Table 5.3: Variable Description

Variables	Description	Calculation
R_{it}	Excess return of stock *i* at time *t*	$r_{it} - r_f$
Size	The natural logarithm market capitalization	$Log\ (ME)$
Book-to-Market Ratio	The natural logarithm of the firm's book value of equity to the market value of equity. As in Fama and French (1992), the book value of equity for July of year t to June of year $t+1$ is calculated using accounting data at the end of year $t-1$	$Log\ (B/M)$
Cumulative Stock Returns	The natural logarithm of cumulative stock returns over three main horizons: short horizon (from month t-3 to t-2), intermediate horizon (from month t-6 to through t-4) and long horizon (form month t-12 to t-7).	$\log(1+r_c)$ where, $r_c = \prod_{i=1}^{n}(1+\mathrm{ri})$
Turnover	The natural logarithm of the ratio of trading volume to the number of outstanding shares.	$\log(\frac{Volume}{Outstanding\ Shares})$
Dividend Yield	The dividend yield on the 50 most active stocks in the Egyptian stock market.	DY

5.3 Research Methods

Lozano (2009) argues that the econometrics techniques available to test asset pricing models can be divided into two main categories. The first is the traditional beta framework, while the second is the stochastic discount factor (SDF) framework. Under the traditional beta framework, the econometric techniques normally employed are the time-series and the cross-sectional regression approaches. Alternatively, the GMM approach is the main econometric technique under the SDF framework. Since this thesis falls within the first category of the traditional beta framework, the following subsections analyse the details of the main econometrics techniques employed under this framework.

5.3.1 Time-Series Regression

Time-series regression can be used in testing and evaluating asset pricing models only if the factors are tradable portfolios that can be expressed in the form of returns. There are numerous examples in the literature that use this methodology to evaluate asset pricing models such as Fama and French (1993, 1996). The main parameters of interest in time series regression are the intercepts, the slopes of the risk factors and the risk premia. In order to estimate these parameters and judge the ability of the model to explain the historical variability of returns, the excess returns of stocks/portfolios are regressed on the risk factors under consideration as follows:

$$R_{it} - R_{ft} = \alpha_i + \sum_{k=1}^{K} \beta_{ik}{}' f_{kt} + \varepsilon_{it}\,, \quad t = 1,2,\dots,T, \quad i = 1,2,\dots,N \qquad (5.19)$$

where α_i represent the intercepts, $\beta_{ik}{}'$ represent the factors' loadings, and f_{kt} is a vector of the risk factors which include the Fama and French three factors and the investor sentiment factor. The results of Equation 5.19 give estimates of the intercepts and the slopes of the risk factors, whereas the risk premium of each factor is obtained as the sample mean of this factor (Cochrane, 2001). Specifically, the estimate of the market risk premium is obtained as the average return of the market portfolio in excess of the risk-free rate over the sample period as follows:

$$E(\hat{\lambda}_M) = \overline{R_M - R_f} \tag{5.20}$$

After estimating the parameters of interest, the main test to judge the validity of the model is to determine whether all the N intercepts from Equation 5.19 are jointly equal to zero. This implication can be tested using the Gibbons, Ross, and Shanken (GRS) (1989) test.

The GRS test is one of the most important tests in the asset pricing literature. To perform this test, the time series regression in Equation 5.19 is first estimated for each portfolio and then the null hypothesis that all the intercepts are jointly different from zero is tested.

H_0: $\alpha_1 = \alpha_2 = \cdots = \alpha_N = 0$

When errors are independently and identically distributed over time, homoscedastic and independent of the factors, the asymptotic joint distribution of the intercepts gives the model test statistics as follows:

$$T[1 + \left(\frac{E_t(f)}{\hat{\sigma}(f)}\right)^2]^{-1}\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha} \backsim \chi_N^2 \tag{5.21}$$

where $E_t(f)$ is the sample mean of the factor, $\hat{\sigma}(f)$ is the sample standard deviation of the factor. The $N \times 1$ vector of the intercepts is defined as $\hat{\alpha} = [\hat{\alpha}_1\hat{\alpha}_2 \ldots\ldots \hat{\alpha}_N]'$, and $\hat{\Sigma}$ is the estimated covariance matrix of the residuals $E(\varepsilon_t\varepsilon_t')$.

The GRS test is a multivariate, finite sample counterpart to this statistic calculated in Equation 5.21 that is distributed as an F distribution as follows:

$$\frac{T-N-K}{N}(1 + E_t(f)'\hat{\Omega}^{-1}E_t(f))^{-1}\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha} \backsim F_{N,T-N-K} \tag{5.22}$$

where T is the number of observations, N is the number of portfolios, K is the number of factors, and $\widehat{\Omega}$ is the variance-covariance matrix of the factors. The GRS test rejects the asset pricing model if the statistic is greater than the critical value.

Despite its popularity, the GRS test suffers from the following shortcomings. First, if the cross-section is large and the time-series is small (large number of assets and small number of months), then the variance-covariance matrix of the residuals cannot be estimated and this makes the estimation of the GRS test difficult. Second, the test does not answer the most important question in asset pricing literature which is why different assets yield different returns. Thus, the cross-sectional regression approach is considered the most important approach in asset pricing literature (Goyal, 2011). Therefore, the main focus of this thesis is on cross-sectional regression approach, as discussed in the following section.

5.3.2 Cross-Sectional Regression

The simplest way to understand why average returns vary across assets is to run a cross-sectional regression of average excess returns of stocks/portfolios on estimated betas (β'_{ik}), and estimate the factor risk premia (λ) via an OLS regression (Cochrane, 2001):

$$E(R_i) = \alpha_i + \sum_{k=1}^{K} \beta'_{ik}\, \lambda_k \qquad\qquad i = 1,2, \dots, N \qquad\qquad (5.23)$$

where N is the number of assets, K is the number of risk factors. The main parameters of interest in the above regression are the estimated risk premia (λ_k) and the pricing errors (α). The sign and the significance of these λ show whether the risk factors under investigation are significantly rewarded by the market. Furthermore, the significance of the intercept (α) shows whether the asset pricing model under investigation can explain the cross-sectional variations in stock/portfolio returns.

To test whether the estimated risk premia are significant, a t-test can be estimated as in Fama-Macbeth procedure or the Black, Jensen and Scholes approach as described in the following sections. To test whether the pricing errors are significant, a t-test can also be used as in the Fama-Macbeth procedure or the Black, Jensen and Scholes approach, or the following statistic can be used as in Cochrane (2001):

$$\hat{\alpha}' cov(\hat{\alpha})^{-1}\hat{\alpha} \backsim \chi^2_{N-1} \qquad (5.24)$$

5.3.2.1 Black, Jensen and Scholes (BJS) Single Cross-Sectional Regression

The Black, Jensen and Scholes cross-sectional regression is considered one of the initial approaches used to estimate and evaluate asset pricing models. This approach is called a two-pass regression as first a time-series regression is run as in Equation 5.19, then, the second step involves running a single cross-sectional regression of average excess returns on estimated betas to estimate the factors' risk premia:

$$\bar{R}_i = a_0 + \sum_{k=1}^{K} \hat{\beta}_{ik}\, \lambda_k \ \text{ for } i = 1,2, \dots, N \qquad (5.25)$$

The main estimates of interest are: the intercept (a_0) which should be insignificant, and the factor risk premia (λ_k) which should be positive and significant.

Despite its simplicity, this approach suffers from some shortcomings that make it inappropriate for use in this thesis. First, the error terms in the cross-sectional regression are likely to be cross-sectionally correlated which may jeopardise the results as the OLS distribution theory is likely to be wrong and typically provides standard errors that are much too small. Second, the single cross-sectional regression does not easily handle the idea that betas vary over time and thus it is not suitable in the case of testing conditional asset pricing models (Cochrane, 2001). Thus, Fama and Macbeth (1973) provide an alternative way to estimate factor risk premia while adjusting for the shortcomings of the BJS single cross-sectional regression.

5.3.2.2 Fama-Macbeth Cross-Sectional Regression

The Fama-Macbeth cross-sectional regression is considered one of the seminal approaches in testing asset pricing models due to its simplicity. Similar to the BJS cross-sectional regression, the Fama-Macbeth cross-sectional regression is called a two-pass regression framework as it involves running a time-series regression in the first step to estimate betas, followed by a cross-sectional regression to estimate the factor risk premia. However, it differs from the BJS approach in several aspects. First, rather than running a time-series regression to estimate full sample constant betas, the Fama-Macbeth procedure involves running a rolling time-series regression to obtain estimates of time-varying betas. Specifically, for each stock there are $T-24$ time-series regressions (based on rolling regressions of 24 months).

$$R_{i\tau} - R_{f\tau} = a_i + \sum_{k=1}^{K} \beta_{itk} \, f_{k\tau}, \qquad (5.26)$$

$$\tau = t-23, t-22, \ldots, t \text{ for each } t = 24, \ldots, T$$

Then, in the second step, a cross-sectional regression for each period of time (each month in this thesis) is run in order to estimate the factor risk premia and the intercept as follows:

$$R_{it} - R_{ft} = \alpha_t + \sum_{k=1}^{K} \hat{\beta}_{itk} \, \lambda_{kt} \quad i = 1,2, \ldots, N \quad \text{for each } t = 24, \ldots, T \qquad (5.27)$$

The final estimates of the intercept and the factor risk premia are computed as the average of the cross-sectional estimates that are obtained each month as follows:

$$\bar{\lambda} = \frac{1}{T} \sum_{t=1}^{T} \hat{\lambda}_t \qquad \bar{\alpha} = \frac{1}{T} \sum_{t=1}^{T} \hat{\alpha}_t \qquad (5.28)$$

Once the estimates of the average alphas and lambdas are obtained, their sample standard deviations can be calculated. The logic of estimating the standard deviations is that each period of time (month) represents a sample from which the alphas and the risk premia are estimated, and therefore the variations in these estimates over time allow for deriving the variation across samples (Cochrane, 2001).

$$S^2(\hat{\lambda}) = \frac{1}{T^2} \sum_{t=1}^{T} \left(\hat{\lambda}_t - \bar{\lambda}\right)^2, \qquad S^2(\hat{\alpha}) = \frac{1}{T^2} \sum_{t=1}^{T} (\alpha_t - \bar{\alpha})^2 \qquad (5.29)$$

Thus, the Fama-Macbeth approach provides a simple and intuitive way to correct for cross-sectional correlation. The final step is to calculate the t-test to test for the significance of the risk premia and the alphas as advocated by Fama and Macbeth (1973):

$$t(x) = \frac{x}{s(x)/\sqrt{T}} \tag{5.30}$$

where x is a sample mean, and $s(x)$ is the sample standard deviation.

However, the Fama-Macbeth approach also has some shortcomings. Similar to the BJS approach, the Fama and Macbeth does not correct for the fact that betas are estimated (errors-in-variables (EIV) bias). This problem is one of the main challenges facing asset pricing models, and several approaches have been suggested to deal with it. Initially, researchers suggest using highly diversified portfolios as the main test assets rather than individual stocks as their betas are more accurate (Black *et al.*, 1972; Fama and Macbeth, 1973). However, this thesis cannot depend on this approach for the following reasons. First, there is only a small number of stocks listed in the Egyptian stock market, thus forming highly diversified portfolios is very challenging. To form portfolios for the Egyptian stock market and ensure reasonable diversification, ten portfolios double-sorted on size and the book-to-market ratio are formed and used as test assets. Nonetheless, even with only 10 portfolios, the number of stocks in each portfolio is still relatively small with a maximum of 20 stocks in each portfolio. This data limitation may outweigh the benefits of forming portfolios. Second, Ang *et al.* (2010) state that using portfolios as the test assets leads to losing information by shrinking the dispersion of betas, leading to larger standard errors. Thus, they propose that using individual stocks permits more efficient tests of whether factors are priced. Thus, to guard against the sensitivity of asset pricing tests to the portfolio grouping procedure, this thesis employs individual stocks as the main test assets. Therefore, the second approach commonly employed in this thesis to account for the EIV bias is the Shanken (1992) correction.

Shanken provides an easy way to correct for the EIV bias under the assumption of normally distributed errors (Goyal, 2011). Shanken argues that under the assumption of homoscedasticity in the variance of asset returns conditional upon the realization of factors, the standard errors based on Fama-Macbeth procedure overstate the precision of the estimated parameters. However, Jagannathan and Wang (1998) argue that by relaxing the assumption of homoscedasticity, the Fama-Macbeth standard errors do not necessarily overestimate the precision of the estimates. Thus, in this thesis, both the t-statistics based on Fama-Macbeth procedure and based on the Shanken correction are reported.

The Shanken correction introduces a quadratic term, $c = \lambda' \Sigma_f^{-1} \lambda$, that enters multiplicatively in the expression of the variance of the risk premium as follows:

$$\sigma^2(\hat{\lambda}) = \frac{1}{T}[(\beta'\beta)^{-1}\beta'\Sigma\beta(\beta'\beta)^{-1}(1 + \lambda'\Sigma_f^{-1}\lambda) + \Sigma_f] \tag{5.31}$$

where Σ_f is the variance-covariance matrix of the risk factors, $\sigma^2(\hat{\lambda})$ is the covariance matrix of the risk premia with dimension $k + 1$. Σ is the NxN covariance matrix of the residuals from the N time series regressions (from which the N betas were estimated). β is Nxk matrix of regressors.

A serious limitation of the Shanken correction is that it is basically developed for unconditional betas and thus it will not be appropriate to use for the tests that employ time-varying betas (Vendrame *et al.*, 2018). Thus for conditional asset pricing models, a wild bootstrap is used as the main approach to correct for the EIV bias. MacKinnon (2002) supports the use of the p-values calculated using a bootstrap procedure as they can lead to accurate inferences compared to traditional approaches as a result of not imposing strong distributional assumptions.

MacKinnon highlights that there are some cases in which bootstrap tests are challenged. One of these cases is when the error terms are heteroskedastic and the form of heteroskedasticity is unknown. Thus, to deal with this challenge, a wild bootstrap is used in this thesis. The main advantage of a wild bootstrap is that it preserves the first and second moments of the parent distribution (Vendrame *et al.*, 2018). The residuals (ε_{it}) are defined as the difference between the factor risk premia ($\hat{\lambda}_{it}$) at time t and the average value of each risk premium over time $\overline{\lambda_\iota}$ as in the following Equation:

$$\widehat{\varepsilon_{\iota t}} = \hat{\lambda}_{it} - \overline{\lambda_\iota} \tag{5.32}$$

Then, the bootstrapped residuals ($\widehat{\varepsilon_{\iota t}^{*}}$) are created as the product of the original residuals and an independent random variable (η_t) that has a zero mean and unit variance. This, in turn, ensures that the bootstrap variance is similar to that of the parent distribution. Specifically, when η_t is standard normal, the mean and the variance of the bootstrapped residuals can be summarized as follows:

$$E\left(\widehat{\varepsilon_{\iota t}^{*}}\right) = E(\eta_t)E(\widehat{\varepsilon_{\iota t}}) = 0 \tag{5.33}$$

$$var\left(\widehat{\varepsilon_{\iota t}^{*}}\right) = var(\eta_t)var(\widehat{\varepsilon_{\iota t}}) = var(\widehat{\varepsilon_{\iota t}}) \tag{5.34}$$

In this thesis, 1,000 bootstrap replications are generated where in each replication, a standard normal variable is drawn and the t-statistic is computed. Finally, the p-value is estimated from the empirical distribution of the bootstrapped t-statistic (Vendrame *et al.*, 2018).

5.3.3 Time-Varying Risk Premia

Motivated by the theoretical and empirical evidence about the importance of modelling time-variation in risk premia as highlighted in Chapter 4, this thesis aims to test conditional asset pricing models that allow risk premia to change over different regimes of the world, but to be constant within the regime. The main logic behind modelling the time-variation in risk premia in this thesis is derived from Pettengill *et al.* (1995). Specifically, Pettengill *et al*. argue that the relationship between betas and realized returns should be positive when realized market return is higher than the risk-free rate, while it should be negative when realized market return is lower than the risk-free rate. The rationale behind this proposed relationship is that although high beta stocks/portfolios should earn higher expected returns than low beta ones due to their high risk, there must be some periods in which they earn lower realized returns or otherwise, no investors will hold the low beta stocks/portfolios. These time periods should correspond to periods in which the realized market returns are lower than the risk-free rate to reflect the riskiness of these stocks/portfolios.

In a similar vein, Hur *et al.* (2014) argue that there should be intertemporal inconsistency in the size effect if it represents payment for risk. Specifically, although small firms should have higher expected returns because they have higher distress risk (Fama and French, 1993), there must be some periods in which small firms underperform big ones or otherwise no investor will be inclined to hold big stocks. These periods of time should correspond to states of the world in which the economy is facing recession and tighter credit conditions that adversely affect small firms more than big ones (Perez-Quiros and Timmermann, 2000). Similarly, if the value premium represents payment for risk, there should be some periods in which value firms underperform growth firms. These periods according to Zhang (2005) should correspond to periods of unstable economic conditions in which value firms are more loaded with unproductive capital than growth firms.

The above evidence implies that the relationship between the betas of the Fama and French three factors and returns is expected to be conditional on the state of the world. Specifically, the relationship between realized returns and the betas of the Fama and French factors is expected to be positive during bull markets, whereas it is expected to be negative during bear markets. To test for this relationship, this thesis applies the approach of Vendrame *et al.* (2018) who propose a new conditional test for the CAPM based on the probability of being in one of the states of the world (bull or bear markets) that is estimated using a Markov switching process, but extends it to multifactor models. Thus, this thesis fills a gap in academic literature by modelling time-variation in risk premia within the context of multifactor models. For simplicity, all the steps involved in testing the conditional relationship between betas and returns are explained within the context of the CAPM. Then, the main obstacles faced in extending these steps to multifactor models are highlighted.

The rationale behind Vendrame *et al.* test is as follows. Suppose an investment opportunity in which the investor is paid a return $\hat{\gamma}_1\beta_i$ in case of winning (upmarket regime) and $\hat{\gamma}_2\beta_i$ in case of losing (downmarket regime). In order to estimate the expected return of this investment, it is important to consider the probability of occurrence of each regime. For example, assume that the probability of an upmarket regime is p. Then, the expected return is as follows:

$$E(R_{it}) = (p\hat{\gamma}_1 + (1-p)\hat{\gamma}_2)\beta_i \tag{5.35}$$

The investor is inclined to consider this investment only if the expected return is positive and significant and this occurs only if the wins are larger and/or more frequent than the losses. Within the context of the CAPM, assuming that the states are not known with certainty, each period t, returns are generated by the up state with probability p_t and down state with one minus this probability as follows:

$$R_{it} = \hat{\gamma}_{0t} + (p_t\hat{\gamma}_1 + (1-p_t)\hat{\gamma}_2)\beta_{it} + \varepsilon_{it} \tag{5.36}$$

Taking unconditional expectations gives

$$E(R_{it}) = E(\hat{\gamma}_{0t}) + E(\Gamma_t)E(\beta_{it}) + Cov(\Gamma_t, \beta_{it}) \tag{5.37}$$

where $\Gamma_t = p_t\hat{\gamma}_1 + (1-p_t)\hat{\gamma}_2$.

where $\hat{\gamma}_1$ is the bull risk premia, and $\hat{\gamma}_2$ is the bear risk premia. The main test that can be derived from Equation 5.37 is concerned with examining whether the average of the (conditional) slope of beta is positive and significant.

$H_0: E(\Gamma_t) = 0$

$H_1: E(\Gamma_t) > 0$

To test the above hypothesis, three estimates are required which are: (i) an estimate of β_{it} which can be obtained using rolling regression approach or the DCC-GARCH approach; (ii) an estimate of the state probability (p_t) which can be obtained using a Markov switching process; and (iii) an estimate of the risk premia. To obtain the estimate of the risk premia, the Fama-Macbeth cross-sectional regression cannot be used, as there is only one beta but two parameters that should be estimated. Thus, to overcome this problem, Vendrame *et al.* use a panel data technique to estimate the two risk premia as follows:

$$R_{it} - R_{ft} = \gamma_0 + \gamma_{12} p_t \beta_{it} + \gamma_2 \beta_{it} + \varepsilon_{it} \qquad (5.38)$$

where $\gamma_{12} = \gamma_1 - \gamma_2$ is the difference between the bull and bear risk premia. Once the estimates of the bull and bear risk premia are obtained, several tests are undertaken. First, although the above proposed model is a conditional model in which the risk premia are allowed to vary between regimes, but to be constant within a regime, it includes the unconditional model as a special case. Specifically, the unconditional model implies that the bull and bear risk premia should be positive and equal. Thus, the first test from the above equation is to examine the equality and positive sign of the two risk premia ($\hat{\gamma}_1$ and $\hat{\gamma}_2$). Second, following the proposition of Pettengill *et al.* (1995), a test of whether the bull (bear) risk premium is positive (negative) is undertaken. Finally, the last test is concerned with testing whether or not the average of the (conditional) slope of beta ($E(\Gamma_t)$) is positive and significant. To perform this test, each month an estimate of $\Gamma_t = p_t\hat{\gamma}_1 + (1 - p_t\hat{\gamma}_2)$ is obtained and then a test of its time-series average is conducted as in Fama-Macbeth.

Although all the above steps are explained within the context of the CAPM, extending these steps to a multifactor model framework seems straightforward, the only challenge that is faced is related to determining the state probabilities using a Markov switching process. One approach that can be followed to determine these state probabilities is to identify economic regimes using the joint distribution of the Fama and French three factors, following Chung *et al.* (2012). The authors model the joint distribution of the returns of the Fama and French three-factors[7] using a multivariate Markov switching process driven by a common discrete regime variable s_t that takes only two values. However, estimating such a model is cumbersome as it is highly non-linear and it includes many parameters to be estimated. Given the small sample employed in this thesis, pursuing such an approach is infeasible as convergence problems may arise. Another approach that can be followed is to estimate state probabilities applied to each one of the Fama and French factors. However, in trying to follow this approach, the Markov switching model shows many problems when applied to the SMB and the HML factors and the model did not converge and the transition probability form bull to bear regime was zero. Thus, this thesis estimates state probabilities applied to the real excess return of the market portfolio to identify the main bull and bear regimes that Egyptian stock market passed by during the sample period. Given the ability of the market portfolio to track business cycles well, these state probabilities are expected to be able to identify the main regimes accurately.

Once estimates of the state probabilities are obtained, the following panel data regression is run.

$$R_{it} - R_{ft} = \gamma_0 + \Gamma_{M,t}\beta_{Mit} + \Gamma_{SMB,t}\beta_{SMBit} + \Gamma_{HML,t}\beta_{HMLit} + \varepsilon_{it} \tag{5.39}$$

where $\Gamma_{M,t} = p_t\hat{\gamma}_{M,1} + (1 - p_t\hat{\gamma}_{M,2})$, $\Gamma_{SMB,t} = p_t\hat{\gamma}_{SMB,1} + (1 - p_t\hat{\gamma}_{SMB,2})$, $\Gamma_{HML,t} = p_t\hat{\gamma}_{HML,1} + (1 - p_t\hat{\gamma}_{HML,2})$. Then, the hypothesis that each of these conditional risk premia is positive and significant is tested.

The following section highlights how the state probabilities are estimated using a Markov switching process.

[7] They use the orthogonalised returns of the Fama and French three-factors obtained by regressing the Fama and French factors on the Baker and Wurgler's sentiment index.

5.3.3.1 Markov Switching Process

There is sufficient empirical evidence that the Fama and French three factors exhibit significant variation over time, as highlighted in Section 5.3.3. In order to capture this dynamic behaviour of the three factors, a Markov switching process is used which is one of the most popular nonlinear time series models in the literature.

The Markov switching model of Hamilton (1989) involves multiple structures (equations) that can characterize the time series behaviours in different regimes. By allowing switching between these structures, the model is able to capture complex dynamic patterns. Kuan (2002) argues that one of the important features of the Markov switching model is that the switching is controlled by an unobservable state variable that follows a first-order Markov chain.

In general, the essence of Markov switching models is that the set of parameters in one model depends on the prevailing regime assumed by a latent unobservable variable. Consequently, the model can have two or more different specifications according to the prevailing regime.

In order to account for this regime switching process, Markov switching models assume that the state variable is an unobservable latent variable following a Markovian process, and that the transition probability, or the probability to switch from one regime to another is expressed in terms of a probability matrix. The Markovian property proposes that the current value of the state variable (s_t) depends only on its immediate past value as follows:

$$P\{s_t = j | s_{t-1} = i, s_{t-2} = k, \dots. = P\{s_t = j | s_{t-1} = i\} = p_{ij} \quad (5.40)$$

where p_{ij} is the transition probability of $s_t = j$ given that $s_{t-1} = i$. The transition matrix can be defined as follows assuming that there are only two states or regimes {0, 1}:

$$P = \begin{bmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{bmatrix} \quad (5.41)$$

The properties of this transition matrix are as follows. First, it must satisfy that $p_{i0} + p_{i1} = 1$. Second, this transition matrix governs the random behaviour of the state variable and it contains only two parameters which are (p_{00} and p_{11}). Finally, the transition probability shows the persistence of each regime.

The next step is to identify the switching model for the variable y_t whose parameters tend to vary over different regimes. The conditional density function of y_t is given by:

$$f(y_t|s_t = j, \Omega_{t-1}; \theta) \tag{5.42}$$

where s_t is the state variable, θ represents the vector of the parameters characterizing the conditional density function, and Ω_{t-1} is the information set that contains all the observations through date $t-1$.

$$\Omega_{t-1} = \{y_{t-1}, \dots, y_{t-n}, x_{t-1}, \dots, x_{t-n}\} \tag{5.43}$$

where x_t represents the vector of independent variables. Assume that y_t can be expressed in terms of the following linear model:

$$y_t = \beta x_t + \varepsilon_t \tag{5.44}$$

Then the conditional density function of the residuals (assumed to come from different stochastic processes with a different mean and standard deviation) according to state i, that takes only two values $\{0, 1\}$, can be expressed as follows:

$$\begin{cases} f(y_t|s_t = 0, \Omega_{t-1}; \theta) = \frac{1}{\sqrt{2\pi\sigma_0}} \exp\left(\frac{-(y_t - \beta_0 x_t)^2}{2\sigma_0}\right) \\ f(y_t|s_t = 1, \Omega_{t-1}; \theta) = \frac{1}{\sqrt{2\pi\sigma_1}} \exp\left(\frac{-(y_t - \beta_1 x_t)^2}{2\sigma_1}\right) \end{cases} \tag{5.45}$$

In order to estimate the parameters of the model. The likelihood function should be identified which is the sum of the probability-weighted state densities across the possible states:

$$\log f(y_t|x_t, \Omega_{t-1}; \theta) = \sum_{i=0}^{1} log f(y_t|\Omega_{t-1}, S_t = i; \theta) Prob(S_t = i|\Omega_{t-1}; \theta) \tag{5.46}$$

where $Prob(S_t = i|\Omega_{t-1};\theta)$ are the conditional probabilities of state i at time t given the information set at time $t-1$. These conditional state probabilities is obtained recursively as follows:

$$Prob(S_t = i|\Omega_{t-1};\theta) = \sum_{i=0}^{1} prob(S_t = j|S_{t-1} = i;\Omega_{t-1};\theta) prob(S_{t-1} = i|\Omega_{t-1};\theta) \quad (5.47)$$

where the conditional probability ($prob(S_{t-1} = i|\Omega_{t-1};\theta)$) can be obtained by the Bayesian rule:

$$prob(S_{t-1} = i|\Omega_{t-1};\theta) = \frac{Prob(S_{t-1}=i|\Omega_{t-2};\theta)\times f(y_{t-1}|\Omega_{t-2}, S_{t-1}=i;\theta)}{\sum_{i=0}^{1} f(y_{t-1}|\Omega_{t-2}, S_{t-1}=i;\theta)\times Prob(S_{t-1}=i|\Omega_{t-2};\theta)} \quad (5.48)$$

To estimate the parameters, maximum likelihood is employed using the Expected Maximization (hereafter EM) algorithm. This algorithm is an iterative technique that starts from a given set of parameters or initial values ($\theta^{(0)}$), estimates the probabilities, the parameters, and the variance which results in a new set of parameters ($\theta^{(1)}$), and repeats these steps iteratively until the likelihood reaches its maximum, a point where it does not change given a small range or criterion of convergence.

5.3.3.1.1 Estimating State Probabilities

The aim of this section is to provide the main steps involved in estimating the state probabilities for the real excess return of the market portfolio. Full details on the estimation procedures are provided in Hamilton (1989). In thesis, two states are assumed (bull and bear states) which is the simplest Markov process.

The real excess return of the market portfolio is determined by the following the stochastic process:

$$RR_{Mt} = \mu_{Mi} + \sigma_{Mi}\varepsilon_t \quad (5.49)$$

Where, RR_{Mt} is the real excess return of the market portfolio calculated using $((1 + Real\ Return) = (1 + Nominal\ Return)/(1 + Inflation\ Rate))$. μ_{Mi} and σ_{Mi} are assumed to vary across the regimes (as stated above there are only two regimes which takes the value of either 0 or 1), and ε_t is the random error term that is assumed to follow a normal distribution.

To identify how the state change over time, the state transition probability, which is assumed to follow a first order Markov chain, should be identified. Let $P_{11} = Prob(S_t = 1|S_{t-1} = 1)$ be the probability of staying in state 1, and $P_{10} = Prob(S_t = 1|S_{t-1} = 0)$ be the probability of switching from state 0 to state 1. At an given time, t, the probabilities and the likelihood functions are estimated recursively as follows:

$$\pi_{t|t-1} = p_{11}\pi_{t-1|t-1} + p_{10}(1 - \pi_{t-1|t-1}) \tag{5.50}$$

$$LogLik_t = \log\{\pi_{t|t-1}f_0(RR_{Mt}|\Omega_{t-1},\theta) + \left(1 - \pi_{t|t-1}\right)f_1(RR_{Mt}|\Omega_{t-1},\theta)\} \tag{5.51}$$

Then the updated probability can be obtained from the likelihood function by a Bayesian rule as follows:

$$\pi_{t|t} = \frac{\pi_{t|t-1}f_0(RR_{Mt}|\Omega_{t-1};\theta)}{\pi_{t|t-1}f_0(RR_{Mt}|\Omega_{t-1};\theta)+(1-\pi_{t|t-1})f_1(RR_{Mt}|\Omega_{t-1};\theta)} \tag{5.52}$$

The parameters of the model are estimated using the maximum likelihood method. Let θ represent the vector of the parameters in the likelihood function. In order to estimate θ, the conditional density function in Equation 5.52 should be expressed in terms of the parameters that are allowed to vary within regimes (mean and standard deviation) as follows:

$$f_i(RR_{Mt}|\Omega_{t-1};\theta) = \frac{1}{\sqrt{2\pi\sigma_{it}}}\exp\left(\frac{-(RR_{Mt}-\mu_{Mit})^2}{2\sigma_{it}}\right) \tag{5.53}$$

where $i = 0,1$ denotes the prevailing regime, and Ω_{t-1} represents the information set available at time $t-1$. The filtered probabilities are estimated using the EM algorithm of Hamilton (1989) and they are used in the panel regressions in Equation 5.39 to estimate the risk premia for each state.

5.4 Conclusion

This chapter describes the methodologies employed in testing static and conditional asset pricing models. An overview of time-series and cross-sectional regressions which are the main methodologies used to estimate the parameters of asset pricing models under the traditional beta framework are presented first. In this context, a special focus is given to the Fama and Macbeth cross-sectional regression which is the main methodology used in this thesis.

Motivated by the increased focus of many researchers on conditional asset pricing models that allow for time-variation in risk and risk premia and the political and economic instability in the Egyptian stock market, this chapter gives special focus to the approaches employed to capture the time-variation in betas and risk premia. Specifically, this thesis focuses on the rolling regression approach, the scaled factor model approach, and the DCC-GARCH to capture time-variation in betas.

Finally, the chapter describes the Markov switching process which is the main approach employed to capture the time-variation in risk premia. The introduction of switching regimes to a multifactor factor model framework is an important innovation given the wide use of multifactor models in academic research and given their success to explain the cross-sectional variation in stock returns compared to the CAPM.

Chapter 6

Data Description and Descriptive Statistics

6.1 Introduction

The aim of this chapter is to describe the data employed in this thesis. Specifically, this chapter presents the descriptive statistics for the Fama and French three factors, as well as the descriptive statistics for individual stocks and for the portfolios sorted on market capitalization, the book-to-market ratio, and double sorted on both market capitalization and the book-to-market ratio which are the main test assets. This chapter also provides some preliminary evidence on the existence of the size and value effects for the Egyptian stock market. Furthermore, the main events that occurred in the Egyptian stock market during the sample period are highlighted.

The outline of this chapter is as follows. First, Section 6.2 presents descriptive statistics for the Fama and French three factors. Section 6.3 explains the construction of the test portfolios sorted on market capitalization, the book-to-market ratio, and double-sorted on both factors for the Egyptian stock market and their descriptive statistics. Section 6.4 shows the descriptive statistics of individual stocks. Finally, Section 6.5 concludes.

6.2 Descriptive Statistics for the Fama and French (FF) Factors

The aim of this section is to present descriptive statistics for the Fama and French three factors for the Egyptian stock market that are formed by the author as described in Chapter 5. The importance of this section emerges from the following reasons. First, since this thesis is among the first studies that provide in-depth analysis of the FF3 in the Egyptian stock market, analysing the descriptive statistics of the factors can provide new insights to add to the vast empirical evidence on the characteristics of emerging markets generally and the Egyptian stock market specifically. Second, the results of this section present some evidence on the existence of the size and value premiums for the Egyptian stock market.

Panel A of Table 6.1 shows that the mean return of the market portfolio is 1.19% per month which is equivalent to 14.28% per year, with a monthly standard deviation of 8.39%. It is apparent that the Egyptian stock market achieves high returns and is highly volatile compared to previous results of developed market which is consistent with the argument of Harvey (1995) that emerging markets are characterized by high return and high volatility.

According to Harvey, in a segmented market like Egypt, the variance of the market portfolio is normally high because it is not a diversified portfolio in a world context. Furthermore, this high variance may be due to the concentration of firms in the Egyptian stock market in only 17 industries, as is highlighted in Chapter 5, with most of their operations tied to the local economy. Consequently, the returns of these firms tend to move together in any given day leading to the observed high variance. As for the high returns observed in emerging markets, Harvey argues that the extreme volatility of these markets deters investors from investing. Thus, corporations that aim to raise capital by issuing stocks are forced to sell these stocks at low price (expected rewards should be high) to attract investors to invest.

A graph of the returns of the market factor over the sample period is shown in Panel A of Figure 6.1 to illustrate some important events that the Egyptian stock market witnessed during the sample period. During the period 2004-2005, the market was characterised by positive sentiment. In particular, the year 2004 witnessed the highest value of the main market index since its inception which can be attributed to the revival of the privatization program, the appointment of a new government, as well as the reform measures that were announced during this period including tariff and customs restructuring and the announcement of a new draft tax code (Egyptian Economic Monitor, 2005). Further, in 2005, the market outperformed both developed and emerging markets due to: the growth in foreign direct investment, along with the efforts of the investment ministry to support the investment climate; the appreciation of the Egyptian pound; and three major IPOs of public companies, SIDPEC, AMOC, and Telecom Egypt (EGX Report, 2005).

Table 6.1 Descriptive Statistics for the FF Factors (July 2004 to June 2016)

Panel A: Descriptive Statistics for the FF Factors

Factors	Mean (%)	Standard Deviation (%)	Sig. Level (Mean = 0)	Min. (%)	Max. (%)	Skewness	Excess Kurtosis	Jarque-Bera (Sig. Level)
Market Factor	1.19	8.39	0.09	-30.37	27.80	-0.04	1.13	7.615 (0.02)
SMB	1.82	8.24	0.01	-12.47	31.32	1.22	2.24	64.57 (0.00)
HML	-0.03	7.79	0.96	-38.06	35.15	-0.23	8.06	385.85 (0.00)

Panel B: SMB and HML in Up and Down Markets

Factors	Mean (%) (Up Market)	Standard Deviation (%) (Up Market)	Sig. Level (Mean = 0) (Up Market)	Mean (%) (Down Market)	Standard Deviation (%) (Down Market)	Sig. Level (Mean = 0) (Down Market)
SMB	2.13	8.93	0.04	1.47	7.43	0.11
HML	-1.43	7.40	0.099	1.5	7.97	0.12

Panel C: Correlation Matrix between the FF Factors

Factors	Market Factor	SMB	HML
Market Factor	1.00	0.09	-0.15
SMB	0.09	1.00	-0.27
HML	-0.15	-0.27	1.00

Notes: Panel A shows the descriptive statistics for the FF factors for the sample period July 2004 to June 2016. Panel B presents the descriptive statistics for the SMB and the HML in up and down markets defined as the periods with positive and negative market returns, respectively. Finally, Panel C presents the correlation matrix between the three factors.

Nonetheless, this strong performance was interrupted by three major shocks that hit the market in 2006 which were: the Gulf stock market crash, the Lebanon War, and the escalation of violence in Iraq. This political unrest in the MENA region, along with the 2006 stock market crashes in the Gulf area, resulted in waves of stock selling by Gulf investors to cover their losses, and an overall panic in the market that resulted in a severe drop in the main index which concluded the first half of the year with a 24.5% loss. However, the strong performance of the market in 2004 and 2005, along with the reform programs undertaken by the government, enabled the market to absorb the negative impact of these shocks and to recover by the end of the year.

In 2007 the government took several steps to enhance the confidence of both local and foreign investors through applying strict listing rules and activating corporate governance practices. Furthermore, Egypt was chosen by the World Bank as the best country in 2007 in terms of improving investment and business climate. All of these actions had a positive impact on the market which concluded the year by achieving a strong year-on-year growth rate of more than 50% (EGX Report, 2007). It is worth noting that the subprime mortgage crisis in the US and the rising fears of a global recession in 2007 affected the market negatively by the end of 2007.

Year 2008 was one of the toughest years for world economies and stock markets due to the global financial crisis which was considered the worst crisis since the Great Depression in the 1920s (Mathiason, 2008). Despite the widespread impact of the global financial crisis, Merrill Lynch found the Egyptian economy to be one of the world's least vulnerable economies to the global financial crisis (EGX report, 2008). This was attributed to the economic reform programs undertaken by the government since 2004. Furthermore, the banking system in Egypt performed well compared to others due to its limited exposure to real estate and mortgage lending, and was thus able to avoid the negative impact of mortgage financial risk (Egyptian Economic Monitor, 2010). Nonetheless, the wave of investor panic and the tendency of foreign investors to liquidate their portfolios to cover their losses in their home countries, along with the rumours of the government imposing capital gains taxes, caused the market to retreat by 56% over 2008.

The market, then, witnessed a recovery in 2009. The Egyptian economy performed better than expected during 2009 by achieving one of the highest growth rates compared to its peer countries. This favourable economic performance enabled the market to recover quickly and overcome the negative impact of the financial crisis with Egyptian indices realizing gains of around 35% during the year (EGX Report, 2009).

After two tough years, the global economy witnessed a recovery from the negative effects of the financial crisis in 2010. Similar to the world economy, the Egyptian economy achieved a favourable growth rate during 2010. On the back of this positive economic outlook, the market outperformed many Middle East stock indices with the main index achieving gains of around 15% for the year. However, this strong market performance was interrupted by the Greek debt crisis, causing the market to fall to its lowest point during the year in July. Nonetheless, the market was able to overcome this downtrend and witnessed a moderate recovery by the end of that year.

The year 2011 was a remarkable year not only in the history of the country but also for the Egyptian stock market as it faced both internal and external tensions simultaneously. Domestically, the year 2011 started with the Egyptian revolution which is considered a major turning point in political and economic conditions. This political unrest that started in January forced the Capital Market authority to close the market for almost two months. At an external level, the MENA region witnessed a period of political instability due to instability or revolutions in countries such as Iraq, Yemen, Syria, and Tunisia. In addition, the year suffered from the heightening of the economic crisis attributable to the debt-ceiling crisis in the US which spread to other countries, leading to an era of uncertainty and financial instability. All of these factors resulted in severe losses during 2011 with the main index recording year-on-year losses of around 50%.

The year 2012 was also affected by the political and economic uncertainty that the whole region faced since the so-called Arab Spring of 2011. Among the negative effects that hit Egypt during this year was the sharp decline in international reserves which led to a sharp depreciation of the Egyptian pound. However, despite the economic instability facing the whole country during this period, the market achieved remarkable performance during this year by achieving growth rate of around 51% which was considered the highest growth among all emerging and developed markets after Turkey in 2012 (EGX Report, 2012). This favourable performance can be attributed to the attempts by the Capital Market Authority to increase investors' confidence in the market by ensuring information dissemination and improving control levels. However, despite the overall favourable performance during 2012, the market deteriorated in May and June due to the political unrest related to the constitutional committee and the presidential elections. Furthermore, in November, the political tensions that prevailed in the country negatively affected the market until the beginning of December.

After these two tough years, the economy started to recover in 2013 following the presidential elections. During this year, the Capital Market Authority enhanced the legislative and regulatory infrastructure of the market and it took serious steps to attract more investors. These steps along with the improved political stability allowed the market to take second place among emerging markets during the year (EGX Report, 2013). However, the market retreated by 13% during the first half of the year due to the political unrest that prevailed in the country until the eruption of the second revolution in June.

The economic outlook for 2014 was also favourable, especially due to the decisions taken by the new government to restructure the subsidy system to minimize the budget deficit. As a result of these decisions, Egypt's credit ratings increased for the first time since 2011. This, in turn, increased confidence in the economy and its ability to recover. Consequently, the main market index achieved gains of around 32% during the year which allowed the country to be one of the best performers among other stock markets as per Morgan Stanley indices (EGX Report, 2014). However, the Egyptian economy faced severe regional and global challenges during 2015 which had a negative impact on the stock market. On the global arena, the world saw slow economic growth, mainly led by China's weak economic performance. The currency war between the US and China fuelled global economic uncertainty, which negatively affected many countries. At a regional level, the recurring tensions and the increased conflicts in many countries in the Middle East reduced economic growth rates of the whole region. Moreover, the Middle East was strongly hit by the sharp decline in the oil prices due to its strong dependence on the oil sector. All of these factors negatively caused the main index to fall by 25% during 2015.

These unstable economic conditions were extended to the year 2016 which can be considered one of the toughest years for the Egyptian economy generally. The economy was negatively affected by many factors such as the slow global economic growth, the sharp decline in revenues from the tourism sector due to political instability, the decline in the revenues from the Suez Canal, and the sharp decline in foreign investments and exports. These factors lead to severe pressure on the Egyptian pound which resulted in the appearance of a black market. This affected the investment climate negatively, especially as the gap between the official exchange rate and the black market rate widened ("Egypt allows its currency to float freely", 2016). As a result, the government adopted fiscal and monetary reform programs, with the floatation of the Egyptian pound and the restructuring of the subsidy system adding to the reform programs. The government also took several steps to encourage exports and reduce imports in an attempt to boost international reserves. All of these actions, despite their difficulty, are expected to contribute in stabilizing the economy in the long-run. The Egyptian stock market was able to absorb all of these challenges and it was able to reside on top of all emerging markets this year, and realize one of its highest records (EGX Report, 2016).

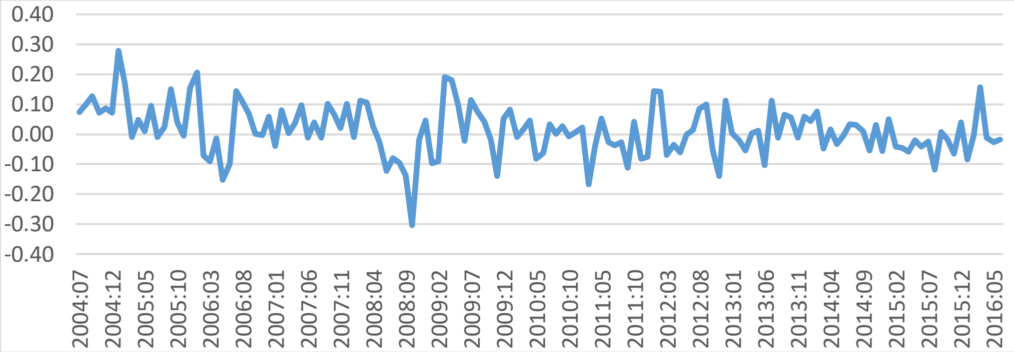
After reviewing the major events that the Egyptian stock market witnessed during the sample period, it is apparent that the Egyptian economy faced political, economic and financial instability during the sample period which may pose severe challenges for standard asset pricing models as they often fail to account for these specific characteristics of emerging markets. This necessitates testing whether conventional asset pricing models can account for these characteristics and explain the cross-sectional variation in stock returns in the Egyptian stock market. Furthermore, these characteristics provide an interesting environment to test whether conditional asset pricing models that allow for time-variation in risk and risk premia can explain the cross-sectional variation in stock returns in such contexts.

The second factor to analyse is the SMB factor which is long in the small firms' portfolio and short in big firms' portfolio. According to Fama and French (1993), this portfolio aims to mimic the risk factor in returns related to size. They argue that the average risk premium for the common risk factors in returns such as the SMB can be proxied by the average values of these factors over time. Thus, to provide some preliminary evidence concerning the average premium for the size-related factor in return before running more formal tests, Panel A of Table 6.1 shows that the mean of the SMB factor is 1.82 per month which is equivalent to 21.84% per year with a monthly standard deviation of 8.24%.

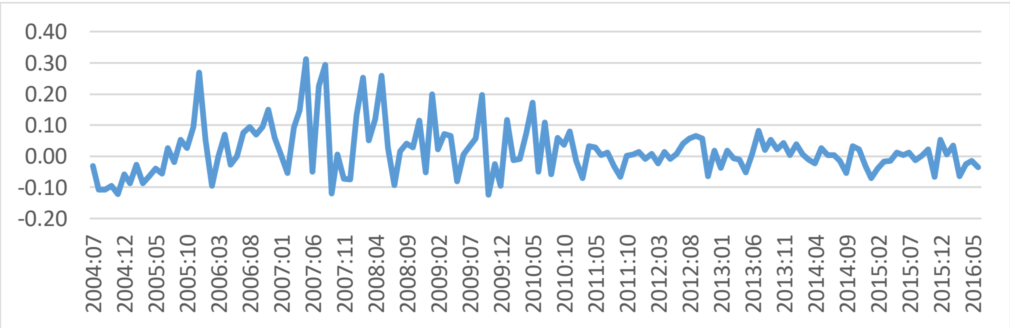
The average premium for the size-related factor is statistically and economically significant which may cast some doubt on whether this premium is rational. De Pena *et al.* (2010) advise that before applying the FF3 for other countries, it is important to find whether the factors are proxies for risk. One way to achieve this for the Egyptian stock market is to follow the approach of Hur *et al.* (2014) who argue that if the size premium[8] represents payment for distress risk as argued by Fama and French (1996), then it should vary over time. Specifically, there should be some market states in which small stocks underperform large stocks. In this regard, Perez-Quiros and Timmermann (2000) argue that if small firms stocks earn higher return because of being exposed to distress risk, this payment should be received during good market conditions when investors are generally more optimistic. Conversely, during a recession when credit conditions are tighter and investors are pessimistic, small firms stocks should be expected to earn lower returns because they are more adversely

[8] In this context, the size premium is the difference between the returns of small and big stocks.

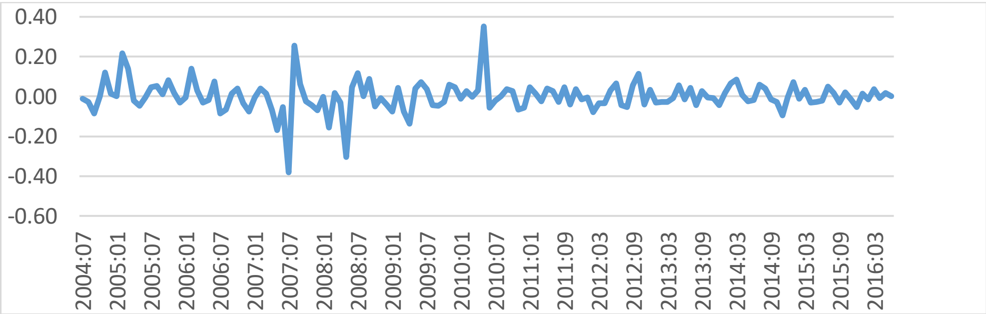
affected by these tighter credit conditions. This argument implies that small stocks should underperform large ones in a down market, but they should outperform large stocks in up markets in order to reward investors for bearing distress risk (Hur *et al.*, 2014).



Panel A: Variation in Market Returns (July 2004 to June 2016)



Panel B: Variation in SMB Returns (July 2004 to June 2016)



Panel C: Variation in HML Return (July 2004 to June 2016)

Figure 6.1: Graphical Representation of the FF Factors for the Egyptian market

The graphical representation of the SMB factor in Panel B of Figure 6.1 provides some preliminary evidence on the proposition that the size premium tends to vary over different market conditions. From the graph, it is apparent that there are episodes where small firm stocks significantly outperform large firm stocks especially during 2005, the first half of 2007, and 2010, on the back of the favourable market performance during these periods as discussed before. Furthermore, the graph shows that stocks of small firms underperform those of big ones during the first half of 2006, 2008 and 2009, on the back of the unfavourable economic conditions during these periods as discussed above. Thus, these results suggest some support for the arguments that the SMB factor is a proxy for distress risk

To provide further evidence that the size return differs between up and down markets, the 142 sample observations are divided into 'up' and 'down' markets. A monthly observation is designed as an up (down) market if excess market return is positive (negative). The total observations are divided into 75 up markets and 67 down markets. Panel B of Table 6.1 shows that the mean of the SMB factor in an up market is 2.13%, and it is significantly different from zero, while the mean in the down market is 1.47%, but it is statistically insignificant. However, although the size premium is insignificant in a down market, the observation that it is positive poses some challenges to the proposition that small firms stocks should underperform big ones in down markets. Nonetheless, these results are strongly dependent on the definition of up and down markets used in this analysis. Thus, in Chapter 8, a Markov switching model is used to provide better identification of bull and bear regimes.

Furthermore, these results should also be interpreted with caution given the argument of Hur *et al.* (2014) that the relationship between firm size and returns during different market conditions may be spurious due to ignoring the effect of market beta risk. Specifically, they argue that although their findings show that small-firm stocks outperform (underperform) big-firm stocks in up (down) markets which support the distress risk explanation for the size effect in the US market, this relation may be due to the inverse relation between firm size and market beta that is reported by Reinganum (1981) and Fama and Fama and French (1992). Specifically, the high (low) returns for small-firm stocks in up (down) markets may be due to the argument of Pettengill *et al*. (1995) that that high-beta stocks outperform (underperform) low-beta stocks in up (down) markets. Thus, to test for this possibility, Hur *et al.* adjust portfolios returns to market beta risk and then they test the relationship between risk-adjusted return and size during up and down markets. Their results show that, contrary to distress risk explanation, the size premium is paid mainly during down markets after adjusting for market risk in the US market. Thus, to account for this argument, in Chapter 8, the size premium is tested in both up and down markets after adjusting for both the market risk and the value effect.

The final factor to analyse is the HML factor which is long in the portfolio of stocks with high B/M ratios and short in the portfolio of stocks with low B/M ratios. According to Fama and French (1993), this portfolio aims to mimic the risk factor in returns related to the book-to-market ratio. Panel A of Table 6.1 shows that the mean return for the HML factor is -0.03% per month which is equivalent to -0.36% per year with a monthly standard deviation of 7.79%. Thus, the value premium for the Egyptian stock market over the sample period is negative, but statistically and economically insignificant. In addition, Panel C of Figure 6.1 shows that the return of the HML factor is very close to zero except for some minor episodes in which the return was significantly lower or higher than zero. This provides further support to the insignificance of the mean return of the HML factor.

To analyse whether the value premium varies over different market conditions, the results of Panel B of Table 6.1 show that the average return of the HML factor during up markets is negative but insignificant, while it is positive and insignificant during down markets. The insignificance of the mean return of the HML factor during up and down markets, defined as periods of positive and negative returns of the market factor respectively, may be attributed to the poor definition of up and down markets in this test. Thus, before concluding that the HML factor does not show substantial variation over time, better definitions of up and down markets should be employed as in Chapter 8.

Finally, Panel C of Table 6.1 shows that the correlation coefficients between the three factors within the Egyptian stock market are weak.

6.3 Descriptive Statistics for the Test Portfolios

The aim of this section is to present the descriptive statistics for the test portfolios. In this regard, there are three sets of portfolios that are studied which are portfolios sorted on market capitalization, portfolios sorted on the book-to-market equity and portfolios double sorted on market capitalization and the book-to-market equity. Since these portfolios are not readily available for the Egyptian stock market, the first subsection summarizes the portfolio construction.

6.3.1 Portfolio Construction for the Egyptian stock Market

This section provides the details of constructing the three main sets of portfolios used as test assets. The first set to construct is sorted on market capitalization. At the end of June of year t, all stocks listed on the Egyptian stock market are sorted based on market capitalization, and the median of the market capitalization is calculated. Stocks whose market capitalization is lower (higher) than the median are considered small (big) stocks. By the end of this step, two portfolios are constructed which are the small stock portfolio and the big stock portfolio rather than 10 portfolios as in Fama and French (1993) to ensure reasonable diversification due to the small number of listed stocks on the Egyptian stock market.

The value-weighted return for each portfolio is calculated from July of year t to June of year $t + 1$. The portfolios are then reformed each June and the stocks included in each portfolio may differ from one year to another as stocks may migrate from one characteristic to another. Specifically, small stocks may grow in size and move from the small stock portfolio to the big stock portfolio. Finally, the choice of June each year as the portfolio construction date is to ensure that the accounting variables are known in advance of the returns they are used to explain. Specifically, the accounting data at the end of the fiscal year $t-1$ are matched with the returns for July of year t to June of year $t+1$.

The second set of portfolios to construct is sorted on the book-to-market equity. At the end of June of year t, all stocks listed on the Egyptian stock market are ranked based on the book-to-market ratio, which is calculated as the ratio of the book value of the stockholder's equity for the fiscal year ending in calendar year $t-1$, to the market equity at the end of December $t-1$, and divided into quintiles. The justification of dividing the portfolios sorted on the book-to-market equity into quintiles rather than only two portfolios as in the case of portfolios sorted on market capitalization is to determine whether using a finer sort based on the book-to-market equity can change the conclusion obtained in the previous section that value stocks underperform growth stocks in the Egyptian stock market. By the end of this step, five portfolios are formed, where the first portfolio represents the portfolio that includes stocks with the lowest B/M ratio (growth portfolio), while the fifth portfolio includes stocks with the highest B/M ratio (value portfolio). Then, the value-weighted return of each portfolio is calculated from July of year t to June of year $t+1$ in the same way as the portfolios sorted on market capitalization. Similarly, the portfolios are reformed each June.

Finally, the last set of portfolios includes the portfolios that are double sorted on both market capitalization and the B/M ratio. This last set of portfolios is formed based on the intersection of the two portfolios formed on market capitalization and the five portfolios formed on the B/M ratio. By the end of this step, 10 portfolios are formed and their value-weighted returns are calculated from July of year t to June of year $t+1$. The portfolios are also reformed yearly in each June.

6.3.2 Descriptive Statistics for the Portfolios Sorted on Market Capitalization

Panel A of Table 6.2 shows the descriptive statistics for the portfolios sorted on market capitalization. The average excess return for the small portfolio is 3.77% per month which is equivalent to 45.24% per year, with a monthly standard deviation of 13.82%.

The beta of this portfolio, which is calculated as the ratio of the covariance between the excess return of the small portfolio and the market portfolio, over the variance of the market portfolio, is 1.26 which means that the small portfolio is riskier than the market. The average excess return for the big portfolio is 1.04% per month which is equivalent to 12.48% per year, with a monthly standard deviation of 8.33% and a beta of 0.99. Although the beta of the small portfolio is higher than the beta of the big portfolio, it is still questionable whether this difference in betas can explain the big difference in returns between the two portfolios.

To address this issue, the returns of both portfolios are adjusted for market risk as suggested by the CAPM, and then the risk-adjusted returns of both portfolios are compared to determine whether the small portfolio continues to outperform the large portfolio even after adjusting for market risk. The excess return (R_{it}^e) for each size portfolio is regressed on the excess return of the market portfolio (R_{Mt}^e) as follows.

$$R_{it}^e = \alpha_i + \beta_i R_{Mt}^e + \varepsilon_{it} \qquad \text{for } i = 1,2 \qquad (6.1)$$

Then the risk-adjusted return is calculated as follows:

$$R_{it}^* = R_{it}^e - \beta_i R_{Mt}^e = \alpha_i + \varepsilon_{it} \qquad (6.2)$$

where R_{it}^* is the risk-adjusted return for portfolio i in month t, α_i is the regression intercept and ε_{it} is the error term for portfolio i in month t estimated from Equation 6.1.

Panel B of Table 6.2 shows that even after adjusting for market beta risk, the small portfolio continues to outperform the big portfolio by 2.41% per month. These results are consistent with previous studies that show that small firm stocks have higher returns compared to large firm stocks both on a risk-adjusted and unadjusted basis (Perez-Quiros and Timmermann, 2000).

The ability of small firms stocks to outperform big firms stocks on a (market) risk-adjusted basis may be attributed to either market inefficiency or the inadequacy of the

CAPM as the benchmark model used for risk adjustment. As was highlighted in the Section 6.2, Hur *et al.* (2014) argue that for small stocks to be considered as fundamentally riskier than big ones, they should underperform big stocks in periods of unstable market and economic conditions. To test this hypothesis, Panel C of Table 6.2 shows that small portfolios tends to significantly outperform big ones only in up markets. Specifically, in up markets, the small portfolio earns an average return of 10.73% compared to an average return of 7.05% for the big portfolio.

Table 6.2 Descriptive Statistics for the Size Portfolios (July 2004 to June 2016).

Panel A: Descriptive Statistics for the Size Portfolios							
Portfolios	Mean (%)	Standard Deviation (%)	Sig. Level (Mean = 0)	Skewness	Excess Kurtosis	Jarque-Bera (Sig. Level)	Beta
Small	3.77	13.82	0.00	0.66	0.44	11.39 (0.00)	1.26
Big	1.04	8.33	0.14	-0.03	1.14	7.69 (0.02)	0.99
Small-Big	2.73	9.54	0.00	1.01	1.51	37.88 (0.00)	0.26

Panel B: Descriptive Statistics for the Risk-Adjusted Return for the Size Portfolio			
Portfolios	Mean (%)	Standard Deviation (%)	Sig. Level (Mean = 0)
Small	2.28	8.95	0.00
Big	-0.13	0.43	0.00
Small-Big	2.41	9.23	0.00

Panel C: Descriptive Statistics for the Size Portfolios in Up and Down Markets						
Portfolios	Mean (%) (Up Market)	Standard Deviation (%) (Up Market)	Sig. Level (Mean = 0) (Up Market)	Mean (%) (Down Market)	Standard Deviation (%) (Down Market)	Sig. Level (Mean = 0) (Down Market)
Small	10.73	12.24	0.00	-4.02	10.94	0.00
Big	7.05	5.56	0.00	-5.68	5.15	0.00
Small-Big	3.68	10.17	0.00	1.66	8.74	0.12

Notes: Panel A shows the descriptive statistics for the size portfolios for the sample period July 2004 to June 2016. Panel B shows the means and the standard deviations for the size portfolios after adjustment for market risk as suggested by the CAPM. Panel C shows the descriptive statistics for the size portfolios during up and down markets defined as periods with positive and negative market returns, respectively.

In contrast, in down markets, the difference between the returns of small and big portfolios is 1.66% per month which is statistically insignificant. Although these results show that small firms stocks significantly outperform big ones in an up market, the observation that the difference between the returns of small and big stocks is positive in a down market, despite being insignificant, poses some challenges to the proposition of Hur *et al.* that small stocks should underperform big stocks in down markets. However, as mentioned in Section 6.2, these results are dependent on the definition of up and down markets used.

6.3.3 Descriptive Statistics for the Portfolios Sorted on the Book-to-Market Ratio

Given the results in Section 6.2 about the insignificance of the average return of the HML factor for the Egyptian stock market, which may imply the absence of a value premium, in this section, stocks are sorted into five portfolios based on the B/M ratio to provide finer tests about the existence of value premium.

The results of Table 6.3 show that although there is no clear pattern concerning the relationship between returns and the B/M ratio, the portfolio that includes the stocks with the highest B/M ratio (value portfolio) earns the highest and the only significant average return compared to the other four portfolios. The return difference between the value portfolio and the portfolio that includes the stocks with the lowest B/M ratio (growth portfolio) is 2.5% per month. Similarly, although, there is no pattern that can be observed for either the betas or the standard deviations of the five portfolios, the value portfolio has the highest beta and highest standard deviation compared to the other four portfolios which may imply that it is riskier compared to them. Nonetheless, the dispersion in betas between portfolios is too small to explain the return differences between them.

To provide more formal tests concerning whether the dispersion in betas can explain the value premium, the risk adjusted returns for all portfolios are calculated as in Equation 6.1 to determine whether the value portfolio continues to outperform the growth portfolio, even after adjusting for the market risk. The results of Panel B of Table 6.3 show that even after adjusting for market risk, the value portfolio continues to outperform the growth portfolio on average by 2.39%. Thus, this supports the existence of a value premium for the Egyptian stock market on both a risk-adjusted and unadjusted basis.

Table 6.3-Descriptive Statistics for the B/M Portfolios (July 2004 to June 2016)

Panel A: Descriptive Statistics for the B/M Portfolios

Portfolios	Mean (%)	Standard Deviation (%)	Sig. Level (Mean = 0)	Skewness	Excess Kurtosis	Jarque-Bera (Sig. Level)	Beta
Low	1.00	9.34	0.20	0.32	1.03	8.68 (0.01)	1.07
H2	0.73	8.57	0.31	-0.41	1.95	26.36 (0.00)	0.83
H3	1.12	9.34	0.16	0.19	0.88	5.53 (0.06)	0.91
H4	0.61	10.69	0.50	1.51	6.79	327.39 (0.00)	0.96
High	3.50	14.09	0.00	1.35	4.00	137.89 (0.00)	1.16

Panel B: Descriptive Statistics for the Risk-Adjusted Return for the B/M Portfolios

Portfolios	Mean (%)	Standard Deviation (%)	Sig. Level (Mean = 0)
Low	-0.27	2.52	0.20
H2	-0.26	4.93	0.52
H3	0.02	5.26	0.96
H4	-0.54	6.99	0.36
High	2.12	10.15	0.01

Panel C: Descriptive Statistics for the B/M Portfolios in Up and Down Markets

Portfolios	Mean (%) (Up Market)	Standard Deviation (%) (Up Market)	Sig. Level (Mean = 0) (Up Market)	Mean (%) (Down Market)	Standard Deviation (%) (Down Market)	Sig. Level (Mean = 0) (Down Market)
Low	7.55	6.85	0.00	-6.33	5.51	0.00
H2	5.61	5.69	0.00	-4.74	7.95	0.00
H3	6.75	7.31	0.00	-5.19	7.09	0.00
H4	6.29	10.67	0.00	-5.75	6.25	0.00
High	9.95	13.62	0.00	-3.71	10.76	0.01
High-Low	2.39	12.99	0.11	2.62	9.33	0.02

Notes: Panel A shows the descriptive statistics for the B/M portfolios for the sample period July 2004 to June 2016. Panel B shows the means and the standard deviations for the B/M portfolios after adjustment for market risk, as suggested by the CAPM. Panel C shows the descriptive statistics for the B/M portfolios during up and down markets defined as periods with positive and negative market returns, respectively.

Lakonishok *et al*. (1994) argue that the interpretation of why value stocks outperform growth stocks is highly debatable. On the one hand, value stocks may outperform growth stocks because they are fundamentally riskier (Fama and French, 1993, 1996). On the other hand, Lakonishok *et al.* argue that value strategies may produce these superior returns because they are contrarian to naïve strategies followed by investors who tend to extrapolate the favourable (unfavourable) past performance of growth (value) stocks too far into the future. This, in turn, results in the overvaluation of growth stocks and the undervaluation of value stocks. Given these scenarios, it is possible that the value premium observed for the Egyptian stock market is due to either market inefficiency or the inadequacy of the CAPM as the main asset pricing model used for risk-adjustment.

To gain some insight concerning whether the superior returns earned by value stocks are due to risk rather than market inefficiency, Lakonishok *et al.* argue that if value stocks are fundamentally riskier, then they must underperform growth stocks with some frequency, and particularly when the marginal utility of wealth is high. To perform this test, they check the frequency of superior and inferior performance of value strategies, as well as their performance in severe market downturns and economic recessions.

Following their simple approach, the value premium is calculated in up and down markets to determine whether value stocks underperform growth stocks during market downturns. Panel C of Table 6.3 presents the results for the average returns for each portfolio in up and down markets. Similar to the results for the full sample, there is no clear pattern that can be observed concerning the relationship between returns and the B/M ratio. However, in an up market, the value portfolio continues to earn the highest average return of 9.95% compared to the average return achieved by the growth portfolio which is equal to 7.55%. The difference between the average returns of value and growth portfolios is 2.39% but it is statistically insignificant. In contrast, during down markets, although all portfolios achieve negative average returns, the value portfolio has the lowest losses, while the growth portfolio has the highest losses. Specifically, the average difference between both portfolios is 2.62% which is significantly different from zero.

The results of Panel C show that the value portfolio outperforms the growth portfolio in both up and down markets, but the difference between both portfolios is significant only during a down market. These results cast doubt on the proposition that value stocks tend to outperform growth stocks because they are fundamentally riskier. Nonetheless, some points may be noted. First, the small number of stocks listed on the Egyptian stock market implies that the portfolios formed on the B/M ratio are not well diversified. This may imply that company-specific risk distorts the results. Second, the results are based on the definition of up and down markets which represent periods in which the market return is above or below the risk-free rate of return respectively. This definition of up and down periods may jeopardise the results as the highly volatile nature of the Egyptian stock market may cause the market to witness positive and negative returns that do not necessarily correspond to periods of economic booms and recessions. Thus, different results may be obtained if a better identification of periods of economic recessions and booms is used. Finally, since this thesis compares the monthly returns of each portfolio rather than annual buy and hold return as in Lakonishok *et al.* (1994), the results may suffer from market microstructure issues such as bid-ask spread and thin trading. Thus, given these points, a risk-based explanation for the value effect cannot be rejected.

6.3.4 Descriptive Statistics for the Portfolios Double-Sorted on Size and the Book-to-Market Ratio

Consistent with the previous results reported in this chapter, the results of Panel A of Table 6.4 show that there is no clear pattern regarding the relationship between average returns and the B/M ratio for the Egyptian stock market. Nonetheless, value stocks tend to outperform growth stocks in both size portfolios. Specifically, the value premium is 0.21% per month for small stocks, versus 1.58% for big stocks. These results give new insights about how the value premium varies across size groups as they show that value premium is only significant for big stocks which contradict the previous results for developed markets that value premium is only significant for small firms stocks (Fama and French, 1993), or is at least significant in both small and big firms stocks (Fama and French, 2006).

Table 6.4-Descriptive Statistics for the 10 Size and B/M Portfolios (July 2004 to June 2016)

Panel A: Descriptive Statistics for the 10 Size and B/M Portfolios													
	Q1	Q2	Q3	Q4	Q5	Avg.		Q1	Q2	Q3	Q4	Q5	Avg.
	Means							Standard Deviations					
Small	4.64	3.23	1.09	2.64	4.85	3.29	Small	23.29	13.56	11.01	14.05	18.59	16.10
Big	0.94	0.63	1.12	0.29	2.52	1.10	Big	9.31	8.52	9.39	10.79	13.05	10.21
Avg.	2.79	1.93	1.11	1.47	3.69		Avg.	16.30	11.04	10.20	12.42	15.82	
	Skewness							Excess Kurtosis					
Small	2.66	0.93	0.52	0.90	2.37	1.48	Small	15.17	2.35	1.26	1.62	8.82	5.84
Big	0.33	-0.37	0.28	1.61	1.04	0.58	Big	1.04	2.09	1.27	7.52	4.45	3.27
Avg.	1.50	0.28	0.40	1.26	1.71		Avg.	8.11	2.22	1.27	4.57	6.64	
	Jarque-Bera							Betas					
Small	0.00	0.00	0.00	0.00	0.00	0.00	Small	1.42	0.96	0.99	1.23	1.27	1.17
Big	0.01	0.00	0.00	0.00	0.00	0.00	Big	1.07	0.82	0.89	0.94	1.01	0.95
Avg.	0.01	0.00	0.00	0.00	0.00		Avg.	1.25	0.89	0.94	1.09	1.14	

Panel B: Value Premium across Size Portfolios			
Portfolios	Mean (%)	t-Statistic (Mean=0)	Sig. Level (Mean=0)
Small	0.21	0.10	0.92
Big	1.58	1.71	0.089

Panel C: Adjusted Value Premium across Size Portfolios			
Portfolios	Mean (%)	t-Statistic (Mean=0)	Sig. Level (Mean=0)
Small	-0.19	-0.16	0.87
Big	0.62	1.23	0.22

Panel D: Size Premium across B/M Portfolios			
Portfolios	Mean (%)	t-Statistic (Mean=0)	Sig. Level (Mean=0)
Growth	3.70	2.11	0.04
Q2	2.59	2.72	0.01
Q3	-0.03	-0.04	0.97
Q4	2.34	2.74	0.01
Value	2.33	1.52	0.13

Notes: Panel A shows descriptive statistics for the 10 portfolios double-sorted on size and the B/M ratio for the sample period July 2004 to June 2016. Panel B shows the value premium across size portfolios calculated as the difference between the average return on the highest B/M quintile and the average return on the lowest B/M quintile for each size portfolio. Panel C shows the value premium across size portfolios calculated as the difference between the average returns on the two highest B/M quintiles and the two lowest B/M quintiles for each size portfolio. Panel D shows the size premium across B/M quintiles calculated as the difference between the average on the smallest portfolio and the average return on the biggest portfolio in each B/M quintile.

Furthermore, to determine whether this value premium can be attributed to differences in risk between value and growth stocks, Panel A of Table 6.4 shows the results for the standard deviations and betas of each portfolio. There is no clear pattern regarding the relation between betas and standard deviations and the B/M ratio within each size group. For the small stocks group, growth stocks have higher betas and standard deviations compared to value stocks. Although these results contradict the results in the previous section which shows that value stocks have higher betas and standard deviations compared to growth stocks, there are some data-specific issues that can help explain these results. First, the portfolio that includes small stocks with low B/M ratios consists of only a very limited number of stocks, and is thus not well-diversified, and this may explain its high variability. Firms in the smallest size group have low market capitalizations and thus they are less likely to be in the extreme growth (low B/M) quintile. Second, given the small number of stocks in this portfolio, its results are more likely to be affected by company-specific risk and this may, in turn, bias the results. In the big stocks portfolio, although growth stocks have a lower standard deviation compared to value stocks, they have slightly higher betas. Thus, this means that betas cannot explain the significant difference in returns between value and growth stocks for the big size group. This, in turn, necessitates testing whether other risk factors can explain the difference in returns between value and growth stocks for the big size group.

Given the small number of stocks employed in this thesis, Fama and French (2006) argue that one way to deal with the impact of the small number of stocks in the extreme value and growth portfolios is to calculate the value premium as the difference between the average returns on the two highest B/M portfolios and the two lowest B/M portfolios. By replicating their approach for the Egyptian stock market, it is apparent from Panel C that the value premium for both size groups is insignificant. Thus, these results are consistent with the results obtained in Section 6.2 regarding the insignificance of the average returns for the HML factor.

Panel A of Table 6.4 shows that the size premium for the Egyptian stock market is more significant compared to the value premium. Specifically, the average return decreases monotonically with market capitalization for all B/M quintiles except in the middle quintile where the average return is almost the same for both small and big stocks (1.09% versus 1.12%, respectively). Furthermore, the betas and standard deviations of the small and big stocks also show a consistent pattern across all B/M quintiles. Specifically, small stocks tend to have higher betas and standard deviations compared to big stocks, and thus this supports the view that they are fundamentally riskier. However, the dispersion in betas is too small to explain the dispersion in returns between small and big stocks.

Finally, as shown in Panel D, the size premium across the B/M quintiles ranges from -0.03% per month for the third B/M quintile to 3.70% per month for the growth quintile. These results imply that the size premium is more pronounced in the growth portfolio than the value portfolio which contradicts previous results in developed markets that there is no size premium in the growth portfolio (Cochrane, 2008). Overall, the descriptive statistics for the test portfolios show that there is a wide range of average returns on the size and B/M portfolios which present an interesting challenge for competing asset pricing models.

6.4 Descriptive Statistics of Stocks Returns and Firm Characteristics

Table 6.5 shows the descriptive statistics of both individual stocks excess returns as well as the descriptive statistics of firm characteristics that are believed to be significant predictors of expected returns (see for example, Avramov and Chordia, 2006; Brennan *et al.*, 1998). These firm characteristics are: (i) size defined as the market value of equity; (ii) the book-to-market ratio defined as the ratio firm book value of equity to the market value of equity where the book-to-market ratio for July of year t to June of year $t+1$ is computed using accounting information at the end of year $t-1$; (iii) turnover defined as the ratio of the monthly trading volume to the number of shares outstanding; (iv) the cumulative returns over the second through third, fourth through sixth, and seventh through twelfth months before the current month.

Table 6.5 shows that the mean excess returns of the 134 stocks listed in the Egyptian stock market is 0.92% per month with a monthly standard deviation of 19.64%. The skewness of individual stocks is 6.72, this positive skewness implies that the sample period includes some extreme gains which is consistent with the review of the main milestones the Egyptian stock market passed by during the sample period. Specifically, the sample period witnessed periods in which the Egyptian stock market outpaced both emerging and developed market especially during the first half of the sample. This high skewness imply that the Egyptian stock market depart from normal distribution which is a normal characteristic of emerging markets.

Furthermore, Table 6.5 shows that the mean of the market capitalization is 2.33 billion Egyptian pounds. This value is small when compared to developed markets, especially when considering the depreciation of the Egyptian pound after the government has announced the floatation of the pound in 2016. The monthly turnover has a mean value of 50.27% but with a monthly standard deviation of 446% which reflects that there is high variability in turnover in the Egyptian stock market. This high variability may imply that trading in the Egyptian stock market varies significantly between stocks. Specifically, some stocks attract investors and witness high trading volume while other stocks suffer from thin trading which is another common characteristic of emerging markets. The mean book-to-market ratio is 0.87. Finally, by reviewing the skewness of all of the firm characteristics, it is apparent that all variables display considerable skewness. Thus, when these variables are used in cross-sectional regressions in Chapter 7, the logarithmic transformation of all of these variables are employed as in Avramov and Chordia (2006).

Table 6.5: Descriptive Statistics of Individual Stocks Excess Returns and Firm Characteristics (July 2004 to June 2016)

	Mean	Standard Deviation	Median	Skewness	Kurtosis
Excess Return	0.92%	19.64%	-1.07%	6.72	197.95
Size (EGP billions)	2.33	7.03	0.35	7.29	72.78
Book-to-Market	0.87	80.23%	0.66	2.32	24.78
Turnover	50.27%	446.74%	3.35%	31.77	1456.77
Cumulative Return (2-3 months)	3.98%	30.15	0	5.22	80.22
Cumulative Return (4-6 months)	6.18%	4.76%	0.18%	5.86	78.59
Cumulative Return (7-12 months)	14.18%	80.19%	0.64%	13.16	840.35

Notes: Table 6.5 presents the time-series averages of the cross-sectional means, medians, and standard deviations of 134 stocks listed on the Egyptian stock market for the sample period July 2004 to June 2016. Size represents the market capitalization in billions of Egyptian pounds. Book-to-market ratio represents the ratio of book value of equity to market value equity. Turnover represents the ratio of monthly trading volume to the number of outstanding shares. Cumulative returns (2-3 months), (4-6 months), and (7-12 months) represent the cumulative returns over the second through third, fourth through sixth, and seventh through twelfth months before the current month.

6.5 Conclusion

This chapter provides the descriptive statistics of the FF factors as well as the descriptive statistics of the portfolios sorted on market capitalization, the book-to-market equity, and double-sorted on market capitalization and the book-to-market equity and individual stocks for the Egyptian stock market. By analysing these results, several observations can be highlighted. First, consistent with Harvey's (1995) argument that emerging markets are characterized by high returns and high volatility, the return of the market portfolio in the Egyptian stock market is 1.19% per month with a monthly standard deviation of 8.39%.

Since this thesis is among the first studies that study the FF3 in the Egyptian stock market, a thorough analysis of the SMB and HML factors is also presented to gain some preliminary insights about the existence of the size and value effects. The average return of the SMB factor is 1.82% with a monthly standard deviation of 8.24%. These results show that there is a significantly positive size premium in the Egyptian stock market. These results are supported by the results derived from analysing the returns of the portfolios sorted on market capitalization. Specifically, the portfolio of small stocks significantly outperform the portfolio of large stocks on both a risk-adjusted and an unadjusted basis.

The return of the HML factor is -0.03% per month with a monthly standard deviation of 7.79%. These results imply that the value premium for the Egyptian stock market over the sample period is statistically and economically insignificant. To get some finer tests about whether value stocks outperform growth stocks, the stocks are divided into quintiles based on their book-to-market ratio. The results of analysing these portfolios reveal that although there is no clear pattern regarding the relationship between average returns and book-to-market ratio in the Egyptian stock market, value stocks outperform growth stocks both on a risk-adjusted and an unadjusted basis. Further, the results reveal that value stocks outperform growth stocks in both up and down markets. These results may defy risk-based explanation for value premium given the argument of Lakonishok *et al.* (1994) that if value stocks are fundamentally riskier than growth stocks, they should underperform growth stocks with some frequency. Nonetheless, the small sample employed in this thesis and the simple definition of up and down market employed in these tests may distort the results.

The chapter then proceeds by analysing the main test assets which are the portfolios double-sorted on size and the book-to-market ratio and individual stocks. The 10 portfolios double-sorted on size and the book-to-market ratio show wide variations in returns that range between 0.29% and 4.85%. These wide variations in returns pose a significant challenge for asset pricing model to capture. The CAPM fails to capture these wide variations in returns, as the dispersion in the betas of the 10 portfolios is too small to explain these wide variations in returns. This, in turn, opens a fertile avenue for alternative asset pricing models to explain the cross-sectional variations in returns. As for individual stocks, the average returns of individual stocks in the Egyptian stock market is 0.92% with a monthly standard deviations of 19.64%, this high variability of the returns of individual stocks challenges asset pricing models to capture.

Finally, the results presented in this chapter provide the basis upon which the following chapters are built. As far as asset pricing models are concerned, high returns observed in emerging markets should be associated with high exposure to risk factors. Thus, the main aim of the next chapter is to analyse whether the Fama and French three-factor model, that uses country-specific risk factors, can explain the cross-sectional variation in stock returns. Furthermore, by reviewing the main milestones that Egypt passed by during the sample period, it is apparent that the Egyptian stock market like all emerging markets faces political, economic and institutional instability which outwardly pose severe challenges for asset pricing models. According to Iqbal *et al.* (2010), these highly volatile political, macroeconomic and institutional conditions imply that the parameters of asset pricing models (beta and risk premia) and expected returns are more likely to vary over time. This, in turn, creates an urge to study conditional asset pricing models in the Egyptian stock market. Thus, Chapters 7 and 8 employ different techniques to capture time-variations in betas and risk premia.

Chapter 7

The Three-Factor Model and The Cross-Section of Stock Returns

7.1 Introduction

This chapter aims to test whether the conditional versions of the FF3 can explain the cross-sectional variation in stock returns in the Egyptian stock market. The contribution of this chapter is twofold. First, since the main focus of this thesis is on the Egyptian stock market which is a useful example of a growing emerging stock market, the results of this chapter adds to the asset pricing literature, that argues that emerging markets poses severe challenges to standard asset pricing models. Second, by employing different approaches to capture time-variation in betas, this thesis can provide useful insights on the differences between these approaches and which one is more appropriate to capture time-variation in betas in the Egyptian stock market.

This chapter aims to address the following empirical questions. (i) What are the prevalent risk factors in the Egyptian stock market? (ii) Are these risk factors rewarded in equilibrium, and how might their risk premia be estimated? (iii) How should the time-variation in betas be modelled? (iv) How might the performance of the different approaches employed to capture time-variation in betas be best compared?

Given the increased interest among academics in testing and evaluating conditional asset pricing models, and supported by the highly volatile nature of the Egyptian stock market, it is sensible to assume that an appropriate specification of asset pricing models should take time-variation in both betas and risk premia into consideration. Thus, in this chapter, several techniques are employed to capture the time-variation in betas which are: (i) rolling beta regression; (ii) scaled factor models; and (iii) multivariate GARCH models with dynamic conditional correlations (DCC) to determine whether modelling time-variation in betas can improve the ability of the

FF3 to capture the cross-sectional variation in stock returns in the Egyptian stock market. Then, Chapter 8 extends these results by modelling time-variation in both risk and risk premia.

The outline of this chapter is as follows. Section 7.2 reports the results of the conditional FF3 by employing different techniques to capture the time-variation in betas which are: (i) the rolling regression approach; (ii) the scaled factor model approach; and (iii) Multivariate GARCH Models with Dynamic Conditional Correlations (DCC). Section 7.3 compares the models tested in this chapter. Finally, Section 7.4 concludes.

7.2 Conditional Tests of the FF3

The FF3 proposes that the expected return of a stock in excess of the risk-free rate of return can be explained by the sensitivity of its return to three factors which are: (i) the excess return on the market portfolio; (ii) the SMB factor; and (iii) the HML factor (Fama and French, 1996). In order to test the model empirically, researchers initially assume that betas and expected returns are constant over time. However, the validity of this assumption is strongly criticised given the substantial empirical evidence that betas and expected returns tend to vary over time. Furthermore, the results of Table A.2 in Appendix A reveal that the static FF3 fails to capture the cross-sectional variation in stock returns in the Egyptian stock market.

This failure of the static FF3 does not necessarily imply that the Fama and French factors are not the appropriate risk factors in the Egyptian stock market. Rather, it may reflect that the model suffers from misspecification as a result of ignoring time-variation in risk and risk premia. Thus, the aim of this section is to test whether allowing betas to vary over time can save the model and lead to better results. To test this possibility, three main approaches are used to capture time-variation in betas which are: (i) rolling beta regression; (ii) scaled factor models; and (iii) multivariate GARCH models with dynamic conditional correlations (DCC).

7.2.1 Rolling Beta Regressions

Given the theoretical and empirical support for conditional asset pricing models and the unfavourable results of the static FF3 documented in Appendix A, the aim of this section is to determine whether allowing betas to vary overtime using the rolling regression approach can lead to better results.

The estimation of betas using the rolling regression approach involves running time-series regressions for individual stock/portfolio excess returns ($R_{i\tau} - R_{f\tau}$) on the Fama and French three factors ($f_{k\tau}$). Specifically, for each stock/portfolio, there are $t - 24$ time-series regressions as follows:

$$R_{i\tau} - R_{f\tau} = a_i + \sum_{k=1}^{3} \beta_{itk} f_{k\tau} \quad (7.1)$$

$$\tau = t - 23, t - 22, \dots, t \text{ for each } t = 24, \dots, T$$

Then, cross-sectional regressions of expected returns on estimated betas are run each month to estimate the factors' risk premia:

$$R_{it} - R_{ft} = \alpha_t + \sum_{k=1}^{K} \hat{\beta}_{itk} \lambda_{kt} \quad i = 1,2, \dots, N \quad \text{for each } t = 24, \dots, T \quad (7.2)$$

Before presenting the results of this section, it is worth noting that all the tests are applied both on the 10 portfolios double-sorted on size and the book-to-market ratio and individual stocks. However, the results applied on the portfolios should be interpreted with caution due to the small number of portfolios used in this thesis which may lead to some small sample bias.

7.2.1.1 Results Based on the 10 Size/Book-to-Market Portfolios

Before presenting the results of the Fama-Macbeth cross-sectional regression, it is of interest to determine whether betas vary significantly over time in the Egyptian stock market in order to emphasise the importance of modelling time-variation in betas while testing asset pricing models.

Similar to Lewellen and Nagel (2006), the average conditional betas from the rolling regressions along with their standard deviations are reported for the 10 portfolios double-sorted on size and the B/M ratio in Table 7.1. The results show that the average conditional betas of the three Fama and French factors are consistent with their unconditional betas reported in Table A.1 in Appendix A. Nonetheless, these betas exhibit significant variations over time which necessitates modelling time-variations in betas. Specifically, the market betas have standard deviations ranging between 6% and 37%, the SMB betas have standard deviations ranging between 8% and 58%, and the HML betas have standard deviations ranging between 9% and 67%. Furthermore, the results show that the betas of small stocks exhibit higher variability over time compared to big ones which is consistent with the argument of Perez-Quiros and Timmermann (2000) who argue that there is a link between firm size and risk due to the greater adverse effect of tighter credit market conditions on small firms compared to big ones.

Lewellen and Nagel (2006) argue that the rolling regression approach provides a simple way to determine whether the conditional alphas are zero without having to determine any state variables that may jeopardise the results. The test here focuses on the average conditional alpha for each portfolio and it uses the time-series variability of the estimates to determine the standard errors following the same logic of Fama and Macbeth (1973). Overall, the average conditional alphas in Table 7.1 provide evidence against the conditional FF3 as most of the alphas are significant.

The final observation from Table 7.1 is related to the average excess returns of the 10 portfolios. It is apparent that there is significant variation in the average excess returns that range from 0.29% to 4.85% per month which poses a significant challenge for the model to capture. Thus, to test whether the model can accommodate this substantial variation in average returns, the next step is to run the Fama-Macbeth cross-sectional regression to determine whether capturing time-variations in betas by using rolling regression approach can improve the ability of the FF3 to explain the cross-sectional variation in stock returns.

Table 7.1: Coefficients of the FF3 of the 10 Size/Book-to-Market Portfolios Estimated Using a Rolling Regression Approach

	Growth	B2	B3	B4	Value
Excess Return (%)					
Small	4.64	3.23	1.09	2.64	4.85
Big	0.94	0.63	1.12	0.29	2.52
Average Market Beta					
	Growth	B2	B3	B4	Value
Small	1.43(29%)	1.03(33%)	0.95(19%)	1.15(24%)	1.21(37%)
Big	1.03(6%)	0.90(13%)	0.89(18%)	0.98(20%)	1.07(29%)
Average SMB Beta					
	Growth	B2	B3	B4	Value
Small	0.91(58%)	0.89(23%)	0.74(25%)	0.81(30%)	1.04(52%)
Big	-0.14(8%)	0.08(23%)	0.27(20%)	0.13(23%)	0.15(25%)
Average HML Beta					
	Growth	B2	B3	B4	Value
Small	-0.41(44%)	0.09(35%)	0.09(33%)	0.18(41%)	0.57(67%)
Big	-0.21(9%)	0.23(20%)	0.11(13%)	0.33(28%)	0.38(23%)
Average Intercept					
	Growth	B2	B3	B4	Value
Small	0.022***	0.009***	-0.008***	-0.003***	0.0069***
	(5.31)	(10.29)	(-16.9)	(-3.25)	(4.66)
Big	-0.001***	-0.003***	-0.001	-0.007***	0.006***
	(-3.88)	(-3.59)	(-1.08)	(-6.15)	(3.46)

Notes: Table 7.1 shows the average excess returns of the 10 portfolios double-sorted on size and book-to-market ratio as well as the slopes of the Fama and French three risk factors estimated using a rolling regression approach, along with their standard deviations in brackets. Furthermore, the Table reports the average alphas from the time-series regressions and their t-statistics in brackets. The time-series regression is as follows:

$$R_{i,\tau} - R_{f,\tau} = \alpha_i + \beta_{1i}(R_{M,\tau} - R_{f,\tau}) + \beta_{2i}SMB_\tau + \beta_{3i}HML_\tau$$
$$\tau = t - 23, t - 22, \ldots, t \text{ for each } t = 24, \ldots, T$$

* reflects significance at the 10% level
** reflects significance at 5% the level
*** reflects significance at 1% the level

However before presenting the results of Table 7.2, it is important to highlight that the reported t-statistics are calculated using standard errors corrected for heteroskedasticity and autocorrelation to mitigate their impact on the results and provide more accurate inferences compared to t-statistics estimated in the usual way.

Table 7.2 shows that although the intercept of the model is negative but statistically insignificant, its magnitude is quite high at 1.7% which implies that the model cannot fully capture the cross-sectional variation in stock returns. Despite the unfavourable implications derived from the estimates of the intercept, the estimates of the risk premia provide some supportive evidence. Although the market risk premium is significantly positive, its magnitude is inconsistent with the sample average return of the market factor which poses some challenges to the model. Similarly, the risk premium of the SMB factor is significantly positive but its magnitude is consistent with the sample average return of the SMB factor. Thus, these results imply that the size-related risk factor is significantly priced in the Egyptian stock market. Finally, the estimate of the risk premium for the HML factor shows that it is statistically different from zero but it is negative. These results run counter to the argument of Fama and French (1996) that the HML factor is a proxy for distress risk. Another puzzling phenomenon is related to the magnitude of the risk premium for the HML factor which is significantly higher than its sample average return.

Table 7.2: Fama-Macbeth Cross-Sectional Regression Tests on the 10 Portfolios Double-Sorted on Size and the Book-to Market Equity and on Individual stocks Using Rolling Betas

Test Assets	α	λ_M	λ_{SMB}	λ_{HML}
10 Size/Book-to-Market Portfolios	-0.017	0.025	0.019	-0.024
	(-1.37)	(2.37)***	(2.21)**	(-2.73)***
Individual Stocks	0.0003	-0.0003	0.0109	-0.004
	(0.05)	(-0.05)	(2.14)**	(-0.87)
	[0.05]	[-0.03]	[1.39]	[-0.52]
Fama and French Factors		$\overline{R_M - R_f}$	$\overline{SMB}$	$\overline{HML}$
Sample Average Return		1.19%	1.82%	-0.0317%

Notes: Table 7.2 present the intercepts and slopes of the Fama-Macbeth cross-sectional regression of monthly excess returns for 10 portfolios double-sorted on size and the B/M ratio and for individual stocks based on their rolling regression betas. T-statistics reported in brackets are derived from heteroskedasticity and autocorrelation consistent regression for. The t-statistics based on Shanken's (1992) correction are given in square brackets. The results are obtained from the following regression:

$$R_{it} - R_{ft} = \alpha_t + \hat{\beta}_{it}\lambda_t$$

* reflects significance at 10% level
** reflects significance at 5% level
*** reflects significance at 1% level

To sum up, the overall conclusion is that modelling time-variation in betas using the rolling regression approach does not enable the FF3 to fully explain the cross-sectional variation in stock returns in the Egyptian stock market.

7.2.1.2 Results Based on Individual Stocks

To augment the results of the previous section, the results are repeated using individual stocks as the main test assets in order to provide more rigorous test of the model. The results of Table 7.2 show that the intercept is economically and statistically insignificant which implies that the model can capture the cross-sectional variations in stock returns. These results represent an improvement compared to the results of Section 7.2.1.1 as the magnitude of the intercept is significantly lower.

Nonetheless, despite the more favourable estimates of the intercept, the estimates of the risk premia of the three Fama and French factors provide less supportive evidence concerning the performance of the model. First, contrary to the results obtained in Section 7.2.1.1, the market risk premium is negative but is economically and statistically insignificant. These results are consistent with the argument of Lewellen *et al.* (2010) that the strong factor structure of the portfolios double-sorted on size and the B/M ratio makes it more probable that betas on almost any proposed factor will be related to expected returns which may result in overestimating the ability of the model to capture the cross-sectional variation in stock returns. Second, the risk premium for the HML factor is negative and insignificant which implies that the HML factor is not significantly priced in the Egyptian stock market. Finally, although the risk premium for the SMB factor is significantly positive, its magnitude is inconsistent with the sample average return of the SMB factor which pose some challenges to the model. It is worth mentioning here that if Shanken correction is used then the size premium tends to be insignificant, but given the unrealistic homoscedasticity assumption employed in this correction, the Fama-Macbeth t-statistics are more reliable. These results imply that although allowing betas to vary over time improves the performance of the model, as apparent from the insignificant intercept, the model is still strongly challenged given the estimates of the risk premia.

To sum up, the results of the rolling regression approach show that the FF3 cannot be accepted as a valid asset pricing model for the Egyptian stock market. However, given the well-documented criticisms of the rolling regression approach, Sections 7.2.2 and 7.2.3 employ alternative ways to capture the time-variation in betas to determine whether using more advanced techniques can save the model.

7.2.2 Scaled Factor Models

This section presents the results of the scaled factor model approach as an alternative way to capture time-variation in betas. The scaled factor model approach defines beta as a linear function of investors' information set. But, since investors' information is unobservable, due care is given in choosing the appropriate set of conditioning variables to use in this thesis.

Although previous research on developed markets suggests some instrumental variables to use (Lettau and Ludvigson; 2001; Avramov and Chordia, 2006), Hadhri and Ftiti (2017) show that the same set of conditioning variables cannot be used for different markets as each country has its own specific domestic factors that can predict stock returns. Thus, rather than determining *a priori* the set of conditioning variables to use based on previous results, the following section assesses the predictive power of different instrumental variables to provide a firm basis upon which the final set of conditioning variables is determined.

7.2.2.1 Predictability Tests

The literature provides some useful guidelines to determine the appropriate set of conditioning variables to use when testing scaled factor models. First, instrumental variables should be correlated with the business cycle. In this regard, two variables are chosen which are: (i) the dividend yield on the Egyptian stock market; and (ii) the three-month Treasury bill rate. The choice of these variables is supported by the sufficient theoretical and empirical evidence about the predictive ability of these variables and their relationships with business and economic conditions as shown in Chapter 4 (Fama and French, 1989; Chen, 1991)

This thesis also evaluates the predictive ability of size and the book-to-market ratio, supported by the sufficient empirical evidence that these variables can predict the time-variation in expected returns and that they have separate roles as determinants of betas (Lewellen, 1999; Gomes *et al.*, 2003; Avramov and Chordia, 2006)[9].

To assess the predictive ability of these instrumental variables, two approaches are followed. First, the average adjusted R^2 values from the time-series regressions of excess stock returns of individual stocks on the lagged instrumental variables are presented. Second, the results of panel data regression of excess returns on the lagged instrumental variables are also presented to provide an overview of the coefficients of each along with their significance levels. In this regard, the following model is estimated:

$$R_{it} - R_{ft} = \alpha_{it} + \beta_1 Size_{it-1} + \beta_2 BM_{it-1} + \beta_3 DY_{t-1} + \beta_4 TB_{t-1} \qquad (7.3)$$

Where $Size_{it-1}$ is the natural logarithm of the firm's market capitalization, BM_{it-1} is the natural logarithm of the firm's book-to-market ratio, DY_{t-1} is the dividend yield on the 50 most active stocks listed in the Egyptian stock market, TB_{t-1} is the three-month Treasury bill rate.

Three main specifications of the above model are assessed in order to determine the final set of instrumental variables to use. Jagannathan and Wang (1996) argue that although several variables are useful to predict business cycles, researchers should restrict themselves to only a small number of variables in order to ensure precision in

[9] This is not a comprehensive variable set as there are other variables that may have strong predictive ability for stock returns, but they are not included here due to data availability. Specifically, although the default spread and term spread are among the most important variables in predicting stock returns, they are not included here as the bond market is relatively weak in Egypt.

the estimation of the parameters of the model. Thus, a comparison between the predictive ability of the dividend yield and the Treasury bill rate is undertaken to determine which of the two variables has a stronger role in predicting stock returns in the Egyptian stock market.

Panel A of Table 7.3 shows that the average adjusted R^2 of the full model that includes the four variables is 6.62%. When dividend yield is dropped from the model, the average adjusted R^2 decreases to 4.60%, while eliminating the Treasury bill rate from the model leads to a severe reduction in the value of the average adjusted R^2 to 2.65%. Thus, the results of the time-series regressions show that the Treasury bill rate has a stronger explanatory power in the predictive regressions compared to dividend yield.

Furthermore, the time-series regressions of the Fama and French three factors on dividend yield and the Treasury bill rate show the strong predictive ability of both variables. However, as apparent from the results of Panel B of Table 7.3, the predictive ability of the Treasury bill rate is stronger than that of the dividend yield given its high significance level across all models. Furthermore, Panel B of Table 7.3 shows that both the market factor and the SMB factor produce adjusted R^2 values that are consistent with the average adjusted R^2 for the individual stocks, but the HML produces a significantly lower adjusted R^2 of only 2.43%. These results imply that the HML factor does not contribute towards explaining the time-varying conditional expected returns as postulated by Ferson and Harvey (1999).

Before presenting the results of the panel-data regression, the Hausman test is performed to determine whether the fixed-effects or the random effects model is more appropriate. The result of the Hausman test, which tests whether the random effects are uncorrelated with the explanatory variables, is strongly rejected, suggesting that the fixed-effects model is more appropriate. Panel A of Table 7.3 shows that all of the variables are strongly significant and with the expected signs. Thus, these results give further support to the use of these variables as instrumental variables. Furthermore, by following Akaike information criterion (AIC) and the Bayesian information criterion (BIC) to determine the best set of instrumental variables to use, it is apparent that the model that uses size, the book-to-market ratio and the Treasury bill rate outperforms the model that uses size, the book-to-market ratio and the dividend yield, as the former model has lower AIC and BIC values.

Table 7.3: Predictability Tests

Panel A: Predictability Tests for Individual Stock Excess Returns				
Panel-Data Regression (Fixed-Effect)	Size	BM	DY	TB
Coefficient	-0.0635***	-0.0107*	0.0232***	-32.778***
T-stat	-25.26	-1.78	19.17	-27.30
	AIC(BIC) Criterion			
Full Model	-10,671.21(-10,632.86)			
Model Excluding DY	-10,306.8(-10,276.11)			
Model Excluding TB	-10,033.38(-10,002.66)			
Time-Series Regressions	Average Adjusted R^2			
Full Model	6.62%			
Model Excluding DY	4.60%			
Model Excluding TB	2.65%			

Panel B: Predictability Tests of the Fama and French Three-Factors			
	Market Factor	SMB	HML
Dividend Yield	0.014***	0.005	-0.011**
	(2.46)	(0.83)	(-1.94)
Treasury Bill	-19.4***	-17.56***	12.71**
	(-3.33)	(-3.09)	(2.3)
Adjusted R^2	6.12%	7.51%	2.43%

Notes: Panel A of Table 7.3 reports the slopes and the t-statistics in brackets, estimated from the panel-data regression for monthly individual stock excess returns on size, the book-to-market ratio, the dividend yield on the 50 most active stocks in the Egyptian stock market, and the Treasury bill rate. Panel A also presents the values of the average adjusted R^2 obtained from time-series regressions of individual stock excess returns on the four variables, on all of the variables excluding dividend yield, and on all of the variables excluding the Treasury bill rate. The results of the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) are also reported. Panel B reports the results of the time-series regressions of the Fama and French three-factors on the dividend yield and the Treasury bill rate.

* reflects significance at the 10% level
** reflects significance at the 5% level
*** reflects significance at the 1% level

Overall, given the results of Table 7.3 and the argument of Jagannathan and Wang (1996) that only a small set of instrumental variables should be used when testing conditional asset pricing models, the three main conditioning variables used in this thesis are: (i) size; (ii) the book-to-market ratio; and (iii) the Treasury bill rate.

7.2.2.2 Cross-Sectional Regressions of Excess Stock Returns on Firm Characteristics

The aim of this section is to present the results of the Fama-Macbeth cross-sectional regressions of excess returns (risk-unadjusted returns) on a set of firm characteristics that are believed to be important determinants of expected returns. The importance of this section emerges from the need to determine whether the significant relationship between these firm characteristics and expected returns that is documented in several developed markets (see for example, Avramov and Chordia, 2006; Bauer *et al*., 2010) also holds for the Egyptian stock market. Furthermore, these results provide a benchmark against which the results of the cross-sectional regressions that use risk-adjusted returns as the main dependent variable are compared to see whether adjusting for risk can eliminate the role of these variables as determinants of stock returns.

The firm characteristics that are included in the cross-sectional regression are: (i) firm size; (ii) the book-to-market ratio; (iii) turnover; and (iv) cumulative returns over the 2^{nd} through 3^{rd}, 4^{th} through 6^{th}, and 7^{th} through 12^{th} months before the current month. Cumulative returns are constructed to exclude the returns during the immediate month prior to month t and the size and turnover variables are lagged two months with respect to excess returns or risk-adjusted returns to avoid any spurious association due to either thin trading or bid-ask spread effects. Furthermore, following Brennan *et al.* (1998) and Avramov and Chordia (2006), all firm characteristics for a given month are expressed as deviations from their cross-sectional mean for that month. This implies that the average stock will have values for each non-risk characteristic that are equal to zero. Thus, under the null hypothesis that firm characteristics do not have significant incremental power for capturing the cross-section of returns or the alternative hypothesis that they have significant explanatory power, the return on the average stock is determined solely by its risk characteristics (Bauer *et al.*, 2010).

Table 7.4 presents the results of the Fama-Macbeth cross-sectional regression of excess stock returns on the firm characteristics. The results show that the average adjusted R^2 is 13.37% which implies that the firm characteristics employed in the regression capture substantial cross-sectional variations in stock returns. The coefficient of firm size is significantly negative which supports the results of previous studies that small firms earn higher returns compared to large ones (Avramov and Chordia, 2006). The coefficient of the book-to-market ratio is negative but statistically insignificant which implies that the value effect is absent in the Egyptian stock market, supporting the results in Chapter 6. The coefficient of the turnover ratio is positive and insignificant which contrasts with the previous results in developed markets that show that high turnover stocks earn lower returns compared to lower turnover stocks (Brennan *et al.*, 1998; Avramov and Chordia, 2006).

Finally, by analysing the coefficients of the three variables that are used as proxies for momentum in stock returns, it is apparent that both the coefficients of the cumulative returns over the 7^{th} through 12^{th} months and over the 4^{th} through 6^{th} months before the current month are positive but insignificant, while the coefficient of the cumulative returns over the 2^{nd} through 3^{rd} months before the current month is negative and insignificant. These results support the previous results of Sakr *et al.* (2014) that document that there is weak momentum in stock returns in the Egyptian stock market.

After presenting the results of Fama-Macbeth cross-sectional regressions of excess stock returns on the firm characteristics that are believed to be significant determinants of stock returns, the aim of the next section is to determine whether adjusting for risk can eliminate the role of these characteristics as determinants of stock returns.

Table 7.4: Cross-Sectional Regressions of Risk-Unadjusted (Adjusted) Returns on Firm Characteristics

	Risk-Unadj. Returns	CAPM	FF	CAPM (TB)	FF (TB)	CAPM (Size & BM)	FF (Size & BM)	CAPM (Size, BM&TB)	FF (Size, BM&TB)
Constant	0.009 (0.86) [0.314]	0.0036 (0.74) [0.45]	-0.0083 (-2.14)** [0.030]	0.0037 (0.76) [0.421]	-0.0069 (-1.87)* [0.080]	0.0049 (0.98) [0.335]	-0.0066 (-1.93)* [0.051]	0.0045 (0.89) [0.400]	-0.0062 (-1.79)* [0.072]
Size	-0.0043 (-1.91)** [0.027]	-0.0038 (-1.76)* [0.054]	-0.0008 (-0.53) [0.708]	-0.0036 (-1.69)* [0.068]	-0.001 (-0.63) [0.607]	-0.0039 (-1.86)* [0.073]	-0.0006 (-0.42) [0.779]	-0.0035 (-1.75)* [0.073]	-0.0004 (-0.31) [0.769]
Book-to-Market Ratio	-0.0005 (-0.07) [0.923]	-0.00021 (-0.03) [0.942]	0.00084 (0.13) [0.902]	-0.00045 (-0.07) [0.910]	-0.0020 (-0.32) [0.748]	-0.0003 (-0.05) [0.912]	-0.0007 (-0.12) [0.942]	-0.0005 (-0.09) [0.872]	-0.0016 (-0.31) [0.747]
Turnover	0.0039 (1.38) [0.171]	0.0037 (1.53) [0.135]	0.0026 (1.05) [0.26]	0.0044 (1.82)* [0.072]	0.0035 (1.53) [0.096]	0.0049 (1.79)* [0.049]	0.0046 (2.13)** [0.034]	0.0055 (2.26)** [0.027]	0.0051 (2.47)** [0.015]
Cumulative Return(2-3 months)	-0.042 (-1.45) [0.146]	-0.048 (-1.83)* [0.078]	-0.0414 (-1.72)* [0.112]	-0.043 (-1.71)* [0.096]	-0.037 (-1.68)* [0.112]	-0.0513 (-2.21)** [0.024]	-0.0417 (-2.03)** [0.052]	-0.0522 (-2.26)** [0.03]	-0.0451 (-2.29)** [0.017]
Cumulative Return(4-6 months)	0.031 (1.16) [0.254]	0.025 (1.08) [0.296]	0.022 (0.97) [0.332]	0.024 (0.98) [0.342]	0.0236 (1.02) [0.336]	0.0189 (0.84) [0.426]	0.0168 (0.78) [0.442]	0.0183 (0.81) [0.395]	0.0188 (0.93) [0.377]
Cumulative Return(7-12 months)	0.017 (1.25) [0.281]	0.014 (1.11) [0.349]	0.0004 (0.03) [0.952]	0.016 (1.27) [0.271]	0.0079 (0.70) [0.601]	0.0077 (0.62) [0.606]	0.0037 (0.32) [0.793]	0.0096 (0.79) [0.451]	0.0065 (0.58) [0.599]
Average Adjusted R^2	13.37%	10.13%	6.67%	9.99%	7.0%	9.43%	5.94%	9.37%	6.04%

Notes: Table 7.4 presents the time-series averages of individual stock cross-sectional OLS regression coefficients. The second column presents the results when the risk-unadjusted return is used as the dependent variable. The third and fourth columns report the results when the dependent variable is the excess return risk-adjusted using market risk and the Fama and French three factors, respectively. The fifth and sixth columns report the results when the dependent variable is the excess return risk-adjusted using the market risk and the Fama and French factors when the loadings are scaled by the Treasury bill rate, respectively. The seventh and eighth columns report the results when the dependent variable is the excess return risk-adjusted using the market risk and the Fama and French three factors when the loadings are scaled by size and the B/M ratio, respectively. Finally, the ninth and tenth columns report the results when the dependent variable is the excess return risk-adjusted using the market risk and the Fama and French three factors when the loadings are scaled by the Treasury bill rate, size, and the B/M ratio, respectively. The t-statistics reported in brackets are from heteroskedasticity and autocorrelation consistent regressions. The bootstrap p-values are reported in square brackets.

* reflects significance at the 10% level
** reflects significance at the 5% level
*** reflects significance at the 1% level

7.2.2.3 Cross-Sectional Regressions of Risk-Adjusted Returns on Firm Characteristics

The aim of this section is to evaluate the performance of different specifications of asset pricing models to determine whether taking the time-variation in risk into consideration using a scaled factor model approach can explain the size, book-to-market, turnover, and momentum effects on expected returns, all of which are considered as financial markets anomalies (Avramov and Chordia, 2006). To achieve this aim, a time-series regression is estimated of excess stock returns on risk factors with loadings that may vary cross-sectionally and over time with stock-level size and the book-to-market ratio as well as with the Treasury bill rate:

$$R_{it} = \alpha_{i0} + \sum_{k=1}^{3}(\beta_{ik0} + \beta_{ik1} Z_{it-1}) FF_{kt} + \varepsilon_{it} \qquad (7.4)$$

where Z_{it-1} represents a vector of the conditioning variables, 2while FF_{kt} represents the Fama-French factors (R_M, SMB and HML).

Then, a cross-sectional regression is estimated of risk-adjusted returns (r_{it}^*), calculated as the sum of the pricing errors and the residuals from the time-series regression in Equation 7.4, on the firm characteristics (Y_{it-1}) as in Equation 7.5. Under the null hypothesis of exact pricing, all of these characteristics should be insignificant in the cross-sectional regressions. Furthermore, Avramov and Chordia (2006) argue that if the asset pricing model employed in the first-pass time-series regression is well-specified, then the average of the adjusted R^2 values from the cross-sectional regression estimated each month should be low.

$$r_{it}^* = c_{0t} + c_t Y_{it-1} + e_{jt} \qquad (7.5)$$

Several models are assessed and their results are compared to detect which model specification provides the best explanation of the cross-sectional variation in stock returns for the Egyptian stock market. The first model is the unconditional CAPM to be used as a benchmark against which all other models are compared as it is one of the basic tenets in finance (Avramov and Chordia, 2006). Table 7.4 shows that adjusting returns for market risk does not lead to major changes in the coefficients for all of the firm characteristics compared to the results of Section 7.2.2.2. Specifically, the coefficient of firm size remains significantly negative which supports previous results of Avramov and Chordia (2006) and Fama and French (1993) that the CAPM fails to capture the size effect. However, although the coefficient of the short-term cumulative returns remains negative, it is significant at the 10% level after adjusting for market risk. This, in turn, implies that the model is misspecified given the argument of Jagannathan and Wang (1998) that the t-statistics for the coefficients on the firm characteristics generally converge to infinity in probability when an asset pricing model is misspecified. Finally, the slight reduction in the value of the average adjusted R^2 after adjusting for market risk provides further evidence against the unconditional CAPM as a valid asset pricing model for the Egyptian stock market.

The second model is the unconditional FF3 which is the main asset pricing model employed in this thesis. The coefficient of firm size now becomes statistically insignificant which supports the results of Fama and French (1993, 1996) that their model can explain the size effect. However, these results contradict the results of Avramov and Chordia (2006) who find that the unconditional FF3 cannot explain the size anomaly. The ability of the model to capture the size effect provides evidence towards the long debate about whether risk factors or firm characteristics explain stock returns. Daniel and Titman (1997) argue that it is the security's characteristics not the loadings on the SMB and HML factors that have an impact on the cross-section of stock returns. Nonetheless, the results in this section provide evidence to the contrary as the FF3 is able to capture the size effect and this, in turn, supports the risk-based story.

However, the model still fails to explain the short-term reversal. This may indicate that the model is mis-specified as a result of ignoring the time-variation in risk. Another problem with the model is related to the magnitude and the significance of the intercept. The results show that the average stock underperforms relative to the FF3 by 9.96% per year which is an economically significant value. Finally, the value of the average adjusted R^2 decreases to 6.67% which is an improvement compared to the unconditional CAPM.

Given the failure of the unconditional models, the performance of the conditional versions of both models are assessed using different combinations of conditioning variables. The first conditioning variable to use is the Treasury bill rate. The results of the conditional CAPM in which the loading on the market risk factor is scaled by the Treasury bill rate are quite similar to the results of the unconditional CAPM except that turnover becomes significant at the 10% level which implies that the model is not appropriately specified. Similar to the conditional CAPM, scaling the loadings on the Fama and French factors by the Treasury bill rate does not save the model as the intercept remains significantly negative and the average adjusted R^2 value slightly increases compared to the unconditional model. However, the main difference between the results of the unconditional and the conditional FF3 is the marginal reduction in the significance of the short-term cumulative return which implies that time-variation in risk may be the main reason behind the significance of the coefficient of short-term cumulative returns observed in the models tested so far.

To assess whether the performance of the conditional models changes when different combinations of conditioning variables are used, the conditional CAPM and the FF3 are evaluated when size and the book-to-market ratio are used as conditioning variables. The results of the conditional CAPM show that scaling the factor loadings with size and the book-to-market ratio does not save the model. Specifically, the coefficients of firm size, turnover, and short-term cumulative return are significant which imply that model is mis-specified. However, the only improvement achieved by this version of the model is the decrease in the value of the average adjusted R^2 to be 9.43%. Nonetheless, despite this marginal improvement compared to the unconditional model, the value of the average adjusted R^2 is still high which indicates that the model faces a severe challenge to explain the cross-sectional variation in stock returns in the Egyptian stock market.

Similarly, the results of the conditional FF3 in which the loadings are allowed to vary with size and the book-to-market ratio does not show a significant improvement over the unconditional model. Specifically, although the value of the average adjusted R^2 decreased to be 5.94%, the model is still challenged by the negative and significant intercept and by its failure to capture the effects of turnover and short-term cumulative returns.

Finally, the last specification of scaled factor models to test is to determine whether using the Treasury bill rate, size, and the book-to-market ratio together as conditioning variables can provide better results for both the CAPM and the FF3. However, the results of both models show that there are no major changes in the results compared to the models that use size and the book-to-market ratio as the only conditioning variables.

Thus, these results imply that using scaled factor model approach to capture time-variation in betas cannot save neither the CAPM nor the FF3 in the Egyptian stock market. Specifically, consistent with Avramov and Chordia (2006), all of the specifications of the conditional CAPM tested in this thesis fail to capture the size anomaly. In contrast, consistent with Fama and French (1996), the unconditional FF3 can explain the size effect. However, all the conditional versions of the FF3 tested in this section are still challenged by their failure to capture the short-term momentum and turnover effects which is consistent with the results of Avramov and Chordia who show that the conditional FF3 cannot capture momentum and liquidity effects.

Before concluding this section, some methodological aspects should be highlighted. First, the use of risk-adjusted returns in cross-sectional regressions is supported by many researchers to address the errors-in-variables bias when estimating the coefficients of the cross-sectional regression in finite samples (see for example, Shanken, 1992; Avramov and Chordia, 2006). However, it suffers from some criticisms. First, the standard errors estimated using the Fama-Macbeth procedure may be biased due to ignoring the errors involved when estimating the factor loadings in the first-pass time-series regressions (Avramov and Chordia, 2006). Thus, to partly mitigate this effect, wild bootstrap[10] is used and the p-values from the empirical distribution of the bootstrapped t-statistics are estimated and reported in Table 7.4.

Second, the scaled factor model approach imposes the assumption that the zero-beta return is equal to the risk-free rate and that the risk premium of a given factor is equal to the realized return on the underlying factor (Brennan *et al.*, 1998). Zhou and Paseka (2017) criticise the appropriateness of this assumption when factors are non-traded macroeconomic variables rather than excess returns on traded assets. This, in turn, creates some doubts for the assumption inherent in all of the tests performed in this section that the risk premium of any factor is equal to its realized return since some of the factors in scaled models do not represent excess returns on traded assets.

Finally, the reported t-statistics in Table 7.4 are calculated using standard errors corrected for heteroskedasticity and autocorrelation in order to mitigate the potential effects of autocorrelation or heteroskedasticity on the results.

To sum up, the results of this section show that although the conditional versions of the FF3 tested in this section outpaces those of the CAPM, the FF3 is still challenged by its failure to explain the turnover and short-term momentum effects. Furthermore, all of the versions of the FF3 tested have significant and negative intercepts. However, despite these unfavourable results, it should be noted that the results obtained in this section are strongly dependent on the set of conditioning variables used. Thus, in Chapter 8, investor sentiment is used as an additional conditioning variable to test if the conditional FF3 can be saved when the factor loadings are allowed to vary with sentiment.

7.2.3 The FF3 with Multivariate GARCH DCC Betas

Despite the inability of the conditional versions of the FF3 tested so far to fully capture the cross-sectional variation in stock returns, it is still too early to reject the model as

[10] The details about applying wild bootstrap are provided in Chapter 5.

a valid asset pricing model for the Egyptian stock market. Engle (2016) criticises the rolling regression and the scaled factor model approaches for capturing beta dynamics as they require identifying specific assumptions for the path of the betas. Thus, it is possible that these challenges facing the model are due to the inappropriateness of the approaches employed to capture beta dynamics. Consequently, the aim of this section is to test whether adopting conditional betas estimated through dynamic conditional correlations can save the FF3 and lead to better results.

Before presenting the results, several methodological issues should be highlighted regarding the tests that employ individual stocks as the main test assets. First, since the Egyptian stock market is an emerging market that suffers from thin trading, some of the stocks used in the sample may have months where there is no trading, and the problem of missing data may hinder the application of the DCC-GARCH. Thus, to avoid this problem, the missing values are replaced with zero.

Second, when estimating the betas for stocks using the DCC-GARCH, some stocks do not converge even after changing the initial values many times, thus these stocks are deleted from the sample. Consequently, the analysis in this section is performed on only 122 out of the 134 stocks that represent the full sample employed in this thesis.

7.2.3.1 Results Based on the 10 Portfolios Double-Sorted on Size and the Book-to-Market Ratio

The first part of this section aims to present the average conditional betas estimated using the DCC GARCH along with their standard deviations for the 10 portfolios sorted on size and the B/M ratio. The results of Table 7.5 can be summarized as follows. First, although the average market betas estimated using the DCC-GARCH are consistent with the estimates of the market betas obtained from the rolling regression approach, they are more volatile, especially for small stocks. This result is consistent with the argument of Ang and Chen (2007) that estimates of betas using a rolling regression approach understate the variation of the true conditional betas as they ignore the variations in betas in each window. Second, the market betas do not show wide variation across portfolios which imply that they do not play a significant role in explaining the wide variations in average returns across them. Third, the average SMB betas estimated using the DCC-GARCH are higher than those estimated using the rolling regression and are more volatile. However, in contrast to market betas, the SMB betas show substantial variations across the 10 portfolios which highlight the role of the SMB factor to capture the cross-sectional variation in stock returns. Finally, the HML betas estimated using the DCC GARCH are significantly different from those estimated using the rolling regression approach as they are mainly negative and less than 1 and they exhibit the lowest variability. This significant differences between the HML betas estimated using the DCC-GARCH and rolling regression approach may have substantial impact on the results of the Fama-Macbeth cross-sectional regression used to estimate the HML risk premium.

Table 7.5: Coefficients of the FF3 for the 10 Size/Book-to-Market Portfolios Estimated Using the DCC GARCH Approach

			Average Market Beta		
	Growth	B2	B3	B4	Value
Small	1.64(67%)	1.11(57%)	1.06(20%)	1.28(31%)	1.18(74%)
Big	1.04(12%)	0.84(14%)	0.93(14%)	0.97(34%)	1.02(33%)
			Average SMB Beta		
	Growth	B2	B3	B4	Value
Small	1.66(86%)	1.09(51%)	0.82(46%)	1.03(49%)	1.37(61%)
Big	-0.001(15%)	0.29(17%)	0.41(25%)	0.31(17%)	0.27(69%)
			Average HML Beta		
	Growth	B2	B3	B4	Value
Small	-1.05(12%)	-0.39(17%)	-0.27(11%)	-0.24(10%)	0.14(4.7%)
Big	-0.33(10%)	0.008(3.7%)	-0.16(7%)	0.03(3%)	0.22(43%)

Notes: Table 7.5 shows the coefficients of the Fama and French three risk factors estimated using the DCC GARCH, along with their standard deviations in brackets.

The second part of this section aims to analyse the results of the Fama-Macbeth cross-sectional regression reported in Table 7.6 to determine whether using more advanced techniques to capture the time-variation in betas can save the FF3 in the Egyptian stock market. The results can be summarized as follow. First, the intercept is negative and insignificant. However, these results cannot be taken as an evidence for the model as the magnitude of the intercept is high which poses some doubts on the validity of the model. Second, the market risk premium is positive but insignificant. Third, the size premium is significantly positive, but its magnitude is inconsistent with the sample average return of the SMB factor. Finally, consistent with all previous results reported in this chapter, the value premium is negative but statistically insignificant. To sum up, these results show using the DCC GARCH to capture the time-variation in betas does not save the FF3.

Table 7.6: Fama-Macbeth Cross-Sectional Regression Tests Applied to 10 Portfolios Double-Sorted on Size and the Book-to-Market Ratio and Individual Stocks Using DCC-GARCH Betas

Test Assets	α	λ_M	λ_{SMB}	λ_{HML}
Individual Stocks	-0.0055	-0.00096	0.0262	0.00114
	(-0.92)	(-0.16)	(1.86)*	(0.10)
	[0.389]	[0.609]	[0.027]	[0.48]
10 Size/B/M Portfolios	-0.021	0.0173	0.0341	-0.0092
	(-1.43)	(1.34)	(1.83)*	(-0.57)
	[0.173]	[0.105]	[0.023]	[0.689]
Fama and French Factors		$\overline{R_M - R_f}$	$\overline{SMB}$	$\overline{HML}$
Sample Average Return		1.19%	1.82%	-0.0317%

Notes: Table 7.6 presents the intercepts and slopes of the Fama-Macbeth cross-sectional regression of monthly excess returns of individual stocks and the 10 portfolios double sorted on size and the book-to-market ratio based on their DCC betas for the sample period July 2004 to June 2016. T-statistics are reported in brackets and are derived from heteroskedasticity and autocorrelation consistent regression. The bootstrap p-values are reported in square brackets. The results are obtained from the following regression:

$$R_{it} - R_{ft} = \alpha_t + \hat{\beta}_{it}\lambda_t$$

* reflects significance at the 10% level
** reflects significance at the 5% level
*** reflects significance at the 1% level

7.2.3.2 Results Based on Individual Stocks

To augment the results of the previous section and provide more reliable inferences, all the above tests are repeated with individual stocks as the main test asset. Although the intercept is negative and insignificant, the sign, significance, and magnitude of the risk premia of the three Fama and French factors provide less support for the model. In particular, similar to the results of the rolling regression approach, the market risk premium is negative but statistically and economically insignificant. The risk premium associated with the SMB factor is positive and statistically significant, however its magnitude is inconsistent with the sample average return. Finally, the risk premium associated with the HML factor is positive and insignificant. By comparing these results to the results obtained when betas are estimated using rolling regression approach, it is apparent that using the DCC-GARCH to model the time-variation in betas does not lead to a significant difference in the results.

Since this section use individual stocks as the test assets, the results are susceptible to the errors-in-variables bias. Thus, to partly mitigate its effect, a wild bootstrap is used and the p-values estimated from the empirical distribution of the bootstrapped t-statistic are reported in Table 7.6, though there is no change in the main inferences.

To sum up, the results provide less favourable evidence concerning the validity of the FF3 compared to the results obtained when time-variation in betas is modelled using the rolling regression approach, despite the argument that the betas estimated using the DCC-GARCH approach are more accurate. These results are consistent with the results of Grek and Jimaale (2015) who show that for the Swedish stock market, betas estimated using a rolling regression approach outperform betas estimated using the more complex DCC GARCH approach.

7.3 Comparison between the Models

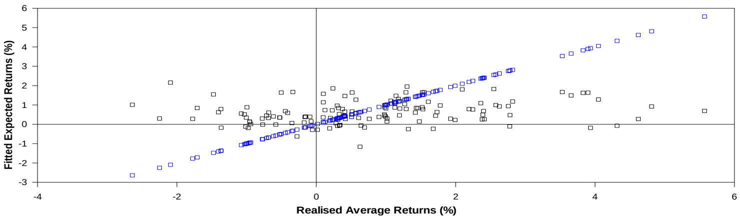
The aim of this section is to provide a more comprehensive picture about the performance of the FF3 by comparing between the different specifications tested in this chapter. In this section, the focus is mainly on the results of the tests that use individual stocks as the main test assets as they are more efficient. To achieve this aim, a visual comparison between the performances of these models is undertaken by plotting the fitted expected returns from the models against the realized average returns. If the model is correctly specified, then the fitted returns should lie on the 45-degree line through the origin. Panel A of Figure 7.1 represents the graph of the fitted expected returns against realized average returns for the FF3 in which the time-variation in betas is captured using the rolling regression approach. Panel A shows that the model is far from a perfect fit which is expected from the results obtained from Table 7.2. Specifically, the model overestimates the average realized returns if they are negative, but underestimates them if they are positive. This may explain why the intercept of the FF3 that uses rolling betas is positive and insignificant in Table 7.2. Finally, to provide further insights about the performance of the model, the pricing error is estimated as follows:

$$\varepsilon_{\ i} = E\left(R_{it} - R_{ft}\right) - E(\lambda_M)E(\beta_{iM}) - E(\lambda_{SMB})E(\beta_{iS}) - E(\lambda_{HML})E(\beta_{iH}) \quad (7.6)$$

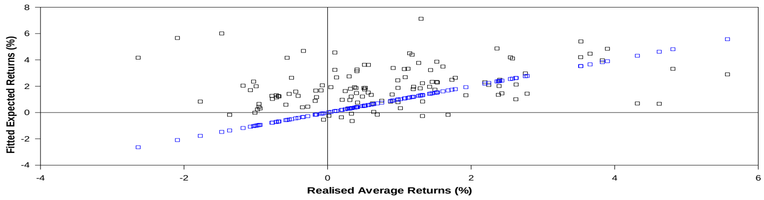
where the expected betas and expected risk premia are proxied by the sample averages. In addition, when calculating the pricing error, the covariance between the betas and risk premia are assumed to be zero. The average absolute pricing error of this model is 1.23% which is significantly different from zero.

Panel B presents the graph that plot the fitted returns from the FF3 that uses the DCC betas. it shows that the model consistently overestimates the average realized returns and achieves an average absolute pricing error of 1.69% which is even higher than that of the model that uses rolling betas supporting the results in Section 7.2.3.2.

Several points are noted from the above analysis. All of the models tested have significant and large pricing errors. Fama and French (1997) argue that there are two main problems that may result in the observed high pricing errors. First, despite the overwhelming empirical evidence documenting the time-variation in betas, Fama and French argue that as long as there is no agreed methodology that can capture time-variations in betas accurately, high pricing errors are expected to be observed. Second, the observed high pricing errors may be due to employing imprecise estimates of the risk premia. In this regard, the risk premia of the Fama and French factors are estimated using the standard Fama-Macbeth procedure and, following Lewellen *et al.* (2010), the magnitude of each risk premium is compared to the sample average return of the associated risk factor. However, the results of the Chapter 6 shows that all of the risk factors exhibit high variability and thus the sample average may not be a valid benchmark against which to compare the estimates of the risk premia (Fama and French, 1997). Furthermore, the results presented in Panel B of Table 7.3 show that both the expected risk premia on the market and the SMB factors can be predicted using the Treasury bill rate and the dividend yield which support the overwhelming empirical evidence that risk premia vary over time. Consequently, ignoring this time-variation in risk premia may result in the observed high pricing errors.



Panel A: Fama and French Model with Rolling Betas



Panel B: Fama and French Model with DCC Betas

Figure 7.1: Fitted Expected Returns versus Average Realized Returns

7.4 Conclusion

The main aim of this thesis is to determine a valuation model for the Egyptian stock market by comparing between conventional and behavioural asset pricing models. Within the context of this aim, this chapter tests whether different conditional versions of the FF3 can explain the cross-sectional variation in stock returns. Standard asset pricing models normally face severe challenges in explaining the cross-sectional variation in stock returns in emerging markets (Dash and Mahakud, 2014). Thus, the results of this chapter add further evidence to the literature about emerging markets and the challenges they pose to asset pricing models.

Specifically, this chapter answers the question of whether the Egyptian version of the Fama and French three risk factors can explain the cross-sectional variation in stock returns. Furthermore, motivated by the highly volatile nature of the Egyptian stock market during the sample period due to the prevalent political and economic instability especially after the Egyptian revolution in 2011, this chapter tests whether the conditional FF3 can explain the cross-sectional variation in stock returns in the Egyptian stock market. The contribution of these tests emerges from two main aspects. First, as highlighted in Chapter 4, there is a significant lack in the studies that test conditional asset pricing in emerging markets generally and the Egyptian stock market particularly, despite the claims of Iqbal *et al.* (2010) that the volatile nature of these markets makes the assumptions of constant betas and risk premia highly questionable. Thus, this thesis fills this gap by analysing whether different versions of the conditional FF3 can explain the cross-sectional variation in stock returns. Second, despite the theoretical appeal of conditional asset pricing models, there is no agreement upon which approach can capture time-variation in betas accurately. Thus, given this controversy, this thesis contributes to the literature by employing three main approaches to capture time-variation in betas which are rolling regression approach, scaled factor model approach and the DCC-GARCH approach and comparing between them to determine which approach provides a superior way to capture time-variation in betas.

The results of this chapter can be summarized as follows. First, the results of the FF3 that uses rolling regression approach to capture time-variation in betas show that the model is far from prefect as it has high and significant pricing errors. Furthermore, the model is weakened by the sign and the significance of the market risk premium which turns to be negative and insignificant. However, these results should not be interpreted as evidence against the validity of the FF3 in the Egyptian stock market given the criticism of Ang and Chen (2007) regarding the use of rolling regression to capture time-variation in betas.

This chapter also analyses whether capturing time-variation in betas using scaled factor model can save the FF3 in the Egyptian stock market. The results show that none of the specifications of the CAPM and the FF3 tested is able to accommodate all of the asset pricing anomalies. Relative to other specifications tested, the FF3 in which the risk factors are allowed to vary with size and the book-to-market ratio is considered the best specification. Nonetheless, this model faces two main criticisms. First, the model is still challenged by its inability to capture the turnover and short-term momentum effects which is consistent with the results of Avramov and Chordia (2006). Second, researchers, analysts and practitioners should be careful when using this model to calculate the cost of equity. Since size and the book-to-market ratio are somehow under managers' control, managers who use these models can change the estimated cost of equity by manipulating size and the book-to-market ratio which may bias the projects that are accepted (Fama and French, 1997).

Finally, despite the claims that the DCC-GARCH model provides more accurate estimates of betas compared to the rolling regression approach, the results provide less favourable evidence concerning the validity of the FF3 that uses the DCC betas in the Egyptian stock market given its high pricing errors.

Given the unfavourable results obtained in this chapter, the aim of Chapter 8 is to extend the results obtained in this chapter by testing two main breakthroughs. The first one is concerned with testing whether the conditional FF3 that takes time-variation in risk and risk premia into consideration can provide better explanation of the cross-sectional variation in stock returns. The second breakthrough is concerned with testing whether augmenting the FF3 with investor sentiment can provide a better valuation model for the Egyptian stock market.

Chapter 8

Conditional Models with Time-Varying Risk Premia and Behavioural Asset Pricing Models

8.1 Introduction

Chapter 7 focuses mainly on testing alternative versions of the conditional FF3 that take time-variation in betas into consideration. However, none of these versions is able to explain the cross-sectional variation in stock returns in the Egyptian stock market. These results provide a useful basis upon which this chapter is built. Specifically, the aim of this chapter is twofold. First, given the results of Ferson and Harvey (1991) and Vendrame *et al.* (2018) about the importance of modelling time-variation in risk premia, the failure of the conditional versions of the FF3 tested in Chapter 7 may be attributed to ignoring modelling time-variation in risk premia. Thus, this chapter aims to determine whether taking time-variation in risk premia into consideration can save the FF3 in the Egyptian stock market.

Second, since identifying the appropriate state variables to use is one of the crucial steps in testing asset pricing models, the failure of the conditional versions of the FF3 tested in Chapter 7 to capture the cross-sectional variation in stock returns in the Egyptian stock market may be attributed to the failure of the model to incorporate the impact of noise traders on prices. The rationale behind this assumption is as follows. First, the Egyptian stock market is an emerging market that is dominated by small investors who are more prone to behavioural biases (Schmitz *et al*., 2006). Second, the Egyptian stock market is characterized by noise and speculative trading behaviour (Metwally and Darwish, 2015; Omran, 2007). Third, De Long *et al.* (1990) provide theoretical model that highlights the impact of noise traders on expected returns. These reasons imply that investor sentiment can have a significant impact on stock prices in the Egyptian stock market. Thus, in this chapter, the role of investor sentiment on stock prices is assessed through two main channels. The first channel uses investor sentiment as a conditioning variable within the context of scaled factor model approach. The second channel uses investor sentiment as additional risk factor to determine whether augmenting the FF3 with an additional behavioural factor can provide better explanation of the cross-sectional variation in stock returns.

The outline of this chapter is as follows. Section 8.2 presents the results of the Markov switching model. Section 8.3 reports the results of the tests of the conditional FF3 that takes time-variation in risk and risk premia into consideration. Section 8.4 analyses the role of investor sentiment on stock prices through testing whether using investor sentiment as a conditioning variable or as a risk factor can improve the ability of the FF3 to capture the cross-sectional variation in stock returns. Finally, Section 8.5 concludes.

8.2 Markov Switching Regimes

One reason behind the unfavourable results obtained in Chapter 7 is that all the tests ignore the time-variation in risk premia. The rationale behind this explanation is the significant empirical evidence that the Fama and French three factors show considerable variation over time (see for example, Vendrame *et al.*, 2018; Perez-Quiros and Timmermann, 2000; Zhang, 2005). Thus, the aim of this chapter is to determine whether taking time-variation in risk premia into consideration can improve the performance of the FF3.

However, similar to the difficulties encountered to determine the appropriate method for modelling time-variation in betas, modelling time-variation in risk premia is also challenging. The main assumption followed here is that there are two risk premia for each factor: one for the bull regime and one for the bear regime. Specifically, it is assumed that there are two regimes (bull and bear) characterizing the market during the sample period. These regimes are obtained using a Markov switching process with a probability that depends on the realization of an unobservable variable, the state or the regime, which is random but assumed to be determined by the realization of the real excess return of the market portfolio. First, a simple nonlinear model for the real excess return of the market portfolio is assumed:

$$RR_{Mt} = \mu_{Mi} + \sigma_{Mi}\varepsilon_t \qquad (8.1)$$

where RR_{Mt} is the real excess return of the market portfolio, the parameters μ_{Mi} and σ_{Mi} are assumed to vary with regime $i = 1,2$, and ε_t is a random error term assumed to be normally distributed. However, the above simple model is not able to probably identify the main events the Egyptian stock market witnessed during the sample period. One reason that may predict the failure of the above model is that it does not account for the impact of the Egyptian revolution in 2011. The Egyptian revolution represents a structural break not only in the Egyptian stock market but also for the whole country. Thus, to account for the impact of the revolution, a dummy variable (D_{Revol}) is added that is equal to 1 for the period after revolution and zero otherwise. The nonlinear model for the real excess return of the market portfolio becomes as follows:

$$RR_{Mt} = \mu_{Mi} + \mu_{Mi}^{*}D_{Revol,t} + \sigma_{Mi}\varepsilon_t + \sigma_{Mi}^{*}D_{Revol,t}\varepsilon_t \qquad (8.2)$$

Equation 8.2 represents a univariate Markov switching model. All the variables in Equation 8.2 are defined as Equation 8.1 except that μ_{Mi}^{*} and σ_{Mi}^{*} are added to account for the impact of the revolution. All the parameters of the above model take only one of two values depending on the prevailing regime $i = 1,2$. The transition probabilities are defined as $p_{ij} = p_{unadij} + p_{ij}^{*} * D_{Revol}$. The filtered probabilities are estimated using the Expected Maximization algorithm of Hamilton (1989) and are outlined in Figure 8.1.

Before presenting the results, it is worth noting that when estimating the above model, the mean return of the market portfolio in the bear regime (μ_{M2}) turns to be insignificant. Specifically, the bear market average return is found to be -0.29% with a t-statistic of -0.31 and a p-value of 0.75. Thus, the model is re-estimated while forcing μ_{M2} to be equal to zero. Table 8.1 reports the results of this restricted model.

The results show that, before the revolution, the market can be characterized by two regimes. The bull regime which has a mean of 3.2% and a standard deviation of 5%, and the bear regime which has low returns (on average zero) and a high standard deviation of 12.3%. These characteristics of the bull and bear regimes are consistent with previous research that shows that the bull regime is mainly a stable regime with high returns, while the bear regime is mainly a highly volatile regime with low returns.

Table 8.1: Parameters of Markov Switching Process

Parameters	Coefficients	T-Statistics (P-Value)
μ_1	0.032	2.94 (0.00)
μ_1^*	0.029	0.63 (0.52)
μ_2	-	-
μ_2^*	-0.043	-3.10 (0.00)
$p_{unadj12}$	0.176	1.70 (0.09)
p_{12}^*	0.55	2.27 (0.02)
$p_{unadj21}$	0.184	1.83 (0.07)
p_{21}^*	0.13	0.47 (0.63)
σ_1	0.05	7.05 (0.00)
σ_1^*	-0.001	-0.06 (0.95)
σ_2	0.123	22.54 (0.00)
σ_2^*	-0.084	-14.65 (0.00)

The transition probabilities also show interesting patterns before the revolution. Specifically, p_{12} which shows the probability of switching from the bull to bear regime is 17.6%, while p_{21} which shows the probability of switching from the bear to bull regime is 18.4%. This shows that the two regimes are persistent, i.e. once in the regime it is difficult to switch to another regime. Specifically, the expected duration of the bull regime is 5.68 months, while the expected duration of the bear regime is 5.43 months[11]. These results are reasonable given the main events the Egyptian stock market witnessed before the revolution. Specifically, as is apparent from Figure 8.1, the period before the revolution is mainly characterized by an overall

[11] Expected Duration is calculated as follows: $ED = 1/(1 - p_{ii})$

positive trend in which the market achieved remarkable performance outpacing both emerging and developed markets especially in 2005 and 2007. However, this overall positive trend was interrupted by a serious of negative events as follows:

1) Gulf stock market crash in 2006,
2) The rumours about imposing capital gain taxes that prevailed in the market from May 2008 till September 2008,
3) The Global financial crisis and its repercussion from September 2008 till February 2009,
4) The Dubai financial crisis in November 2009.

After the revolution, the political instability had a negative impact on the market which results in changing some of the characteristics of the above regimes. First, the bull regime remains to achieve a high significant return of 3.2%[12] with a standard deviation of 5%, while the mean of the bear regime decreases substantially to be -4.3% with a lower standard deviation of 3.9%. Second, the transition probabilities also show considerable changes after the revolution. In particular, p_{12} increases to be 73%, while p_{21} remains 18.4%[13]. These probabilities show that the bull regime is not persistent after the revolution with an expected duration of 1.36 months only. In contrast, the bear regime remains persistent after the revolution with an expected duration of 5.43 months. These results are consistent with the unstable period that the Egyptian stock market witnessed after the revolution that are marked by the following events:

1) The Arab Spring,
2) The trials of the President Hosny Mubarak and the US debt crisis from June to November 2011.

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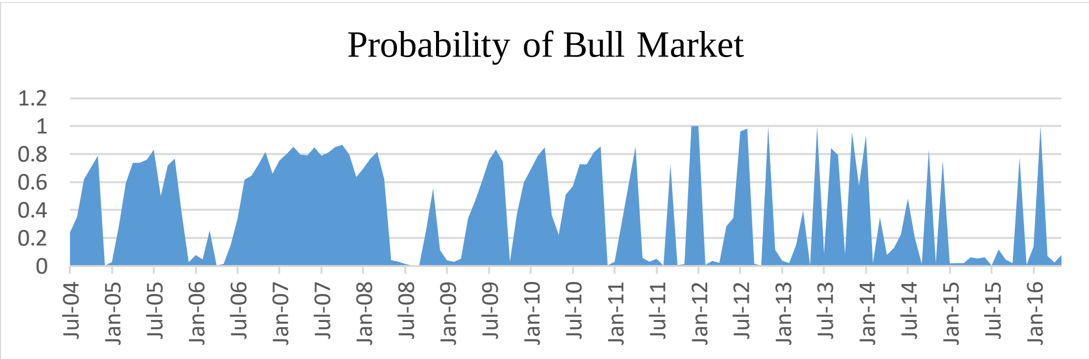
[12] Although μ_{M1}^{*} is equal to 2.9% it is insignificant in the restricted model and thus it was not added to the mean return before the revolution to determine the mean return of the market after the revolution.

[13] Although p_{21}^{*} is 13% it is insignificant and thus it was not added to $p_{unadj21}$ in determining the transition probability after the revolution.

3) Political tension in 2012 due to the constitutional committee and the preparation for the presidential elections,
4) Political unrest that led to the eruption of the second Egyptian revolution in 2013,
5) The slow world economic growth led by China's weak economic performance and the currency war between the US and China in 2015,
6) The slow economic growth rates in the MENA region due to recurring tensions and the increased conflicts in many countries and the sharp decline in the oil prices in 2015,
7) The slow global economic growth in 2016.

It is apparent that the main events that the Egyptian stock market passed by during the sample period are well captured by the regimes identified by the proposed Markov switching model in Equation 8.2. The two regimes are mainly distinguished by their means where the first regime can be described by being a bull regime with high average returns, whereas the second regime is characterized by being a bear regime with negative average returns. Finally, it is worth recalling that since the market risk premium is a function of both risk aversion and volatility, the regimes identified above are assumed to be able to capture the time-variation in risk aversion and thus should reveal time-varying risk premia which is one of the main aims of this chapter. Thus, although, this chapter does not model time-varying risk aversion explicitly, it is captured indirectly through modelling time-varying risk premia that depends on the prevailing regime in the market. In particular, investors are assumed to tolerate negative realized premiums during bear regimes knowing that they will be compensated with positive realized premiums during bull regimes. Vendrame *et al.* (2018) argue that, in such context, the unconditionally risk averse investors may be considered as conditionally risk seekers as they are willing to tolerate negative returns during bear regimes. But, they are willing to do that only if, in probability, they are compensated for bearing these losses during bull regimes.

To conclude, although the regimes identified are determined by the realization of the real return of the market portfolio only, they are able to capture the main business cycles the Egyptian stock market passed by during the sample period. Furthermore, using Markov switching process to identify the regimes provides major advantages over the simple approach followed in Chapter 6 that defines a bull (bear) regime based on whether the excess market return is positive (negative). In particular, defining the regimes based on the sign of the excess market return provide inaccurate description of the regime. A bull (bear) regime may include periods of negative (positive) market excess return but it is fundamentally characterized by an overall up (down) trend. Thus, this means that some periods of positive (negative) returns should be accounted for in the estimation of bear (bull) regime as proposed by the Markov switching model applied in this section.



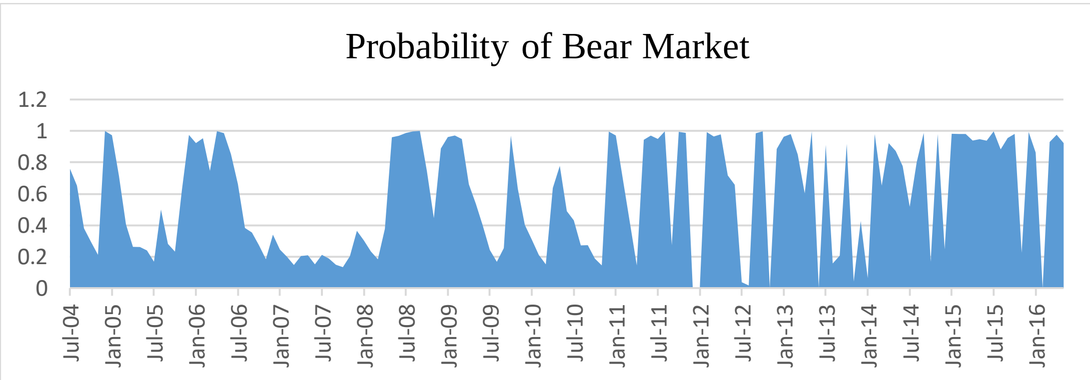


Figure 8.1: Filtered Probabilities of the Bull and Bear Regimes (July 2004 to June2016)

8.3 Time-Varying Risk Premia

The main aim of this section is to analyse whether allowing risk premia to vary over time can improve the ability of the FF3 to capture the cross-sectional variation in stock returns in the Egyptian stock market. To pursue this aim, it is assumed that there are two risk premia for each risk factor associated with bull and bear regimes. To identify these regimes, a Markov switching process is adopted as outlined in Section 8.2.

The main approach followed in this section is as follows. To extend the approach followed in Chapter 7 that allows only for time-varying betas, this section allows for time variation in both betas and risk premia. Specifically, time-variation in betas is captured using two main approaches which are the simple rolling regression approach and the DCC-GARCH model. Then, to estimate the risk premia associated with each regime, panel data regression is adopted in order to overcome the obstacle of having to estimate two sets of risk premia and having only one set of factor loadings (betas) each time. The advantage of panel data regression over the simple cross-sectional regression is that it allows for increasing the dimension of the equations from which the unknown variables are estimated.

As outlined in Chapter 5, given the state probabilities estimated using Markov switching process, the return of any asset i at time t can be modelled as follows:

$$R_{it} - R_{ft} = \gamma_0 + \gamma_{12}^{m} p_t \beta_{Mit} + \gamma_2^{m} \beta_{Mit} + \gamma_{12}^{s} p_t \beta_{Sit} + \gamma_2^{s} \beta_{Sit} + \gamma_{12}^{h} p_t \beta_{Hit} + \gamma_2^{h} \beta_{Hit} + \varepsilon_{it} \qquad (8.3)$$

where for each Fama and French factor (Market, SMB, and HML), $\gamma_{12} = \gamma_1 - \gamma_2$ is the difference between the bull risk premia (γ_1) and the bear risk premia (γ_2). p_t is the probability of the bull market estimated using Markov switching process. β_{it} represent the betas estimated using either the rolling regression approach or the DCC-GARCH model.

Once estimates of $\hat{\gamma}_1$ and $\hat{\gamma}_2$ are obtained, a simple test of the unconditional FF3 can be undertaken which is considered an essential step before testing the conditional version of the model. Specifically, the main proposition of the unconditional model is that the bull and bear risk premia should not only be equal but they should also be positive as follows:

$$\mathrm{H}_0: \begin{cases} \hat{\gamma}_1^m - \hat{\gamma}_2^m = 0 \\ \hat{\gamma}_1^s - \hat{\gamma}_2^s = 0 \\ \hat{\gamma}_1^h - \hat{\gamma}_2^h = 0 \end{cases}$$

$$\mathrm{H}_1: \begin{cases} \hat{\gamma}_1^m - \hat{\gamma}_2^m \neq 0 \\ \hat{\gamma}_1^s - \hat{\gamma}_2^s \neq 0 \\ \hat{\gamma}_1^h - \hat{\gamma}_2^h \neq 0 \end{cases}$$

Rejecting the null hypothesis can be taken as an evidence for the conditional model. However, to provide a full test of the conditional version of the model, the weighted average of the risk premia should be positive which implies that investors require positive risk premium to hold risky assets. To perform this test, a simple time-series test on the average (conditional) risk premia of each factor can be undertaken:

$$\mathrm{H}_0: \begin{cases} E(\Gamma_{mt}) = 0 \\ E(\Gamma_{st}) = 0 \\ E(\Gamma_{ht}) = 0 \end{cases}$$

$$\mathrm{H}_1: \begin{cases} E(\Gamma_{mt}) > 0 \\ E(\Gamma_{st}) > 0 \\ E(\Gamma_{ht}) > 0 \end{cases}$$

where $\Gamma_{mt} = p_t\hat{\gamma}_1^m + (1 - p_t)\hat{\gamma}_2^m$, $\Gamma_{st} = p_t\hat{\gamma}_1^s + (1 - p_t)\hat{\gamma}_2^s$, $\Gamma_{ht} = p_t\hat{\gamma}_1^h + (1 - p_t)\hat{\gamma}_2^h$. The t-statistics of the above test are estimated using Heteroskedasticity and Autocorrelation Consistent (hereafter HAC) standard errors. Furthermore, since the risk premia are estimated using three-pass approach that involves estimating the state probabilities, estimating betas, and estimating the risk premia, the results are subject to the errors-in-variables bias and to mitigate its effect, wild bootstrap is used.

All the tests in this section are applied on individual stocks rather than portfolios to permit more efficient tests of the models under consideration (Ang *et al.*, 2010). Section 8.3.1 tests the conditional FF3 using betas estimated from the simple rolling regression approach. Section 8.3.2 tests the model using betas estimated from the DCC-GARCH model.

8.3.1 Conditional FF3, Time-Varying Risk Premia and Rolling Betas

The panel data regression in Equation 8.3 is presented with its empirical results using betas estimated from the rolling regression approach as in this section or the DCC-GARCH model as in the following section. In the panel data regression, individual fixed effects panel data model is used, where the intercepts are allowed to vary across the individual stocks, but are assumed to be constant over time. Therefore, the intercepts are expected to capture an individual effect that has an impact on the individual stocks used in the sample but does not vary over time. Thus, one consequence of introducing fixed effects model is that the intercepts are removed from the results and only the risk premia are reported in Tables 8.2 and 8.3. Further, in unreported results, random effects model is estimated as an alternative to fixed effects model, but it was rejected by the Hausman (1978) specification test that shows that the fixed effects model is more appropriate.

The main parameters of interest in this section and the following section are: (i) the coefficients of the risk premia of each Fama and French factor; (ii) the results of the tests of the unconditional FF3; and (iii) the weighted average risk premia of each of the Fama and French factors. The t-statistics of the bull and bear risk premia estimated from the panel data regression in Equation 8.3 are calculated using Driscoll and Kraay (1998) heteroskedasticity consistent standard errors that are robust to very general forms of spatial and temporal dependence (Hoechle, 2007).

Table 8.2 shows that, consistent with the theoretical proposition, the bull risk premium of the market factor is significantly positive (5.79%), whereas its bear risk premium is significantly negative (-5.14%). Similarly, the bull risk premium of the SMB factor is significantly positive (2.07%), while its bear risk premium is significantly negative (-2.82). Thus, although the results show that both the market and the SMB factors are significantly priced in the bull regime, their bull risk premia are not high enough to compensate investors for the losses they incur during the bear regime especially for the SMB factor. Finally, inconsistent with the theoretical proposition, the bull risk premium of the HML factor is negative and insignificant, whereas its bear premium is positive (1.85%) and weakly significant.

The hypothesis of whether the unconditional FF3 hold in the Egyptian stock market is tested by analysing whether the bull and bear risk premia for each factor are different. The results strongly reject the unconditional version of the FF3. Specifically, the differences between the risk premia of the market factor and the SMB factor in both regimes are 10.93% and 4.89% respectively and both are statistically significant. In contrast, the results show that there is no significant variation between the bull and the bear risk premia for the HML factor which implies that it does not show considerable variation over time. These results are consistent with the results in Chapter 7 that shows that the HML factor does not contribute towards explaining the time-varying conditional expected returns as postulated by Ferson and Harvey (1999).

The results so far support the conditional version of the FF3. However, a complete test of the conditional model requires testing whether the weighted average risk premia of each factor is positive and significant.

$$\begin{cases} \Gamma_{mt} = p_t\hat{\gamma}_1^m + (1-p_t)\hat{\gamma}_2^m \\ \Gamma_{st} = p_t\hat{\gamma}_1^s + (1-p_t)\hat{\gamma}_2^s \\ \Gamma_{ht} = p_t\hat{\gamma}_1^h + (1-p_t)\hat{\gamma}_2^h \end{cases} \tag{8.4}$$

To test this last hypothesis, the t-test, calculated using the HAC standard errors, is applied to the time-series of the weighted average risk premia of each factor. Table 8.2 reports that the weighted average risk premium of the market factor is -0.63% and statistically insignificant, whereas the weighted average risk premium of the SMB factor is -0.80% and statistically significant. In contrast, the weighted average risk premia of the HML factor is 0.94% and statistically significant.

Before highlighting the main inferences derived from these results, there is an important shortcoming that is worth highlighting. Although asset pricing theories are mainly expressed in terms of ex-ante returns, they need to be linked to ex-post returns in order to be tested. This shift from the ex-ante universe to the ex-post universe is one of the main obstacles in asset pricing literature and many attempts have been proposed to provide accurate proxies for ex-ante returns. One of these attempts is averaging which represents the most commonly used approach to provide an accurate proxy for ex-ante returns. Nonetheless, Jorion and Goetzmann (1999) argue that since we do not have long enough data, averaging cannot always be considered as a way to provide an accurate proxy for ex-ante returns. This is especially true for this thesis, as the analysis is based on 142 months due to the limited data available about the Egyptian stock market. However, given the standard practice in finance, the unobserved ex-ante risk premia in the thesis is proxied by the average realized ex-post risk premia as shown in Equation 8.4.

The main inferences derived from the above results are as follows. The weighted average risk premia of the market and the SMB factors are negative which results in rejecting the null hypothesis that the weighted average risk premia should be positive and significant and this implies that the conditional version of the FF3 is not supported in the Egyptian stock market. However, these results may be attributed to two main reasons. First, Vendrame *et al.* (2018) argue that although conditionally the risk premia should be positive, it is possible to find some empirical cases in which the weighted average ex-post risk premium is negative. The above result may be among these cases due to the short sample period which may negatively impact the accuracy of the weighted average ex-post risk premia as a proxy for ex-ante risk premia.

Table 8.2: Conditional FF3 with Rolling Betas (Fixed Effects Panel Data; July 2004 to June 2016)

	Bull	Bear
γ^m	0.0579 (3.14)***	-0.0514 (-5.43)***
γ^s	0.0207 (2.37)**	-0.0282 (-3.54)***
γ^h	-0.0035 (-0.38)	0.0185 (1.81)*
	Tests of the Unconditional FF3	
$\hat{\gamma}_1^m - \hat{\gamma}_2^m$	0.10927 (6.55)***	
$\hat{\gamma}_1^s - \hat{\gamma}_2^s$	0.04892 (5.48)***	
$\hat{\gamma}_1^h - \hat{\gamma}_2^h$	-0.02204 (-1.62)	
	Weighted Average Risk Premia	
Γ_m	-0.00628 (-1.21) [0.240]	
Γ_s	-0.00804 (-3.46)*** [0.00]	
Γ_h	0.00944 (9.03)*** [0.00]	

Notes: Table 8.2 reports the results of the panel data regressions with individual-fixed effects applied on the individual stocks over the period July 2004 to June 2016 using betas estimated from the simple rolling regression approach for the two regimes: bull and bear. The bull and bear risk premia are reported for each Fama and French factor along with their t-statistics calculated using the Driscoll and Kraay (1998) standard errors and reported in brackets. The Table also reports the results of the tests of the difference between the two risk premia (bull and bear) of each factor along with their t-statistics calculated using the Driscoll and Kraay (1998) standard errors and reported in brackets. Finally, the results of the simple time-series test applied on the weighted average risk premia of each of the factors are reported along with the t-statistics derived from a heteroskedasticity and autocorrelation consistent regression reported in brackets. The bootstrap p-values are reported in square brackets. The risk premia are estimated from the following panel data regression:

$$R_{it} - R_{ft} = \gamma_0 + \gamma_{12}^m p_t \beta_{Mit} + \gamma_2^m \beta_{Mit} + \gamma_{12}^s p_t \beta_{Sit} + \gamma_2^s \beta_{Sit} + \gamma_{12}^h p_t \beta_{Hit} + \gamma_2^h \beta_{Hit} + \varepsilon_{it}$$

* reflects significance at the 10% level

** reflects significance at the 5% level

*** reflects significance at the 1% level

Second, since the bull risk premia of both the market and the SMB factors are not high enough to compensate investors for the losses they incur during the bear regime and since the probabilities of the bull and bear regimes identified using Markov switching model in Section 8.2 show that the bear regime is more prevalent in the Egyptian stock market during the sample period, this may justify why the risk premia of both the market and the SMB factors are negative. Specifically, there was not enough bull markets in Egypt during the sample period to reward investors for holding risky stocks. Nonetheless, as the probability of bull regimes increases and the growth plans undertaken by the Egyptian government start to show their impact, investors are expected to be significantly rewarded for holding risky stocks in the Egyptian stock market.

Since the risk premia of the HML factor during the bear regime is positive and significant, it can be inferred that the HML factor can provide a good hedge against unfavourable market conditions. This is also apparent from the positive and significant weighted average risk premia of the HML factor. This observation about the sign of the HML factor in different regimes can provide some intuition about the controversy of whether the HML factor is compensation for risk. Lakonishok *et al.* (1994) argue that the fact that value firms outperform growth firms (existence of positive value premium) during bad states of the economy may cast doubts on the claims that value stocks are fundamentally riskier than growth stocks. Nonetheless, Fama and French (1996) argue that the observation that periods of low returns on value stocks (negative value premium) does not correspond to periods of low market returns or low GNP does not necessarily imply that the value premium is irrational. They emphasise that the HML factor is not the market factor and it should not be expected to find any relation between it and any variable that generates the market factor. Thus, since the bull and bear regimes in this thesis are identified using the real excess market returns, it may be argued that the positive and significant risk premia of the HML factor during the bear regime is due to the failure of these regimes to appropriately capture the time variation in the HML factor.

Another inference that is derived from the results of Table 8.2 is related to the sign of the bull and bear risk premia of the SMB factor. Consistent with the distress risk explanation of the size effect, the bull risk premia of the SMB factor is significantly positive while its bear risk premia is significantly negative. These results is worth highlighting given the argument of Hur *et al*. (2014) against the distress risk explanation of the size effect in the US market as highlighted in Chapter 6. The results of the Egyptian stock market shows that using Markov switching model to identify the bull and bear regimes, the size premium is paid primarily in up markets even after adjusting for the market and HML factors. These results add to the long controversy regarding whether the size premium is rational or not.

Finally, since estimating the risk premia involves three steps, the results are vulnerable to the errors-in-variables bias. Thus, to mitigate this problem, wild bootstrap is used following Vendrame *et al*. (2018). Specifically, the residuals are defined as $\hat{\varepsilon}_t = \Gamma_t - \bar{\Gamma}$, where Γ_t represents the weighted average risk premium of each Fama and French factor at time t, and $\bar{\Gamma}$ is the mean of each weighted average risk premium over time. Then, bootstrap residuals ($\hat{\varepsilon}_t^*$) are created as the product of the original residuals and an independent random variable η that has a mean of zero and a unit variance. In this thesis, 1000 bootstrap replications are used and the p-values estimated from the empirical distribution of the bootstrapped t-statistic are reported in Table 8.2.

To provide further tests on the performance of the conditional FF3 in the Egyptian stock market, a test on the pricing errors of the model is undertaken. The conditional FF3 tested in this section is as follows:

$$R_{it} - R_{ft} = \Gamma_{mt}B_{Mit} + \Gamma_{st}B_{Sit} + \Gamma_{ht}B_{Hit} \tag{8.5}$$

where Γ_{mt}, Γ_{st}, and Γ_{ht} are defined in Equation 8.4. Since the main aim of this section is to test the ability of the model to explain the cross-sectional variations in the unconditional expected returns on the individual stocks, the unconditional expectation of both sides of Equation 8.5 can be taken to get:

$$E\left(R_{it} - R_{ft}\right) = E(\Gamma_{mt})E(B_{Mit}) + cov(\Gamma_{mt}, B_{Mit}) + E(\Gamma_{st})E(B_{Sit}) + \\ cov(\Gamma_{st}, B_{Sit}) + E(\Gamma_{ht})E(B_{Hit}) + cov(\Gamma_{ht}, B_{Hit}) \tag{8.6}$$

Thus, from Equation 8.6, the pricing errors of the conditional FF3 can be calculated as follows:

$$\varepsilon_i = E(R_{it} - R_{ft}) - E(\Gamma_{mt})E(B_{Mit}) - cov(\Gamma_{mt}, B_{Mit}) - E(\Gamma_{st})E(B_{Sit}) - cov(\Gamma_{st}, B_{Sit}) - E(\Gamma_{ht})E(B_{Hit}) - cov(\Gamma_{ht}, B_{Hit}) \quad (8.7)$$

where the expected betas and expected risk premia are proxied by the sample averages. $cov(\Gamma_{mt}, B_{Mit})$, $cov(\Gamma_{st}, B_{Sit})$, and $cov(\Gamma_{ht}, B_{Hit})$ represent the covariance between the betas and the risk premia of the three Fama and French factors. In the unconditional model these covariances are assumed to be equal to zero. Nonetheless, Jagannathan and Wang (1996) criticise the validity of this assumption by emphasising that it is more reasonable to assume that the conditional risk premia and the conditional betas are correlated.

The average absolute pricing error of the conditional FF3 is 2.12% which is higher than that of the model that only take time-variation in betas into consideration using the rolling regression approach. There are some empirical problems that may justify these high pricing errors. First, the small sample employed in this thesis may negatively impact the accuracy of average betas and average risk premia as proxies for expected betas and expected risk premia. Furthermore, since all the tests in this section employs individual stocks as the main test assets, this may introduce further bias on the estimates of the expected betas and expected risk premia as the results are more affected by the vagaries of individual securities (Blume and Friends, 1973). Finally, the estimation of the covariance between conditional betas and conditional risk premia is also a challenging task, since both variables are unobservable.

Finally, another way to analyse the pricing error of the conditional FF3 is by plotting the fitted expected returns against the average realized returns as in Figure 8.2. It is apparent that the model is far away from perfect fit. The conditional model significantly underestimates the average realized returns. Furthermore, the relationship between the fitted returns and average realized returns is almost flat. These results may be attributed to the small and negative risk premia of the market and the SMB factors observed in this section.

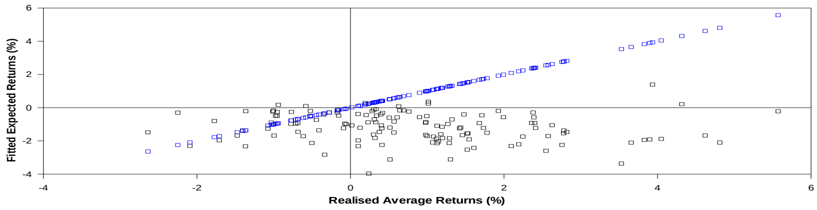


Figure 8.2: Fitted Returns of the Conditional FF3 (with the Rolling Betas) versus the Average Realized Returns

To sum up, the conditional FF3, that captures time-variation in risk using the rolling regression approach and captures time-variation in risk premia using the Markov switching model, fails to capture the cross-sectional variation in stock returns in the Egyptian stock market.

8.3.2 Tests of the Conditional FF3 with Time-Varying Risk Premia and the DCC Betas

The aim of this section is to test whether using the DCC betas can improve the performance of the conditional FF3 given the unfavourable results obtained in Section 8.3.1.

Table 8.3 shows that the bull risk premia of the market factor is significantly positive (4.05%), while its bear risk premia is significantly negative (-4.19%). In contrast with the results of Section 8.3.1, the bear risk premia of the SMB factor is negative but economically and statistically insignificant, while its bull risk premia remains significantly positive (6.59%). Finally, both the bull and the bear risk premia of the HML factor are positive but strongly insignificant. Overall, the results show that although the bull risk premia of the market factor is not high enough to compensate investors for bearing the losses in the bear regime, the bull risk premia of the SMB factor is significantly higher than the bear risk premia. This is a major improvement over the results obtained in Section 8.3.1 that show that investors are not well compensated for bearing the losses achieved in the bear regime.

To test the unconditional FF3, the difference between the bull and bear risk premia for each factor is estimated. The results show that the unconditional model is not supported in the Egyptian stock market as the differences between the bull and bear risk premia of both the market and the SMB factors are positive and significant. Nonetheless, the difference between the two risk premia of the HML factor is positive but insignificant.

The results so far support the conditional model. The final test of the conditional model is obtained by examining the weighted average risk premia of the three risk factors. The weighted average risk premium of the market factor is significantly negative. In contrast, the weighted average risk premium of the SMB factor is significantly positive which is different from the results obtained in Section 8.3.1 that show that the weighted average risk premia of the SMB factor is negative and significant. This difference can be attributed to two main reasons. First, the bull risk premium of the SMB factor is higher in magnitude (6.59%) compared to the results of Section 8.3.1 where the bull risk premium was only 2.07%. Second, the bear risk premium of the SMB factor is economically and statistically insignificant when the DCC betas are used compared to being significantly negative when the rolling regression betas are used. Finally, the weighted average risk premium of the HML factor is positive and significant.

The final test for the conditional FF3 is to estimate the pricing errors of the model and compare it to the results of Section 8.3.1. The average absolute pricing errors of the model is 1.33% which is lower than that of the conditional FF3 that uses the rolling betas. Furthermore, these results show that modelling time-variation in both betas (using the DCC-GARCH) and risk premia (using Markov switching process) can better capture the cross-sectional variation in stock returns in the Egyptian stock market compared to the model that only captures time-variation in betas using the DCC-GARCH approach tested in Chapter 7.

Table 8.3: Conditional FF3 with DCC Betas (Fixed Effects Panel Data; July 2004 to June 2016)

	Bull	Bear
γ^m	0.04053 (2.22)**	-0.04196 (-3.66)***
γ^s	0.06594 (2.92)**	-0.00349 (-0.27)
γ^h	0.01696 (0.42)	0.0051 (0.34)
	Tests of the Unconditional FF3	
$\hat{\gamma}_1^m - \hat{\gamma}_2^m$	0.08249 (3.75)***	
$\hat{\gamma}_1^s - \hat{\gamma}_2^s$	0.06943 (2.64)***	
$\hat{\gamma}_1^h - \hat{\gamma}_2^h$	0.01188 (0.28)	
	Weighted Average Risk Premia	
Γ_m	-0.00805 (-2.31)** [0.021]	
Γ_s	0.02482 (8.45)*** [0.00]	
Γ_h	0.00989 (19.51)*** [0.00]	

Notes: Table 8.3 reports the results of the panel data regressions with individual-fixed effects applied on the individual stocks over the period July 2004 to June 2016 using betas estimated from the DCC-GARCH model for the two regimes: bull and bear. The bull and bear risk premia are reported for each Fama and French factor along with their t-statistics calculated using the Driscoll and Kraay (1998) standard errors and reported in brackets. The Table also reports the results of the tests of the difference between the two risk premia (bull and bear) of each factor along with their t-statistics calculated using the Driscoll and Kraay (1998) standard errors and reported in brackets. Finally, the Table reports the results of the simple time-series test applied on the weighted average risk premia of each of the factors along with the t-statistics derived from a heteroskedasticity and autocorrelation consistent regression and reported in brackets. The bootstrap p-values are reported in square brackets. The risk premia are estimated from the following panel data regression:

$$R_{it} - R_{ft} = \gamma_0 + \gamma_{12}^m p_t \beta_{Mit} + \gamma_2^m \beta_{Mit} + \gamma_{12}^s p_t \beta_{Sit} + \gamma_2^s \beta_{Sit} + \gamma_{12}^h p_t \beta_{Hit} + \gamma_2^h \beta_{Hit} + \varepsilon_{it}$$

* reflects significance at the 10% level
** reflects significance at the 5% level
*** reflects significance at the 1% level

Finally, the graphical representation of the fitted expected returns against the average realized in Figure 8.3 shows that relationship between the fitted and realized returns is steeper than that of the conditional model that captures time-variation in betas using the rolling regression approach. Another observation from Figure 8.3 is that there is no clear pattern regarding the relationship between the fitted and realized returns. Specifically, the predicted (fitted) returns are sometimes overstated and sometimes they are understated.

To sum up, although the results of this section provides some supportive evidence to the conditional FF3, the model still cannot fully capture the cross-sectional variation in stock returns in the Egyptian stock market. Thus, the aim of the next section is to augment the FF3 with a behavioural factor given the large empirical evidence that documents that role of investor sentiment in asset pricing as well as the evidence that the Egyptian stock market is a highly speculative market that is dominated by noise trading (Metwally and Darwish, 2015).

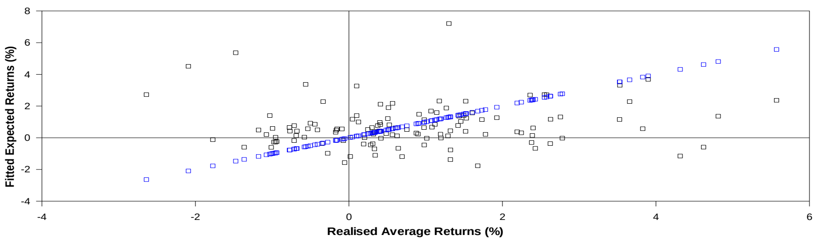


Figure 8.3: Fitted Returns of the Conditional FF3 (with the DCC betas) versus the Average Realized Returns

8.4 Behavioural Asset Pricing Models

Up to this point, this thesis has mainly focused on different versions of conventional asset pricing models, assessing whether they can explain the cross-sectional variation in stock returns in the Egyptian stock market. Nonetheless, all the versions of conventional asset pricing models examined in Chapter 7 and Section 8.3, fail to capture the cross-sectional variation in stock returns. This section aims to test whether this failure can be attributed to the unrealistic assumptions upon which conventional asset pricing models are based. Specifically, conventional asset pricing theory assumes that investor sentiment should have no effect on the prices. However, behavioural finance proponents argue that the wide array of papers that document the aggregate and the cross-sectional predictive ability of investor sentiment strongly refute the claims that investor sentiment should have no effect on stock prices (see for example, Baker and Wurgler, 2006; Schmeling, 2009).

Thus, motivated by the discussions in Chapter 4 about the various attempts to incorporate the effect of sentiment on asset pricing models, this section tests the role of sentiment in asset pricing models either as a conditioning variable or as a risk factor. Before presenting the results of behavioural asset pricing models, the following section presents a preliminary analysis of the Egyptian consumer confidence index as the main proxy of investor sentiment used in this thesis.

8.4.1 The Egyptian Consumer Confidence Index (CCI)

As highlighted in Chapter 5, the main proxy for investor sentiment used in this thesis is the Egyptian consumer confidence index. However, given the controversy about how to measure sentiment as highlighted by Baker and Wurgler (2006), it is important to assess the validity of the Egyptian CCI as a measure of sentiment.

The validity of a proxy is related to its ability to measure what it purports to evaluate (Kimberlin and Winterstein, 2008). Assessing the validity of the Egyptian CCI involves assessments of its face validity, content validity and construct validity. As to face validity, the wide use of consumer confidence indices in academic research and the coverage of monthly newspapers of the results of the Egyptian CCI add to its face validity as it indicates that the measure contains useful information about the beliefs of consumers (Kellstedt *et al.*, 2015).

Content validity deals with how well the items developed to operationalize a construct such as sentiment provide a satisfactory and representative sample of all the items that might affect this construct (Kimberlin and Winterstein, 2008). Since, there is no a statistical test for content validity, it depends mainly on the judgements of experts in the field on whether the measure adequately covers a content area and represents the construct of interest. Fisher and Statman (2003) support the use of consumer confidence as a valid proxy for investor sentiment. Furthermore, since the questions of the Egyptian CCI listed in Chapter 5 shows that the index focuses on consumer's beliefs about both his/her personal situation and the situation of business conditions in the country as a whole and it has both retrospective and prospective components, this adds to its content validity as postulated by Kellstedt *et al.* (2015).

Finally, construct validity is a judgement based on the accumulation of evidence form numerous studies that use specific measurement instruments (Kimberlin and Winterstein, 2008). Behavioural finance literature is full of evidence supporting the use of consumer confidence indices as a proxy for investor sentiment (Schmeling, 2009; Fisher and Statman, 2003). In addition, Baker and Wurgler (2006) state that to ensure the accuracy of quantitative proxies for investor sentiment, knowledge of the major stock market bubbles and crashes is essential to determine the ability of these proxies to track these major episodes and hence judge their accuracy and validity. In this regard, Table 8.4, that provides the descriptive statistics of the Egyptian CCI, and Figure 8.4, which offers a graphical representation of the index over the sample period, provide evidence that the Egyptian CCI can track the major events that the Egyptian stock market witnessed during the sample period.

Table 8.4: Descriptive Statistics for the Egyptian CCI (July 2014 to October 2014)

	Mean	Standard Deviation	Min.	Max.	ρ_1
Egyptian Consumer Confidence Index	98.85	21.21	40	155	0.87
Orthogonalised Index	99.78	21.33	51.51	154.8	0.84
Egyptian Consumer Confidence Index (From 2004-2008)	102.31	26.21	40	155	0.93
Egyptian Consumer Confidence Index (From 2009-2014)	96.17	15.62	50	134.2	0.71

Notes: Table 8.4 presents the descriptive statistics of the raw and orthogonalised values of the Egyptian CCI over the sample period June 2004 to October 2014. The Table also provides the descriptive statistics of the raw values of the index over the sample period July 2004 to December 2008 and over the sample period January 2009 to October 2014.

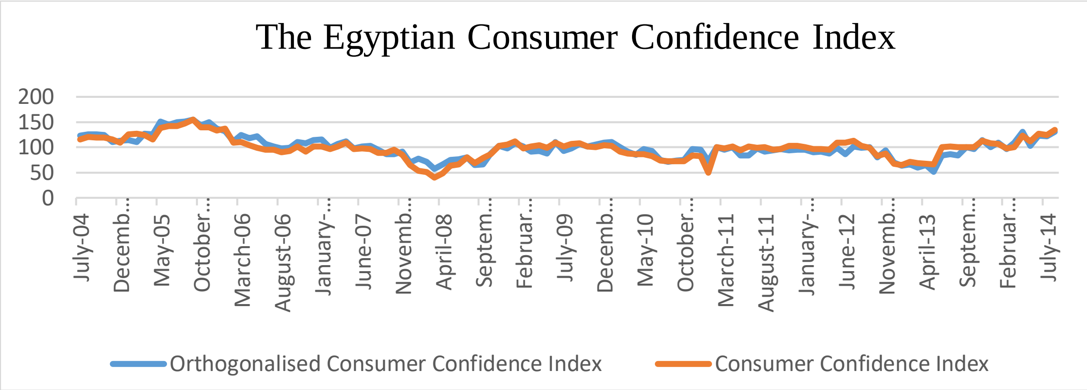


Figure 8.4: The Egyptian CCI (July 2004 to October 2014)

In particular, consistent with the results of the Markov switching model in Section 8.2 that the sample period is dominated by the bear regime, the mean value of the index is 98.85 which implies that the pessimistic views are more dominant in the market. However, despite the domination of the bear regime, Figure 8.4 shows that the index recorded high values during the period from 2004 to 2008 which are consistent with the favourable economic conditions prevalent during this period as highlighted in Chapter 6. Nonetheless, these optimistic views were interrupted by some unfavourable events such as the Gulf stock market crash, the Lebanon War in 2006, the US credit crunch and the rising fears of a global recession in 2007 and the eruption of the Global financial crisis in 2008. Thus, these events imply that the first half of the sample can be characterized by some transitions between optimistic and pessimistic views which is consistent with the results of the Markov switching model in Section 8.2. Table 8.4 shows that the mean value of the index during this period is 102.31 with a high standard deviation of 26.21.

In contrast, the second half of the sample can be characterized by being a pessimistic period with the index recording a mean value of 96.17 and a standard deviation of 15.62 which is significantly lower than that of the first half of the sample. These results are also consistent with the Markov switching model that shows that bear regime is strongly persistent during the second half of the sample. Furthermore, these results are consistent with the serious of negative events that hit the market during this period such as the Arab spring, the two Egyptian revolutions in 2011 and 2013, and the political and economic instability prevalent not only in the Egyptian stock but in the MENA region as a whole.

Thus, overall the results show that the Egyptian CCI lines well with the main bubbles and crashes witnessed in the Egyptian stock market during the sample period which supports its validity as a measure of sentiment. However, there is sufficient empirical evidence that consumer confidence indices include both rational and emotional components (Lemmon and Portniaguina, 2006). Thus, it is important to segregate between these components in order to have a cleaner measure of investor sentiment that is not contaminated by fundamentals. To achieve this aim, the index is regressed on a set of macroeconomic variables which are the dividend yield, the Treasury bill rate, growth in industrial production index, the inflation rate, the exchange rate and the three Fama and French factors and the residuals from this regression are used as a measure of excessive sentiment (optimism or pessimism) unwarranted by fundamentals. However, since the information set used to separate the rational and irrational components of the index is unobservable, this implies that even the orthogonalised index may still be contaminated by some fundamental information.

Overall, the results of the orthogonalised index presented in Table 8.4 show that orthogonalising to macro variables is a second-order issue as it does not qualitatively affect the index. Finally, both the raw and orthogonalised indices are highly persistent as the first-order autocorrelation coefficients are 0.87 and 0.84 respectively. Brown and Cliff (2005) argue that the persistence of investor sentiment is a pleasant characteristic as it implies that the investors are not too fickle and that waves of optimism or pessimism may reinforce themselves.

8.4.2 Investor Sentiment as a Conditioning Variable

This section aims to extend the tests of Chapter 7 that investigate whether the scaled factor models that allow factor loadings to vary with size, the book-to-market ratio, and the Treasury bill rate can explain the size, value, liquidity and momentum effects by using investor sentiment as an additional conditioning variable following the approach of Avramov and Chordia (2006). First, the following time-series regression is run:

$$R_{it} = \alpha_{i0} + \sum_{k=1}^{3}(\beta_{ik0} + \beta_{ik1}Z_{it-1})FF_{kt} + \varepsilon_{it} \quad (8.8)$$

where Z_{it-1} represents a vector of the conditioning variables, while FF_{kt} represents the three Fama-French factors (R_M, SMB and HML).

Then, a cross-sectional regression is estimated of risk-adjusted returns (r_{it}^{*}), calculated as the sum of the pricing errors and the residuals from the time-series regression in Equation 8.8, on the firm characteristics (Y_{it-1}) as in Equation 8.9. Under the null hypothesis of exact pricing, all of these characteristics should be insignificant in the cross-sectional regressions. Furthermore, Avramov and Chordia argue that if the asset pricing model employed in the first-pass time-series regression is well-specified, then the average of the adjusted R^2 values from the cross-sectional regression estimated each month should be low.

$$r_{it}^{*} = c_{0t} + c_t Y_{it-1} + e_{jt} \quad (8.9)$$

Before presenting the results, it is important to highlight that since the Egyptian Cabinet's Information and Decision Support Centre ceased to publish the Egyptian CCI since October 2014, all the tests that use investor sentiment are run on a shorter sample that starts from July 2004 to October 2014. Thus, to have fair comparison between the scaled factor models tested in Chapter 7 and the scaled factor models tested in this chapter, the tests of scaled factor models in Chapter 7 are repeated using the shorter sample period.

Table 8.5 presents the results of the unconditional and conditional versions of the CAPM. The results show that although all the values of the average adjusted R^2 of the unconditional and conditional versions of the CAPM are high, the conditional versions of the model have lower values which reflect the importance of taking the time-variation in risk into consideration. However, despite the results of Ho and Hung (2009) who show that the conditional versions of the CAPM that use investor sentiment as a conditioning variable outperform those that use macroeconomic and microeconomic variables, Table 8.5 shows that the conditional models that use investor sentiment as a conditioning variable underperform those that use macroeconomic and microeconomic variables. Furthermore, the results show that the conditional versions of the CAPM are challenged by their failure to capture the size, turnover and momentum effects.

Given the challenges facing the conditional CAPM, Table 8.6 tests whether scaling the factor loadings of the FF3 with investor sentiment can provide better explanation of the cross-sectional variation in stock returns. In this regard, the results show that the unconditional and conditional versions of the FF3 significantly outperforms those of the CAPM. Specifically, the values of the average adjusted R^2 of both the unconditional and conditional versions of the FF3 are significantly lower than that of the CAPM. Furthermore, despite the failure of all the specifications of the CAPM to capture the size effect, all the versions of the FF3 tested in this section can explain the size effect. These results reflect the marginal explanatory power of the SMB and HML factors and their role in capturing the cross-sectional variation in stock returns. Despite these favourable aspects concerning the performance of the FF3 relative to the CAPM, the model is still challenged by several other aspects.

First, all the specifications of the FF3 have significant negative intercepts. These negative intercepts imply that the average stock underperform relative to the model by at least 9% per year which is a significant amount. Second, almost all the specifications tested are weakened by their failure to capture the short-term momentum effect which contradicts the results of Ho and Hung who show that scaling the loadings of the FF3 with investor sentiment can capture the short-term momentum in the US market.

Table 8.5: The CAPM with Investor Sentiment as a Conditioning Variable

	CAPM	CAPM (Sent)	CAPM (TB)	CAPM (TB & Sent)	CAPM (Size & BM)	CAPM (Size, BM& Sent)	CAPM (Size, BM&TB)	CAPM (Size, BM, Sent & TB)
Constant	0.0051	0.0072	0.0053	0.0071	0.0058	0.0069	0.0051	0.0064
	(0.86)	(1.21)	(0.89)	(1.17)	(0.99)	(1.16)	(0.86)	(1.03)
	[0.45]	[0.030]	[0.421]	[0.080]	[0.694]	[0.066]	[0.730]	[0.193]
Size	-0.0041	-0.0046	-0.0038	-0.0043	-0.004	-0.0044	-0.0036	-0.0039
	(-1.81)*	(-2.06)**	(-1.73)*	(-1.97)*	(-1.93)*	(-2.07)**	(-1.75)*	(-1.91)*
	[0.054]	[0.708]	[0.068]	[0.607]	[0.341]	[0.638]	[0.255]	[0.726]
Book-to-Market Ratio	-0.00008	0.0013	-0.00032	0.0007	-0.00004	0.0012	-0.0004	0.0012
	(-0.01)	(0.18)	(-0.05)	(0.09)	(-0.01)	(0.19)	(-0.07)	(0.18)
	[0.942]	[0.902]	[0.910]	[0.748]	[0.624]	[0.703]	[0.613]	[0.686]
Turnover	0.0042	0.0038	0.0049	0.0046	0.0050	0.0051	0.0057	0.0059
	(1.36)	(1.23)	(1.62)*	(1.54)	(1.66)*	(1.68)*	(1.92)*	(1.99)**
	[0.135]	[0.26]	[0.072]	[0.096]	[0.082]	[0.145]	[0.070]	[0.14]
Cumulative Return(2-3 months)	-0.046	-0.0545	-0.0397	-0.048	-0.0523	-0.0602	-0.0529	-0.0586
	(-1.71)*	(-2.10)**	(-1.54)	(-1.91)*	(-2.14)**	(-2.45)**	(-2.19)**	(-2.44)**
	[0.078]	[0.112]	[0.096]	[0.112]	[0.492]	[0.360]	[0.374]	[0.137]
Cumulative Return(4-6 months)	0.018	0.026	0.0163	0.0251	0.0076	0.0115	0.0059	0.0111
	(0.75)	(1.09)	(0.67)	(1.06)	(0.33)	(0.49)	(0.26)	(0.49)
	[0.296]	[0.332]	[0.342]	[0.336]	[0.892]	[0.915]	[0.984]	[0.938]
Cumulative Return(7-12 months)	0.0113	0.0115	0.014	0.0106	0.0042	0.0046	0.0064	0.00523
	(0.81)	(0.81)	(1.02)	(0.76)	(0.29)	(0.33)	(0.46)	(0.38)
	[0.349]	[0.952]	[0.271]	[0.601]	[0.521]	[0.401]	[0.495]	[0.890]
Average Adjusted R^2	10.45%	10.49%	10.29%	10.08%	9.63%	9.78%	9.59%	9.56%

Notes: Table 8.5 presents the time-series averages of individual stock cross-sectional OLS regression coefficients. The second column presents the results when the dependent variable is the excess return risk-adjusted using market risk. The third column presents the results when the risk loadings are scaled by investor sentiment. The fourth column presents the results when the risk loadings are scaled by the Treasury bill rate. The fifth column presents the results when the risk loadings are scaled by the Treasury bill rate and investors sentiment. The sixth column presents the results when the risk loadings are scaled by size and the book-to-market ratio. The seventh column presents the results when the risk loadings are scaled by size, the book-to-market ratio, and investor sentiment. The eighth column presents the results when the risk loadings are scaled by size, the book-to-market ratio, and the Treasury bill rate. The ninth column presents the results when the risk loadings are scaled by size, the book-to-market ratio, investor sentiment and the Treasury bill rate. The t-statistics reported in brackets are from heteroskedasticity and autocorrelation consistent regressions. The bootstrap p-values are reported in square brackets.

* reflects significance at the 10% level
** reflects significance at the 5% level
*** reflects significance at the 1% level

Third, in contrast to the results of the conditional CAPM that show that specifications that use investor sentiment as a conditioning variable underperform those that use the Treasury bill rate, specifications of the FF3 that use investor sentiment as a conditioning variable outperform those that use the Treasury bill rate. Specifically, models that use investor sentiment as a conditioning variable have lower R^2 and they can capture the turnover effect compared to models that use the Treasury bill rate as conditioning variable.

Table 8.6: The FF3 with Investor Sentiment as a Conditioning Variable

	FF	FF (Sent)	FF (TB)	FF (TB & Sent)	FF (Size & BM)	FF (Size, BM& Sent)	FF (Size, BM&TB)	FF(Size, BM, Sent & TB)
Constant	-0.0093	-0.0077	-0.0079	-0.0074	-0.0081	-0.0077	-0.0076	-0.0075
	(-2.10)**	(-1.77)*	(-1.87)*	(1.77)*	(-2.10)**	(-2.05)**	(-1.96)**	(-1.96)**
	[0.039]	[0.086]	[0.056]	[0.083]	[0.052]	[0.027]	[0.036]	[0.035]
Size	-0.0004	-0.0008	-0.0006	-0.0004	-0.00003	-0.0001	0.00003	0.0002
	(-0.25)	(-0.44)	(-0.34)	(-0.26)	(-0.02)	(-0.07)	(0.02)	(0.13)
	[0.884]	[0.800]	[0.796]	[0.882]	[0.956]	[0.991]	[0.923]	[0.874]
Book-to-Market Ratio	0.0013	0.0013	-0.0017	-0.0006	-0.0011	0.0002	-0.0022	0.0008
	(0.17)	(0.18)	(-0.24)	(-0.09)	(-0.17)	(0.04)	(-0.36)	(0.14)
	[0.875]	[0.874]	[0.816]	[0.956]	[0.915]	[0.935]	[0.726]	[0.843]
Turnover	0.0029	0.0028	0.0039	0.0036	0.0045	0.0036	0.0051	0.0041
	(1.06)	(1.08)	(1.51)	(1.50)	(1.93)**	(1.52)	(2.23)**	(1.87)*
	[0.342]	[0.273]	[0.148]	[0.146]	[0.055]	[0.139]	[0.021]	[0.071]
Cumulative Return(2-3 months)	-0.042	-0.058	-0.037	-0.053	-0.043	-0.043	-0.047	-0.045
	(-1.59)	(-2.50)**	(-1.54)	(-2.48)**	(-1.89)*	(-1.96)**	(-2.14)**	(-2.17)**
	[0.125]	[0.014]	[0.122]	[0.007]	[0.097]	[0.057]	[0.026]	[0.027]
Cumulative Return(4-6 months)	0.016	0.023	0.0153	0.019	0.0107	0.0164	0.0129	0.0186
	(0.64)	(0.88)	(0.59)	(0.73)	(0.45)	(0.66)	(0.58)	(0.81)
	[0.543]	[0.391]	[0.580]	[0.465]	[0.691]	[0.522]	[0.576]	[0.443]
Cumulative Return(7-12 months)	-0.0034	0.0002	0.0065	0.007	0.004	0.008	0.007	0.009
	(-0.28)	(0.01)	(0.57)	(0.55)	(0.32)	(0.67)	(0.56)	(0.84)
	[0.758]	[0.923]	[0.563]	[0.620]	[0.815]	[0.583]	[0.591]	[0.428]
Average Adjusted R^2	6.74%	6.76%	7.14%	6.82%	5.86%	5.92%	6.05%	5.95%

Notes: Table 8.6 presents the time-series averages of individual stock cross-sectional OLS regression coefficients. The second column presents the results when the dependent variable is the excess return risk-adjusted using the Fama and French three risk factors. The third column presents the results when the risk loadings are scaled by investor sentiment. The fourth column presents the results when the risk loadings are scaled by the Treasury bill rate. The fifth column presents the results when the risk loadings are scaled by the Treasury bill rate and investors sentiment. The sixth column presents the results when the risk loadings are scaled by size and the book-to-market ratio. The seventh column presents the results when the risk loadings are scaled by size, the book-to-market ratio, and investor sentiment. The eighth column presents the results when the risk loadings are scaled by size, the book-to-market ratio, and the Treasury bill rate. The ninth column presents the results when the risk loadings are scaled by size, the book-to-market ratio, investor sentiment and the Treasury bill rate. The t-statistics reported in brackets are from heteroskedasticity and autocorrelation consistent regressions. The bootstrap p-values are reported in square brackets.

* reflects significance at the 10% level
** reflects significance at the 5% level
*** reflects significance at the 1% level

Overall the results of this section imply that using investor sentiment as a conditioning variable does not lead to significant changes in the ability of scaled factor models to capture the size, value, liquidity and momentum effects which is a severe contradiction to the results of Ho and Hung (2009). One explanation to this result may be derived from the arguments of Stambaugh *et al.* (2012) and Shen *et al.* (2017) that financial markets tend to be more rational and efficient during low-sentiment periods. In the light of these arguments, since the sample period under consideration is dominated by bear regime and pessimistic views as elaborated in Section 8.4.1, it is expected that investor sentiment may have an insignificant effect on stock prices. Thus, this may justify why using investor sentiment as an additional conditioning variable cannot improve the performance of conventional asset pricing models.

8.4.3 Investor Sentiment as a Risk Factor

The aim of this section is to test whether augmenting the FF3 with a behavioural factor can provide better explanation of the cross-sectional variation in stock returns in the Egyptian stock market. However, a fundamental question that arises before evaluating the performance of behavioural asset pricing models is whether sentiment is an undiversifiable source of risk that warrants an additional premium. Berger and Turtle (2012) argue that this question is one of the debatable areas in finance literature. On the one hand, Elton *et al.* (1998) find that sentiment sensitivity is subsumed by other systematic risk factors and thus they conclude that investor sentiment should not matter in asset valuation. In contrast, Berger and Turtle (2012) support the claims of behavioural finance proponents about the role of investor sentiment as a priced risk factor. Specifically, they find that portfolios formed from opaque firms, which are difficult to value and hard to arbitrage, have higher exposure to investor sentiment than translucent firms. In addition, they find that both simple and multifactor asset pricing models fail to capture the variability in these stocks' returns over time.

Given this debate, the first part of this section aims to examine the characteristics of stocks that have the highest exposure to contemporaneous measure of investor sentiment. Specifically, the main hypothesis is whether, within the context of the FF3, sentiment-prone stocks retain their sensitivity to firm-based characteristics that are closely aligned with opacity such as size, the book-to-market ratio, and stock volatility

(Berger and Turtle, 2012). If this hypothesis is supported, then this implies that sentiment is an undiversifiable risk factor that warrants a premium in equilibrium.

To achieve this aim, the relationship between sentiment and firm characteristics is examined through the following steps. First, the sensitivity of individual stocks to investor sentiment is estimated using the following time-series regression:

$$R_{it} - R_{ft} = \alpha_i + \beta_{i,mkt}\left(R_{mt} - R_{ft}\right) + s_i SMB_t + h_i HML_t + \beta_{i,sent}\Delta sent_t + \varepsilon_{it},$$

for $i = 1, \dots N$ and $t = 1, \dots T$ (8.10)

where $\Delta sent_t$ is the change in the orthogonalised Egyptian CCI. The estimates of $\beta_{i,sent}$ measure the sensitivity of each stock to investor sentiment after controlling for the Fama and French factors.

Second, given the small number of stocks in the Egyptian stock market, stocks are divided into five portfolios based on their full sample constant $\beta_{i,sent}$. In this regard, the estimates of $\beta_{i,sent}$ can be either negative, positive, or negligible. The first portfolio includes the stocks that have the most negative sentiment betas, whereas the fifth portfolio includes the stocks that have the most positive betas. The second, third, and fourth portfolios include the least sensitive stocks to investor sentiment.

Panel A of Table 8.7 reports the average values of firm characteristics within each sentiment portfolio. These characteristics are size, the book-to-market ratio, and firms' volatility as they represent the level of opacity of the firm as highlighted by Baker and Wurgler (2006). If average firm characteristics of the high-sentiment sensitivity portfolio corresponds to opaque characteristics, this implies that this portfolio captures sentiment effects. In this regard, a typical firm in the high-sentiment sensitivity portfolio should have highly volatile returns, smaller size, and high distress risk as proxied by the B/M ratio.

The results of Panel A support the proposition that firms that are more vulnerable to investor sentiment are relatively more opaque. Specifically, the average firm size of stocks assigned to the third and fourth portfolios (least vulnerable to investor sentiment) is higher than that of stocks assigned to the most vulnerable portfolios. Thus, this implies that there is a relationship between sentiment and firm size even after adjusting for the Fama and French three risk factors. Similarly, portfolios that are least vulnerable to investor sentiment show a mean standard deviation of stock returns that ranges between 14.22% and 14.48%, whereas portfolios that are most vulnerable to investor sentiment have a mean standard deviation of stock returns that range between 17.85 and 18.98%. This, in turn, implies a relationship between sensitivity to investor sentiment and stock volatility. However, there is no consistent relationship between the vulnerability of stocks to investor sentiment and the book-to-market ratio. Overall, the results of Table 8.7 are consistent with Baker and Wurgler (2006), Berger and Turtle (2012), and Ho and Hung (2012) that small and highly volatile stocks are more vulnerable to investor sentiment even after adjusting for the Fama and French three risk factors.[14]

Panel B of Table 8.7 reports the results when rolling regression approach is used to estimate the sensitivities of stocks to investor sentiment. In this regard, $\beta_{i,sent}$ is estimated at each month t using the observations from month $t-1$ through $t-24$, rolling one month forward, to verify that sentiment sensitivities retain similar patterns across firms characteristics with ex-ante available information. Then, firms are divided into five portfolios based on the estimates of $\beta_{i,sent}$. Then, for each firm in a given portfolio at a given time t, the averages of the three aforementioned characteristics are estimated across the previous two years to ensure that the estimates of firm characteristics matches the estimation period of sentiment sensitivities using the rolling regression approach. The results of Panel B are consistent with that of

[14] In unreported results, in an attempt to focus more on the characteristics that vary positively with investor sentiment, stocks that have negative sentiment betas are grouped into one portfolio and then all the remaining stocks are divided equally between two portfolios where the third portfolio includes the most sensitive stocks to investor sentiment. The results support the main conclusion reached that stocks that are most sensitive to investor sentiment are smaller in size and have highly volatile returns compared to stocks that have negative sentiment betas or are least vulnerable to investor sentiment.

Panel A supporting the proposition that firms that are more sensitive to investor sentiment tend to be smaller in size and more volatile.

Overall, the main implication derived from the results of Table 8.7 is that, rather than being an idiosyncratic risk that can be diversified away, sentiment sensitivities are systematically related within broad cross-sections of stocks. In other words, as opaque firms exhibit common exposures to investor sentiment, portfolios formed across these stocks are highly vulnerable to shifts in investor sentiment. Thus, this implies that sentiment is an undiversifiable risk factor that warrants an additional risk premia as postulated by Berger and Turtle (2012).

Table 8.7: Sentiment Sensitivity and Stock Characteristics

Panel A: Unconditional Sentiment Sensitivity and Firm Characteristics					
	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5
$\beta_{i,sent}$	-0.0012	-0.00042	-0.00006	0.00036	0.00089
σ	17.85%	14.48%	14.22%	14.61%	18.98%
Size (Billion EGP)	1.013	1.174	5.625	2.594	1.192
B/M	0.79	0.99	0.76	0.89	0.71
Panel B: Rolling Regression Sentiment Sensitivity and Firm Characteristics					
	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5
$\beta_{i,sent}$	-0.00301	-0.00087	-0.00002	0.00085	0.00286
σ	19.74%	14.90%	14.03%	14.98%	20.54%
Size (Billion EGP)	1.494	3.396	3.390	3.333	1.774
B/M	0.84	0.81	0.77	0.74	0.73

Notes: Panel A reports the characteristics of portfolios sorted based on the sensitivity of each stock to investor sentiment estimated using the following regression:

$$R_{it} - R_{ft} = \alpha_i + \beta_{i,mkt}\left(R_{mt} - R_{ft}\right) + s_i SMB_t + h_i HML_t + \beta_{i,sent}\Delta sent_t + \varepsilon_{it}$$

where $\left(R_{mt} - R_{ft}\right)$, SMB_t, and HML_t are the three Fama and French factors. $\Delta sent_t$ is the change in the orthogonalised Egyptian consumer confidence index. Portfolio 1 includes the stocks whose estimates of $\beta_{i,sent}$ are the most negative, whereas Portfolio 5 includes the stocks whose estimates of $\beta_{i,sent}$ are the most positive. For each stock, the averages of each of the firm characteristics are calculated. Then, these average are pooled and the results are reported for each sentiment-prone portfolio. The firm characteristics are: size defined as the market value of equity, the B/M ratio defined as the ratio of book equity to market equity. Finally, for each month t, standard deviation (σ) is calculated using the previous twelve months returns. Panel B reports the characteristics of portfolios sorted based on the sensitivity of each to investor sentiment estimated using rolling regression approach. $\beta_{i,sent}$ for month t is estimated using observations from month $t-1$ through t-24. Then, stocks are assigned to five portfolios based on the estimated of $\beta_{i,sent}$ as in Panel A. The average two year firm characteristics for each stock within the sample at each month t is calculated. Then, these average are pooled and the results are reported for each sentiment-prone portfolio.

These results support augmenting the FF3 with a behavioural factor to provide better explanation of the cross-sectional variation in stock returns in the Egyptian stock market. Before presenting the results of the new model there are several obstacles that may affect the results that should be highlighted. First, as explained in Chapter 5, the sentiment risk factor (SMN) is constructed using the following steps. The sentiment beta of each stock (i) at the beginning of each month t is estimated using observations from month $t - 1$ through month $t - 24$, rolling one month forward, as in Equation 8.10. This means that the sample period employed for testing the FF3 augmented with the SMN factor starts from July 2006 rather than July 2004. Second, the Egyptian CCI is only available till October 2014. Thus, this means that tests that augment that FF3 with the SMN factor are run over a short sample period from July 2006 to October 2014 which may jeopardise the results and the inferences of whether the sentiment factor is priced in the Egyptian stock market.

Table 8.8 presents the descriptive statistics of the Fama and French three factors and the SMN factor using the shorter sample period from July 2006 to October 2014. The results show that the average return of the market factor is 0.79% per month with a monthly standard deviation of 7.99%. These results show that the average return of the market factor during the shorter sample period is lower than that of the full sample and statistically insignificant. In contrast, the results show that the average return of the SMB factor is equal to 3.13% per month which is higher than that of the full of the sample. This, in turn, provides some support that the SMB factor is significantly priced in the Egyptian stock market. The average return of the HML factor is -0.67% per month but statistically insignificant supporting the results of the full sample. Overall, these results show that there are significant differences between the results of the full sample reported in Chapter 6 and the results of the shorter sample period employed in this section especially with respect to the magnitude and significance of the average returns of the Fama and French three factors.

The average return of the SMN factor is 0.78% per month but it is statistically insignificant. These results imply that the portfolio that includes stocks that have the highest positive sentiment betas do not significantly outperform the portfolio that includes stocks with close-to-zero sentiment betas. However, given the small sample period, these results should be interpreted with caution. Furthermore, since the period under investigation is mainly dominated by bear markets, this may provide further justification of the insignificance of the average return of the SMN factor as according to Stambaugh *et al.* (2012) and Shen *et al.* (2017) financial markets tend to be more rational during low-sentiment periods.

Table 8.8-Descriptive Statistics for the Fama and French Factors and the Sentiment Factor (July 2006 to October 2014)

Panel A: Descriptive Statistics for the Fama and French Factors								
Factors	Mean (%)	Standard Deviation (%)	Sig. Level (Mean = 0)	Min. (%)	Max. (%)	Skewness	Excess Kurtosis	Jarque-Bera (Sig. Level)
Market Factor	0.79	7.99	0.32	-30.37	19.14	0.88	2.46	38.68 (0.00)
SMB	3.13	8.41	0.00	-12.47	31.32	1.13	1.80	34.99 (0.00)
HML	-0.67	8.40	0.43	-38.06	35.15	-0.33	7.85	261.14 (0.00)
SMN	0.78	5.23	0.14	-10.34	20.44	0.88	1.87	27.59 (0.00)

Notes: Table 8.8 shows the descriptive statistics for the Fama and French three factors and the sentiment risk factor (SMN) for the sample period July 2006 to October 2014.

The last test in this section is to determine whether the FF3 augmented with a behavioural factor provides a better explanation of the cross-sectional variation in stock returns in the Egyptian stock market. The simplest way to test this hypothesis is through running the Fama-Macbeth cross-sectional regression with full sample betas. In addition to its simplicity, using full sample betas is preferred to rolling regression approach in this section due to having only small number of observations.

Table 8.9 reports the results of the Fama-Macbeth cross-sectional for both the FF3 and the FF3 augmented with the SMN factor to be able to compare between the models. Although the intercept of the FF3 is insignificant at the conventional significance levels, its magnitude and t-statistics are higher than that of the FF3 augmented with the SMN factor. This implies that the SMN factor can contribute towards explaining part of the cross-sectional variations in stock returns missed by the FF3. Despite this contribution of the SMN factor, its risk premia is insignificant. Specifically, although the magnitude of the risk premia of the SMN factor is somehow consistent with its sample average return, its t-statistic is low. This, in turn, implies that the SMN factor is not significantly priced in the Egyptian stock market. Similarly, the risk premia of the market factor for both the FF3 and the FF3 augmented with the SMN factor are positive but insignificant which provide further evidence against the validity of both models. Furthermore, although the risk premia of the SMB factor in both models is positive, it weakly significant at the 10% level which contradicts the previous results obtained in Chapter 7 and Chapter 8 that show that the SMB factor is significantly priced in the Egyptian stock market. Finally, the risk premia of the HML factor is negative and insignificant supporting the previous results that the HML factor is not significantly priced in the Egyptian stock market.

Table 8.9: Fama-Macbeth Cross-Sectional Regression Tests on Individual stocks (July 2006 to October 2014)

Models	α	λ_M	λ_{SMB}	λ_{HML}	λ_{SMN}
FF3	-0.0083 (-1.51) [-1.49]	0.0096 (0.89) [0.75]	0.0241 (1.75)* [1.66]	-0.0136 (-1.02) [-0.81]	-
FF3 with SMN Factor	-0.0073 (-1.39) [-1.38]	0.0095 (0.92) [0.75]	0.0208 (1.71)* [1.49]	-0.0129 (-0.95) [-0.81]	0.0087 (0.98) [0.92]
Factors		$\overline{R_M - R_f}$	$\overline{SMB}$	$\overline{HML}$	$\overline{SMN}$
Sample Average Return		0.79%	3.13%	-0.67%	0.78%

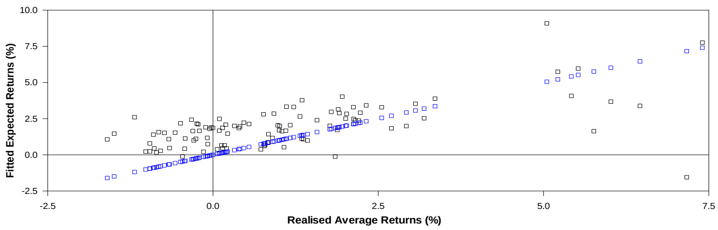
Notes: Table 8.9 presents the intercepts and slopes of the Fama-Macbeth cross-sectional regression of monthly excess returns for individual stocks based on their full-sample betas for both the FF3 and the FF3 augmented with the SMN factor. T-statistics reported in brackets are derived from heteroskedasticity and autocorrelation consistent regression. The t-statistics based on Shanken's (1992) correction are given in square brackets. The results are obtained from the following regression:

$$R_{it} - R_{ft} = \alpha_t + \hat{\beta}_{it}\lambda_t$$

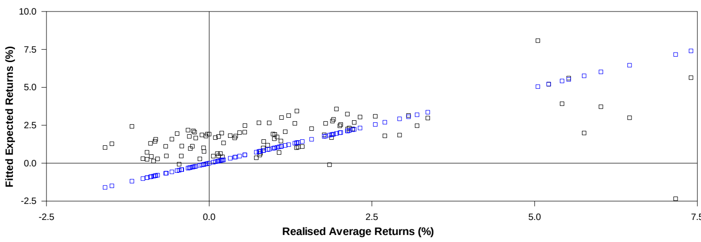
* reflects significance at 10% level
** reflects significance at 5% level
*** reflects significance at 1% level

Given the vulnerability of the tests that employ individual stocks to the EIV bias, the Shanken (1992) correction for standard errors is applied to determine whether the inferences change after taking the bias into consideration. However, no major changes to the inferences are made.

Finally, to provide a more comprehensive picture about the performance of the two models, a visual comparison between the performances of these models is undertaken by plotting the fitted expected returns from the models against the realized average returns. Panels A and B of Figure 8.5 show that there is no significant differences in the performance of both models. Specifically, the fitted returns from both models overestimate average realized returns which is consistent with the negative intercepts observed in Table 8.9. Furthermore, the average absolute pricing errors of the FF3 is 1.38%, whereas the average absolute pricing errors of the FF3 augmented with the SMN factor is 1.32%. Thus, these results implies that augmenting the FF3 with an additional behavioural factor does not lead to significant changes in the model.



Panel A: The Fama and French Model



Panel B: The Fama and French Model Augmented with the SMN factor

Figure 8.5: Fitted Expected Returns versus Average Realized Returns

To sum up, investigating the relationship between the sensitivity of stocks to investor sentiment and stock characteristics reveals that investor sentiment is an undiversifiable risk factor that warrants an additional premium in equilibrium.

However, the results of the Fama-Macbeth cross-sectional regression show that augmenting the FF3 with the SMN factor does not lead to major changes in the performance of the model to capture the cross-sectional variations in stock returns. Nonetheless, the short sample period used in these tests and the domination of the bear regime in the market may have a negative impact on the results.

8.5 Conclusion

This chapter aims to test two further extensions for the approaches employed in Chapter 7 to capture time-variation in betas in an attempt to provide better explanations of the cross-sectional variations in stock returns in the Egyptian stock market. The first extension aims to test the conditional FF3 that captures time-variation in risk and risk premia. In this regard, time-variation in risk is captured using the rolling regression approach and the DCC-GARCH model, whereas the time-variation in risk premia is captured using the Markov switching process. The contribution of this extension is as follows:

First, although Vendrame *et al.* (2018) use the Markov switching process to model time-variation in risk premia within the context of the CAPM, this thesis extends their approach to the context of multifactor models motivated by the vast empirical evidence that the Fama and French three risk factors vary significantly over time (Perez-Quiros and Timmermann, 2000; Zhang, 2005). Second, the highly volatile nature of emerging markets generally and the Egyptian stock market specifically makes the assumptions of constant betas and risk premia employed in previous tests of asset pricing models highly debatable. Thus, this thesis fills this gap by analysing whether the conditional FF3 can capture the cross-sectional variation in stock returns in the Egyptian stock market. Third, as highlighted in Chapter 4, there is a wide variety of approaches available to model time-variation in risk. Nonetheless, there is no clear-cut answer on which approach provides a superior way to capture time-variation in risk. Thus, to circumvent this problem, this thesis uses both the rolling regression approach and the DCC-GARCH to model time-variation in betas and compares between them.

The results of this extension of the FF3 can be summarized as follows: (i) the unconditional FF3 is always rejected in favour of a conditional time-varying risk premia; (ii) the conditional FF3 that captures time-variation in risk using the DCC-GARCH outperforms the conditional FF3 that captures time-variation in risk using the rolling regression approach with respect to the sign and the significance of the weighted average risk premia of the SMB factor and the magnitude of the average absolute pricing errors; (iii) despite the good performance of the conditional FF3 that capture time-variation in risk using the DCC-GARCH model, the model is still challenged by several aspects as follows. Although the average absolute pricing errors of this model is lower than that of the model that uses rolling regression approach, they are still large and significant which poses some doubts on the ability of the model to capture the cross-sectional variation in stock returns. Furthermore, the negative sign of the weighted average risk premia of the market factor poses a severe contradiction to the assumption that investors are risk averse and that they require positive risk premium to compensate them for holding risky assets. Nonetheless, these results should be interpreted with caution due to the small sample period employed in these tests which may negatively impact the accuracy of the weighted average risk premia as a proxy for expected risk premium.

Finally, the results of the conditional FF3 show that the difference between the bull and bear risk premia of the HML factor is insignificant, this may have two main implications. First, it may imply that the HML factor does not play an important role in capturing the time-variation in expected returns as postulated by Ferson and Harvey (1999). Second, it may suggest that the state probabilities used in these tests, that are determined using the real excess return of the market portfolio, are not able to probably capture the time-variation in the HML factor. According to Fama and French

(1996) the HML factor should not be expected to be related to any variable that generate the market factor.

The second extension that this chapter analyses is related to testing the proposition of behavioural finance proponents that the failure of conventional asset pricing models to capture the cross-sectional variation in stock returns is due to ignoring the effect of noise traders on stock prices. Thus, this chapter tests the role of investor sentiment on stock prices through two main channels.

The first channel tests whether using investor sentiment as an additional conditioning variable along with the Treasury bill rate, firm size, and the book-to-market ratio within the context of scaled factor model can capture the size, value, liquidity, and momentum effects as examples of the most prominent anomalies in financial markets. The second channel tests whether augmenting the FF3 with an additional behavioural factor (the SMN) can provide better explanation of the cross-sectional variation in stock returns in the Egyptian stock market. Although Ho and Hung (2009; 2012) test the role of investor sentiment as a conditioning variable and as a risk factor before in the US market, the results of this chapter contributes to the literature in the following sense.

It provides out-of-sample evidence to the results of Ho and Hung (2009; 2012) by presenting evidence from the Egyptian stock market about the role of investor sentiment as a conditioning variable and as a risk factor. This evidence is important as emerging markets generally and the Egyptian stock market specifically represent an interesting environment to assess the impact of sentiment on stock prices for the following reasons. First, the Egyptian stock market is dominated by retail (individual) investors who are mainly characterized by being noise traders. Consequently, they are more affected by the usage of heuristics, rules of thumb, or other simplifying decision rules in their investment decisions (Schmitz *et al*., 2006). This observation about the Egyptian stock market is also supported by recent empirical evidence that shows that the Egyptian stock market is a speculative market that is affected by noise trading (see for example, Omran, 2007; Metwally and Darwish, 2015). Second, the Egyptian stock market like other emerging market is highly restrictive due to its strict institutional settings such as short-sale constraints. These constraints deter institutional investors from participating in price stabilizing activities by trading against irrational investors to drive prices back to their fundamental values. Thus, the Egyptian stock market provides a rich environment to study the effect of investor sentiment on stock prices.

However, the results show that using investor sentiment either as a conditioning variable or as a risk factor does not significantly improve the ability of conventional asset pricing models, tested in Chapter 7 and in this chapter, to capture the cross-sectional variation in stock returns. These unsatisfactorily results may be attributed to the following reasons. First, the short sample period employed in tests that use investor sentiment may negatively affect the power of the tests that analyse the effect of investor sentiment on stock prices.

Second, since the Egyptian CCI is used as the main proxy for investor sentiment, the results are dependent on the accuracy of this proxy as a measure of investor sentiment. In this regard, Han and Li (2017) provide some argument against the use of consumer confidence indices as a measure of investor sentiment as they focus on consumers' general expectations about the overall prospects of the economy rather than the stock market and they are subject to the criticism that the survey respondents may not really act in the way they described in the survey. Thus, this implies that using other proxies for investor sentiment may lead to more favourable results. Third, since the sample period under consideration in this thesis is dominated by bear regimes, the insignificant results obtained may be expected given the arguments of Stambaugh *et al.* (2012) and Shen *et al.* (2017) that financial markets tend to be more rational during low-sentiment periods.

However, despite these unfavourable results for behavioural asset pricing models in the Egyptian stock market, it is worth noting that the relationship between sentiment sensitivities and stock characteristics documented in this chapter may imply that sentiment is an undiversifiable risk factor that warrants additional premium. Thus, future research should test whether using longer sample periods and other proxies for investor sentiment can save behavioural asset pricing models in the Egyptian stock market.

Chapter 9
Conclusion and Suggestions for Future Research

9.1 Introduction

Asset pricing theory has a fundamental role in assessing the fair rate of return of a particular asset which is crucial for the investment decisions facing both corporations evaluating projects and investors forming portfolios. Thus, since asset pricing provides information that is central to many financial decisions, a substantial part of the research effort in finance focuses on understanding how investors value risky cash flows. Consequently, several capital asset pricing models have emerged to meet this vital need and help investors determine the risk premium they should require (Jagannathan and Wang, 1996). Given the importance of understanding the determinants of asset prices, the main aim of this thesis is to determine a valuation model for stocks in the Egyptian stock market by comparing between conventional and behavioural asset pricing models.

The main reason behind the choice of the Egyptian stock market to be the main focus of this thesis is that Egypt has been facing many challenges since the Arab Spring in 2011. Since then, the country has undertaken several steps to boost economic growth which is the main mechanism to alleviate poverty, to ensure equality and to create a better society (UNCTAD Report, 2017). To boost economic growth, the Egyptian government should give due to care to the development of the stock market given the role of stock markets in the growth and the development of both developed and developing countries.

In particular, well-functioning stock markets facilitate the mobilization of financial resources by playing the role of an intermediary between those who need capital to finance successful projects and those who have resources to invest. Although banks participate also in this role, the substantial increase in lending rates over recent years, as shown in Figure 9.1, has led to a marginal reduction in the role of banks in boosting economic growth in Egypt. Thus, this leads to an increased demand for research studies that focus on understanding the role of the stock market and how it operates as well as creating an environment that ensure the development of a well-functioning market.

Figure 9.1: Lending Rates in Egypt (2006-2016) (Source: World Bank)

In response to this need, this thesis aims to study the determinants of stock prices in the Egyptian stock market which is one of the crucial questions facing both investors and the economy as a whole. Specifically, this thesis aims to analyse the ability of different conditional versions of the Fama and French three-factor model to explain the cross-sectional variation in stock returns. Furthermore, this thesis attempts to assess the role of investor sentiment in asset pricing both as a conditioning variable and as an additional risk factor.

9.2 Research Objectives and Questions

In order to achieve its aim, the objectives of this thesis, outlined in the introductory chapter, provide a clear roadmap to follow. Thus, this section revisits the objectives of this thesis and addresses how they were accomplished.

Objective 1: Provide a comprehensive literature review concerning the debate between the EMH and behavioural finance.

The importance of this objective emerges from setting out the main theoretical propositions upon which this thesis is based. Specifically, since this thesis aims to determine a valuation model for stocks in the Egyptian stock market, a critical choice regarding determining the set of assumptions that governs the judgements, preferences, and decisions of investors in financial markets is inevitable. Thus, Chapter 2 accomplishes this task by providing an overview on the EMH and behavioural finance that provide different sets of these assumptions.

The EMH has strong assumptions such as investor rationality, common risk aversion, perfect markets with no frictions, and easy access to information for all market participants. Although the realism of these assumptions is strongly debated, researchers in financial economics have accepted them as their predictions seem to fit the reality well (Szyszka, 2013). Nonetheless, the accumulation of puzzles that challenge standard finance theories leads researchers to reconsider the validity of these assumptions and this has resulted in the emergence of behavioural finance theories whose assumptions are based on the argument that investors sometimes do not act in a rational way and that this irrationality leads the market itself to be irrational due to limits to arbitrage (Barberis and Thaler, 2003).

These different assumptions of the EMH and behavioural finance result in different implications for asset pricing in general, and the relationship between risk and return in particular (Shefrin, 2008). Statman *et al.* (2008) state that in conventional asset pricing, expected returns are explained by utilitarian factors which represent risk alone, while in behavioural asset pricing models sentiment plays a role in asset pricing. However, although the assumptions of behavioural finance seem more realistic than those of the EMH, this does not mean that behavioural asset pricing models are better than conventional asset pricing models. Lucas (1980) emphasises that a "good" model is not the one that is more real than a "poor" one. Rather, a "good" model is the one that provides a better explanation of reality. This, in turn, leads to the second objective of this thesis.

Objective 2: Discuss the relative merits of both conventional (static and conditional) and behavioural asset pricing models and summarize the empirical evidence underlying them

Although behavioural finance has more realistic assumptions, this does not imply that behavioural asset pricing models are better than conventional ones. According to Lucas (1980), the final resolution to this argument is which of conventional and behavioural asset pricing models provide better explanation of reality. This leads to proliferation of papers that test these models empirically to determine whether they can explain the cross-sectional variation in stock returns in both developed and emerging markets. Thus, the second objective of this thesis is to summarize the empirical evidence underlying these models and highlights their relative merits. In this regard, Chapter 3 summarizes the empirical evidence concerning the FF3 which is the main asset pricing model used in this thesis, and it highlights its main challenges, whereas Chapter 4 summarizes the empirical evidence on both conditional and behavioural asset pricing models which are considered among the major breakthroughs in asset pricing literature that emerged to accommodate the challenges facing conventional asset pricing models.

The importance of these chapters emerges from identifying the gaps that this thesis aims to fill. The empirical evidence of the FF3 shows that although the model provides a comprehensive description of most of the anomalies that have challenged empirical research in a parsimonious three-factor framework (Hahn and Yoon, 2016), the model still faces many challenges.

In this regard, as far as this thesis is concerned, the first challenge facing the model is its failure to explain the returns of individual stocks and industry portfolios. According to Fama and French (1997) and Avramov and Chordia (2006), this failure can be due to ignoring modelling the time-variation in risk and risk premia. Thus, they recommend extending the model to conditional specifications to provide better explanation of the cross-sectional variation in stock returns. The second challenge facing the model is related to its failure to explain the cross-sectional variation in stock returns in emerging markets. In this regard, Dolinar (2013) argues that academics should search for additional risk factors that can better characterise stock returns in these markets.

The above challenges facing the FF3 leads to the emergence of two major strands of literature. The first strand is concerned with conditional asset pricing models. Reviewing the literature on conditional asset pricing models reveals that despite their theoretical appeal, they suffer from some difficulties. First, the absence of a theoretical basis upon which researchers can model time-variation in risk and risk premia leads to the emergence of a wide spectrum of approaches to capture time-variation in risk and risk premia. Nonetheless, given the relative merits of each approach, there is no clear-cut answer concerning which approach is superior. Second, although Iqbal *et al.* (2010) argue that the assumption of constant betas and expected returns is more questionable in emerging markets compared to developed ones, most previous studies that test conditional asset pricing models focus mainly on developed markets and there is a significant dearth in studies that test conditional asset pricing models in emerging markets which constitutes the first gap that this thesis aims to fill by testing whether the conditional FF3 can explain the cross-sectional variation in stock returns in the Egyptian stock market.

The second strand is concerned with behavioural asset pricing models. Shefrin (2005) emphasises that the future of asset pricing theory should be based on behaviouralizing asset pricing model. However, despite this argument, Shefrin highlights that most of behavioural asset pricing models are *ad-hoc* models that aim to provide behavioural explanations for particular anomalies. Shefrin argues that this approach does not lead to a unified theory of asset pricing. Thus, recent studies, in behavioural finance literature, attempt to account for this criticism and develop clear behavioural asset pricing models (Potì and Shefrin, 2014; Ho and Hung, 2012). Nonetheless, the empirical coverage of these models is scarce which explains why behavioural asset pricing models are not as popular as conventional models. This, in turn, constitutes the second gap that this thesis aims to fill by testing whether behavioural asset pricing models can explain the cross-sectional variation in stock returns in the Egyptian stock market.

Given the above gaps, this thesis aims to achieve the following objectives that are related to its empirical analysis.

Objective 3: Construct an Egyptian version of the Fama and French three risk factors.

Since the first step in identifying a valuation model for stocks is to determine the appropriate state variables that are priced in equilibrium, the first contribution of this thesis is the construction of an Egyptian version of the Fama and French three risk factors following Fama and French (1993) and Cakici *et al.* (2013). Although the Fama and French three factors are available for the US market, international markets, and the UK market (Fama and French, 1993; 2012; Gregory *et al*., 2012), these factors are unavailable for the Egyptian stock market. Thus, to remedy this situation and fill in this gap, Chapter 5 describes the details of constructing the Fama and French factors which are then made available to researchers and practitioners in an attempt to provide a valuable resource for research proposes and financial decisions.

After determining the appropriate state variables, the next step is to determine the appropriate model specification. In this regard, given the highly volatile nature of the Egyptian stock market, the conditional version of the model is expected to provide better explanation of the cross-sectional variation in stock returns. Thus, the next objective is as follows.

Objective 4: Test the conditional FF3 that captures time-variation in betas using the rolling regression approach, the scaled factor model approach, and

multivariate GARCH with dynamic conditional correlations (DCC) and compare between these three approaches.

The time span of this thesis covers a very rich sample period that is full of remarkable events which are the Global financial crisis, the Arab spring, and the Egyptian revolutions. During such periods, it is highly debatable that betas, expected returns, and risk premia are constant over time. This, in turn, raises the need to test whether the conditional FF3, that captures time-variation in betas using the rolling regression approach, the scaled factor model approach, and the DCC-GARCH model, can explain the cross-sectional variation in stock returns. Up to the author's knowledge, this thesis is among the first studies that provide an in-depth analysis of conditional asset pricing models in the Egyptian stock market.

This task is accomplished in Chapter 7 that presents the results of the various conditional specifications of the model and compares between them and thus provides an answer for the first empirical question of this thesis.

The first approach employed to capture the time-variation in betas is the rolling regression approach. The estimates of the betas of the Fama and French factors for the 10 portfolios double-sorted on size and the B/M ratio show that the betas exhibit high variability over time especially for small stocks portfolios. This, in turn, implies that in determining an appropriate model specification for the Egyptian stock market, a static model that assumes that betas are constant cannot be warranted.

However, the results of the Fama and Macbeth cross-sectional regression show that the conditional FF3 that captures time-variation in betas using the rolling regression approach cannot capture the cross-sectional variation in stock returns in the Egyptian stock market. However, these results should not be taken as evidence against the conditional FF3 due to the following reasons. First, the performance of asset pricing models that capture time-variation in betas using the rolling regression approach is highly dependable on the chosen window length. In this thesis, the window length used in the estimation of the rolling betas is 24 months due to the short sample period employed in the tests and the recommendation of Lewellen and Nagel (2006) that researchers should use short windows when estimating betas. This arbitrarily choice of the window length may adversely affect the performance of the model. Second, Ang and Chen (2007) argue that since estimates of betas using rolling regressions assume that betas change across subsamples but they are constant within each subsample, using rolling regression may result in incorrect inferences about the validity of conditional models as it ignores the variation in betas in each window, and thus it understates the variation of the true conditional betas.

The second approach used to capture time-variation in betas is the scaled factor model approach which defines betas as a linear function of the Treasury bill rate, size and the book-to-market ratio. The choice of these variables is supported by the sufficient theoretical and empirical evidence about the ability of these variables to predict the state of the economy and forecast future returns (Gomes *et al.*, 2003; Fama and French, 1988). The results show that none of the specifications of the CAPM and FF3 tested can provide an explanation for the size, value, momentum, and liquidity effects. However, relative to other specifications, the FF3 in which the risk factors are allowed to vary with size and the book-to-market ratio is considered the best specification.

Nonetheless, this model faces two main criticisms. First, the model is still challenged by its inability to capture the turnover and short-term momentum effects which is consistent with the results of Avramov and Chordia (2006). Second, the model has a negative and significant intercepts which implies that the average stock underperforms, relative to the FF3, by 7.44% per year which is an economically significant value.

However, despite these challenges facing scaled factor models in the Egyptian stock market, it should be noted that the results of this thesis are dependent on the set of conditioning variables employed. Thus, using other conditioning variables may save the FF3 in the Egyptian stock market. Nonetheless, the data availability may be a severe obstacle in employing wider sets of conditioning variables.

The last approach employed in this thesis to capture time-variation in betas is the DCC-GARCH model which is considered as one of the advanced techniques to model time-variation in betas. In this approach, it is assumed that the covariances of the individual returns with the Fama and French factors and the variances of the factors returns are time-varying. To capture the time-variation in these main components of betas, the multivariate GARCH with dynamic conditional correlations is used which is considered one of the main contribution of this thesis as most previous studies model time-variation in betas using the DCC-GARCH within the context of the CAPM rather than multifactor models.

The results show that the using the DCC-GARCH provides less supportive evidence for the FF3 in the Egyptian stock market compared to the rolling regression approach. Specifically, the sign and the significance of the factors risk premia cast doubts on the validity of the model. Furthermore, the high and significant pricing errors of the model compared to that of the model that uses rolling betas provide further evidence against the model.

However, it should be noted that since the Egyptian stock market is an emerging markets that suffer from thin trading, the estimates of the DCC betas may be adversely affected by the missing data problem.

To sum up, the results of the second empirical question of this thesis show that modelling time-variation in betas using the rolling regression approach, the scaled factor model approach, and the DCC GARCH model does not save the FF3 in the Egyptian stock market. These unfavourable results lead us to the fifth objective of this thesis that aims to determine whether taking time variation in both risk and risk premia can lead to better results.

Objective 5: Test the conditional FF3 that captures time-variation in betas, using the rolling regression approach and the DCC-GARCH model, and captures time-variation in risk premia using a Markov-switching regime model.

Up to Chapter 7 the main assumption employed in this thesis was that the relationship between risk and return is linear. However, Ghysels *et al.* (2014) argue that this assumption is very restrictive. Thus, Chapter 8 relaxes this assumption by assuming that this relationship is time-varying and depends on the underlying regime due to the following reasons.

Risk premia should depend on uncertainty (measured usually as volatility) and on risk aversion (Vendrame, 2014). In this regard, since one of the conventional wisdom in finance literature is that risk aversion is countercyclical (Cohn *et al.*, 2015) which means that investors tend to be less (more) risk averse during good (bad) economic conditions, then it is more plausible to assume that risk premia is time-varying. Thus, the second empirical question of this thesis aims to determine whether modelling time-variation in risk premia can save the conditional FF3 in the Egyptian stock market.

In order to answer this question the following steps were followed. First, the assumption made in Chapter 8 was that there are two regimes (bull and bear) characterizing the market during the sample period. These regimes are obtained using a Markov switching process with a probability that depends on the realization of an unobservable variable, the state or the regime, which is random but assumed to be determined by the realization of the real excess return of market portfolio. Following this approach to identify the regimes is of a great benefit as it avoids exogenous identification of the regime (for example, using the sign of the monthly market return). Second, the time-variation in betas or factor loadings is captured using the rolling regression approach and the DCC-GARCH model. Both approaches are used as the results in Chapter 7 do not specify exactly which approach is preferable in modelling time-variation in betas in the Egyptian stock market. Third, it is assumed that there are two risk premia for each Fama and French factor; one for bull regime and one for bear regime. In order to estimate them, panel data regression is used in order to overcome the obstacle of having to estimate two sets of risk premia and having only one set of factor loadings (betas) each time.

Having these estimates of risk premia, several tests were undertaken to determine whether the conditional FF3 can capture the cross-sectional variation in stock returns in the Egyptian stock market and the results reveal the following observations. First, the unconditional FF3 is always rejected in favour of the conditional model in the Egyptian stock market. Second, the conditional FF3 that captures time-variation in betas using the DCC-GARCH is preferred to the model that uses the rolling regression approach due to the following reasons. (i) The average absolute pricing errors of this version of the model is significantly lower; and (ii) the weighted average risk premium of the SMB factor is significantly positive when the DCC betas are used as opposed to being significantly negative when the rolling betas are used.

However, despite the superior performance of the model that uses the DCC betas, it is still challenged by the following observations. First, the weighted average risk premium of the market factor is significantly negative which runs counter to the proposition that investors are risk averse and that they require compensation for bearing any additional risk. Second, both the bull and bear risk premia of the HML factor are positive and insignificant. This is inconsistent with the proposition that the risk premia tends to be positive during the bull regime and negative during the bear regime. Third, the difference between the bull and bear risk premia of the HML factor is insignificant which implies that either the HML factor does not play an important role in capturing the time-variation in expected returns as postulated by Ferson and Harvey (1999) or the state probabilities, that are determined using the real excess return of the market portfolio, are not able to probably capture the time-variation in the HML factor. Finally, the average absolute pricing errors of the model is large and significant which imply that the model cannot fully capture the cross-sectional variation in stock returns.

Given the failure of all of the specifications of conventional asset pricing models tested in this thesis to account for the cross-sectional variation in stock returns, the last objective of this thesis tests whether behavioural asset pricing models can provide better explanation of the cross-sectional variation in stock returns in the Egyptian stock market.

Objective 6: Test the performance of behavioural asset pricing models that incorporate the effect of sentiment into asset pricing models either as a conditioning variable or as a risk factor.

Given the debate presented in Chapter 2 about the different assumptions of the EMH and behavioural finance and the different implications they have for asset pricing, it may be argued that the unfavourable results of the different specifications of the FF3 tested in Chapters 7 and 8 are due to ignoring the impact of noise traders on stock prices as argued by behavioural finance proponents. Thus, the last empirical question of this thesis was about behavioural asset pricing.

Statman (1999) argues that the main focus of researchers should be to develop a behavioural asset pricing model that can incorporate both utilitarian and value-expressive characteristics. Within this context, this thesis tests the effect of sentiment on stock prices through two main channels. The first channel incorporates the effect of sentiment on stock prices by using it as a conditioning variable within the context of scaled factor models. The results reported in Chapter 8 show that using sentiment as a conditioning variable did not save neither the CAPM nor the FF3. These results contradict the result of Ho and Hung (2009) who show that using sentiment as a conditioning variable substantially improve the ability of both models to capture the most prominent anomalies in financial markets.

The second channel incorporates the effect of sentiment on stock prices by using it as an additional risk factor. The results presented in Chapter 8 show that augmenting the FF3 with an additional sentiment risk factor does not lead to major changes in the performance of the model. Specifically, although the sentiment risk factor is positive, it is insignificant which implies that sentiment is not significantly priced in the Egyptian stock market. Furthermore, the pricing errors of the conventional FF3 and the FF3 augmented with sentiment risk factor are not significantly different from each other.

The above results imply that using sentiment either as a conditioning variable or as a risk factor does not provide better explanation of the cross-sectional variation in stock returns in the Egyptian stock market. However, these results should not be taken as an evidence against behavioural asset pricing in the Egyptian stock market due to the following reasons. First, since there is no a definitive or uncontroversial measure of investor sentiment, the results of these tests are dependent on the chosen proxy for sentiment. Thus, different results may be obtained when another proxy for sentiment is used. Second, the short sample period employed in tests that use investor sentiment may negatively affect the power of the tests. Third, since the sample period is dominated by pessimism and down regime, it is expected that sentiment may have an insignificant effect on stock prices as according to Shen *et al*. (2017), financial markets tend to be more efficient during low-sentiment periods.

Finally, the results that small and highly volatile stocks are the most sensitive to changes in sentiment imply that sentiment is a non-diversifiable risk factor in the Egyptian stock market and suggest that further tests for behavioural asset pricing are warranted.

9.3 Limitations of the Research

As with any study, physical, financial, and time constraints cause the present thesis to be affected by several limitations. The work presented in this thesis has offered several extensions of the FF3 to determine which of these extensions can explain the cross-sectional variation in stock returns in the Egyptian stock market. The results show that although some of these extensions appear to be promising, some improvements may well be warranted. Specifically, there are five limitations which can be identified here.

First, the main assumption of this thesis is that the FF3 is the most appropriate asset pricing model for the Egyptian stock market. However, the validity of this assumption may be debated on the basis of the argument of Mckenzie and Partington (2014) who suggest that the use of the FF3 is no longer optimal and may, in turn, lead to invalid and misleading inferences given the sufficient empirical evidence documenting the weaknesses of the model. Thus, it would be interesting to test whether alternative asset pricing models can provide better explanation of the cross-sectional variation in stock returns in the Egyptian stock market. Possible models to consider are the Carhart four-factor model, the Fama and French (2015) five factor model, and the Fama and French model augmented with a Pastor and Stambaugh (2003) liquidity factor.

Second, given the long debate in asset pricing literature concerning whether local or global risk factors should be rewarded in emerging markets, this thesis assumes that the Egyptian version of the Fama and French factors are the most appropriate risk factors following the recommendations of Griffin (2002) that country-specific risk factors should be used in performing cost-of-capital calculation, performance measurement and risk analysis. However, Harvey (2001) argues that the assumption that emerging markets are fully segmented is highly debatable given the observation that many emerging markets liberalized since the late 1980s. In this regard, Harvey (1998) emphasises that the relative importance of local versus global risk factors change over time as financial markets become more integrated. This observation may suggest that global risk factors may be rewarded in the Egyptian stock market. Ignoring the impact of these global risk factors is another limitation of this thesis.

Third, since this thesis focuses mainly on the Egyptian stock market which is an emerging market, data availability and missing data problem are among the serious limitations facing this thesis. In this regard, the short sample period of this thesis and the limited number of stocks listed in the Egyptian stock market adversely affect the power of tests. Furthermore, consistent with emerging markets, the Egyptian stock market suffers from thin trading which intensifies the problem of missing data that may jeopardise the results of this thesis. Additionally, data availability in the Egyptian stock market precludes some of the tests to be undertaken. Specifically, the absence of a simple registry for dividend payments, the unavailability of historical data about the advancing/declining issues, and the weak bond market in Egypt make constructing a market-based proxy for investor sentiment very challenging.

Fourth, in applying the Markov-switching model to capture time-variation in risk premia, it is assumed that there are only two regimes characterizing the market which is an oversimplification of the reality. In particular, for long time periods, it is not appropriate to consider only two regimes when describing the stochastic process generating the observed data. However, this assumption was employed due to the small sample period used in this thesis.

Furthermore, in estimating these regimes, a simple model for the real market return is used. This model includes the intercept but no other exogenous variables. This may not reflect the stochastic process generating market excess returns. Thus, future research should consider incorporating other variables such as default spread, term spread, and interest rates, given the predictive ability of these variables for future returns, in order to provide better characterization of the regimes.

Additionally, using a univariate Markov-switching model to identify the main regimes that Egyptian stock market passed by may be debated by the argument of Kuan (2002) who emphasises that a multivariate model provides a better identification of business cycles. However, given the small sample employed in this thesis, using a multivariate model may not be a viable option.

Fifth, consistent with most previous studies in asset pricing literature, this thesis uses realized returns as a proxy for expected returns. Elton (1999) criticises this approach and emphasises that it may be one of the reasons behind the anomalous results of asset pricing models. Nevertheless, finding an appropriate proxy for expected returns is one of the main challenges in finance literature and it is a common limitation in most of the existing empirical work in asset pricing literature.

9.4 Recommendations for Future Research

This thesis tests several extensions of the FF3 to determine an appropriate valuation model for stocks in the Egyptian stock market by comparing between conventional and behavioural asset pricing models. With respect to conventional asset pricing models, the results show that none of the models tested can fully capture the cross-sectional variation in stock returns. Relative to the conditional versions of the model tested, the conditional FF3 that captures time-variation in risk using the DCC-GARCH and captures time-variation in risk premia using a Markov-switching model is considered as the best model, despite its inability to fully capture the cross-sectional variation in stock returns. Specifically, the results of this model show that the weighted average risk premia associated with the SMB and HML factors are positive and significant which imply that both factors are significantly priced in the Egyptian stock market. It worth noting here that the risk premia associated with the HML factor is positive only when time-variation in risk premia is taken into consideration. Despite these favourable results, the model is still challenged by the negative weighted average risk premium of the market factor. With respect to behavioural asset pricing models, the results show that sentiment does not have a significant impact on stock prices in the Egyptian stock market.

Overall, the results of this thesis show that the search for a more convincing asset pricing model for the Egyptian stock market remains, in that the results fail to provide evidence that the factors investigated in this thesis are consistently and reliably priced, however, the results provide useful recommendations for future research.

First, given the fact that the Egyptian Cabinet's Information and Decision Support Centre has ceased to publish the Egyptian CCI since 2014, there is an acute need to provide a market-based proxy for investor sentiment in the Egyptian stock market due to the following reasons. Han and Li (2017) argue that market-based proxies for investor sentiment are more reliable than survey-based measures. Furthermore, with respect to the Egyptian stock market, having a market-based measure for investor sentiment can enable researchers to have more powerful tests of behavioural asset pricing models as they can cover longer time periods. However, constructing market-based proxy for investor sentiment requires the Capital Market Authority in Egypt to provide data about dividend payment, advancing/declining issues and to give more due to care to the bond market as was mentioned in Section 9.2.

Second, since the Egyptian CCI is available only till 2014, this limited data precludes testing conditional versions of the FF3 augmented with behavioural factor. Thus, future research should attempt to determine whether conditional versions of behavioural asset pricing models can provide better explanation of the cross-sectional variation in stock returns. Furthermore, given the argument of Chung *et al*. (2012) that the return predictive ability of investor sentiment differ across different states of the economy and that it is significant only during bull markets, it is plausible to assume that the results of this thesis that the risk premia associated with the sentiment risk factor is insignificant is due to ignoring time-variation in risk premia. Thus, this creates a need to test whether behavioural asset pricing models that allow for time-varying risk premia can provide better explanation of the cross-sectional variation in stock returns.

Third, since the empirical tests of this thesis are conducted on realized returns as a proxy for expected returns, although the theory of asset pricing is based on expected returns, future research should exert more efforts on finding more appropriate proxies for expected returns, such as using analysts' forecasts and reports, and repeat the tests conducted in this thesis using these proxies to determine whether this can save the models tested.

Finally, since the data in the Egyptian stock market is highly non-normal as was shown in Chapter 6, this implies that the assumption that only covariance risk is rewarded in such context is highly debatable (Harvey, 1998). This, in turn, leads to an increased interest among researchers to study higher-moment asset pricing models that augment traditional models with the third and fourth moment of the distribution of returns (skewness and kurtosis). Doan *et al.* (2008) emphasise that an asset pricing model that goes beyond the first two moments of the return distribution seems to be the next logical step to account for the non-normal behaviour of stock returns. Thus, a further suggestion for future research is to investigate the role that higher moments plays in explaining average returns in the Egyptian stock market.

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Appendix A

A.1 The Fama-Macbeth Regression with Full Sample Betas and the GRS Test

The easiest way to provide a preliminary test of the proposition of Fama and French (1993) that the expected return of a stock in excess of the risk-free rate of return can be explained by the sensitivity of its return to (i) the excess return on the market portfolio; (ii) the SMB factor; and (iii) the HML (Fama and French, 1996) is to run the Fama-Macbeth cross-sectional regression with full sample betas.

The Fama-Macbeth methodology consists of two main steps. First, time-series regression is run over the entire sample in order to estimate full sample constant betas as follows:

$$R_{it}^{e} = \alpha_i + \beta_i R_{Mt}^{e} + s_i SMB_t + h_i HML_t + \varepsilon_{it} \qquad \text{(A.1)}$$

where R_{Mt}^{e}, SMB_t, and HML_t represent the Fama and French three risk factors. β_i, s_i, and h_i represent the risk loadings associated with each risk factor.

Then a cross-sectional regression is run each month to estimate the factor risk premia as follows:

$$R_{it}^{e} = \alpha_t + \beta_i \lambda_{mt} + s_i \lambda_{SMBt} + h_i \lambda_{HMLt} \qquad i = 1,2,\dots.,N \quad \text{for each } t = 1,2,\dots.,T \qquad \text{(A.2)}$$

where λ_{mt}, λ_{SMBt}, and λ_{HMLt} represent the risk premia associated with the market, the SMB, and the HML factors respectively. Although the shortcomings of unconditional asset pricing models are well-known, the results of this test are reported to identify the main shortcomings of this specification and to provide a benchmark against which the performance of conditional models that are tested in Chapters 7 and 8 can be compared.

Another test that is commonly used to assess the validity of asset pricing models is the Gibbons, Ross and Shanken (1989) (GRS) that aims to determine how well the static FF3 can explain the historical variability in returns by testing how small and insignificant the residuals are.

Before presenting the results of these tests, it is worth noting that the Fama-Macbeth cross-sectional regression is applied both on the 10 portfolios double-sorted on size and the book-to-market ratio and individual stocks. However, given the small sample of this thesis, the GRS test is applied only on asset pricing models that use portfolios as test assets as the large cross-section of individual stocks and the small time-series employed in this thesis make the estimation of the variance-covariance matrix of the residuals used in the GRS test difficult.

A.1.1 Results Based on the 10 Size/Book-to-Market Portfolios

Before presenting the results of this section, it is worth noting that the limited number of portfolios used in these tests results in some small sample bias which may affect the results. Thus, these results are augmented with the results derived from the tests applied to individual stocks to provide better inferences about the performance of the model.

The results of the full-sample time-series regressions are presented in Table A.1 that shows the coefficients of the Fama and French three factors along with the intercepts and their significance level. When analysing the results of the time-series regressions, several points can be highlighted. First, since excess returns of the 10 portfolios are used as dependent variables, the intercepts of the time-series regressions should be indistinguishable from zero if the asset pricing model is well specified. In this regard, only 3 out of the 10 portfolios produces intercepts that are significantly different from zero. The significant intercepts are mainly observed for the portfolios with average book-to-market ratio, and they are negative which implies that these portfolios earn lower returns than the model predicts. Overall, these results imply that the FF3 is performing a good job in capturing common variations in stock returns. Nonetheless, these results should be interpreted with caution. As the returns of these portfolios are highly volatile as can be inferred from their high standard deviations that range between 8.52% and 23.29% presented in Chapter 6 of this thesis.

Table A.1: Coefficients of the FF3 for the 10 Size/Book-to-Market Portfolios

Coefficient of Market Factor					
	Growth	B2	B3	B4	Value
Small	1.26	0.90	0.96	1.18	1.27
Big	1.05	0.83	0.88	0.96	1.05
Coefficient of SMB					
	Growth	B2	B3	B4	Value
Small	0.91	0.78	0.52	0.73	1.20
Big	-0.14	0.19	0.24	0.19	0.15
Coefficient of HML					
	Growth	B2	B3	B4	Value
Small	-0.55	0.03	0.08	0.20	0.70
Big	-0.17	0.20	0.08	0.23	0.41
Intercept					
	Growth	B2	B3	B4	Value
Small	0.01	0.01	-0.01**	0.00	0.01
	(0.96)	(0.93)	(-1.97)	(-0.12)	(1.16)
Big	0.00	-0.01*	0.00	-0.01*	0.01
	(-0.23)	(-1.71)	(-0.85)	(-1.83)	(1.19)
Adjusted R^2 (%)					
	Growth	B2	B3	B4	Value
Small	42.00	56.00	71.00	69.00	60.00
Big	95.00	70.00	67.00	56.00	46.00

Notes: Table A.1 shows the slopes, alphas and their t-statistics in parentheses, and adjusted R^2 values of the full sample time-series regression of the FF3 applied on the 10 portfolios double-sorted on size and the B/M ratio. The time-series regression is as follows:

$$R_{it}^{e} = \alpha_i + \beta_i R_{Mt}^{e} + s_i SMB_t + h_i HML_t + \varepsilon_{it}$$

* reflects significance at the 10% level
** reflects significance at the 5% level
*** reflects significance at the 1% level

Fama and French (1993) argue that such high volatility may negatively impact the power of asset pricing tests. Nonetheless, they argue that if the common risk factors employed can capture most of the variations in stock returns, then the inferences drawn from analysing the intercepts can be precise. However, the R^2 statistics from the time-series regressions show that there are substantial variations in stock returns that cannot be captured by the model as most are below 70%. Thus, this casts some doubts on the inferences drawn from analysing the intercepts of the time-series regression. Furthermore, the results show that the FF3 leaves substantial common variations in stock returns that can be captured by other risk factors or by different model specifications.

The slopes of the Fama and French factors provide some direct evidence on whether they can capture common variations in stock returns. The results show that although the market betas decrease monotonically with size, there is no clear pattern that can be observed with regard to their relationship with the B/M ratio. Furthermore, despite the large variation in average returns across portfolios, the variation in market betas across the portfolios is too small to explain this significant variations in average returns. In contrast, the slopes of the SMB factor shows substantial variation across portfolios by ranging between -0.14 and 1.20. Within each B/M quintile, the slope of the SMB factor decreases monotonically with firm size which implies that the SMB factor can capture variations in stock returns related to size. Finally, the slopes of the HML factor also show substantial variation across portfolios by ranging between -0.55 and 0.70. Within each size group, the slope of the HML factor increases almost monotonically with the B/M ratio. These results imply that the HML factor contributes to capturing common variations in returns related to the B/M ratio.

Finally, Cochrane (2001) highlights that in a time-series regression, the most appropriate estimate of the factor risk premium is the sample mean of the factor. Having such estimates of the factor risk premia provides a convenient way to evaluate the role of each risk factor in the cross-section of average returns (Fama and French, 1993). First, as apparent from Table A.1, the market betas of all of the 10 portfolios are around 1, this means that the market factor cannot capture the substantial variations in average returns across the portfolios. Rather, the market factor captures similar common variations in the returns on all of the portfolios. Specifically, the market factor represents a premium for investing in stocks generally as opposed to investing in risk-free assets. However, the substantial variations in the slopes of the SMB factor across portfolios along with the factor risk premium that is estimated as the average return of the SMB factor, which is equal to 1.82% per month, show that the size-related risk factor captures substantial variations in stock returns. Specifically, the predicted spread in average returns across the 10 portfolios due to the size-related risk factor amounts to 2.44% per month which is substantial and highlights the role of the size-related risk factor in explaining the cross-sectional variation in average returns in the Egyptian stock market. Finally, although the slopes of the HML factor shows substantial variations across portfolios, its estimated risk premium, which is equal to -0.0317% per month, is very small to play any significant role in capturing the cross-sectional variation in stock returns.

The final time-series test of the FF3 for the Egyptian stock market is the GRS test. The F-statistic of the GRS test is 2.35 which rejects the null that the intercepts of the 10 portfolios are jointly equal to zero. Nonetheless, since the GRS test assumes that the errors are independently and identically distributed over time and that they are homoscedastic and independent of the factors, these strict assumptions may jeopardise the results of the test. Thus, a robust version of the test that corrects for heteroscedasticity is also evaluated. The robust-GRS statistic strongly rejects the null that the intercepts of the 10 portfolios are jointly equal to zero. Thus, these results imply that the model cannot be accepted as a well-specified model for the Egyptian stock market.

In order to provide more formal tests of the FF3, the results of the Fama-Macbeth cross-sectional regression are presented in Table A.2. Lewellen *et al.* (2010) emphasise that researchers should impose theoretical restrictions on the slopes of the cross-sectional regressions in order to make asset pricing tests more convincing. They argue that researchers should not only focus on the sign and the significance of the slopes, but they should also focus on the magnitude of the slopes, especially when the theory provides some intuition about them. For example, since in this thesis excess returns are used as the main dependent variable, then the estimates of the alphas should be insignificantly different from zero if the asset pricing model is well-specified. Furthermore, Lewellen *et al.* argue that the risk premium on a factor portfolio should be close to its average excess return.

The t-statistics reported in Table A.2 are calculated using standard errors corrected for heteroskedasticity and autocorrelation to provide more accurate inferences compared to t-statistics estimated in the usual way.

The first observation from Table A.2 is that the alpha is negative and significant at the 10% level which implies that the model cannot capture all of the cross-sectional variations in stock returns in the Egyptian stock market. This observation of negative intercepts may imply that the model is mis-specified due to ignoring time-variation in risk and risk premia despite the highly volatile political and economic conditions prevalent in the Egyptian stock market. This, in turn, may result in high pricing errors as postulated by Ghysels (1998).

The results also reveal that the market risk premium is positive and significant. However, the cumulative yearly excess return of the market risk premium is 50.4% which is extremely high given the historical average excess return of the market that is equal to 1.19% per month. Given the suggestions of Lewellen *et al.* (2010), this significant difference between the estimated risk premium and the sample average market excess return creates some doubt for the ability of the model to capture cross-sectional variations in stock returns. Furthermore, this estimate of the market risk premium is very hard to justify using economic fundamentals. However, the high risk premia can be accounted for within the realm of behavioural asset pricing models. Specifically, De Long *et al.* (1990) argue that the observed high risk premium that cannot be justified by economic fundamentals can be explained by noise trader risk that is ignored by conventional asset pricing models such as the FF3. Thus, since the Egyptian stock market is dominated by small investors who are more subject to behavioural biases, an asset pricing model that includes sentiment as an additional risk factor may provide a better explanation of the cross-sectional variation in stock returns.

Similarly, the estimated risk premium of the SMB factor is significantly positive which implies that the size-related risk factor is significantly priced in the Egyptian stock market. However, the magnitude of the risk premium of the SMB factor is inconsistent with its sample average return. Finally, the risk premium for the HML factor is negative but insignificant which implies that the HML factor is not priced in the Egyptian stock market, and it does not have any role in capturing the cross-sectional variation in stock returns. This result strongly contradicts previous results for developed markets concerning the role of the HML factor in capturing the cross-sectional variations in stock returns.

Overall, the analysis of the slopes of the cross-sectional regression shows that both the market and size-related risk factors are significantly priced in the Egyptian stock market, while the HML factor seems to be not priced. Nonetheless, these results should be interpreted with caution given the inconsistency between the estimates of the risk premia and the sample average return of the factors, especially for the market factor. Lewellen and Nagel (2006) highlight that ignoring the restrictions on the cross-sectional slopes may result in overestimating the precision of an asset pricing model, and thus they advocate that time-series and cross-sectional tests should be employed together to provide better asset pricing tests.

The overall conclusion of the above tests is that the FF3 cannot be accepted as a valid asset pricing model for the Egyptian stock market. However, given the limitations of the test and the fact that it ignores time-variation in risk and risk premia, the tests of the conditional FF3 may yield better results. In addition, the limited number of portfolios employed in the above tests may negatively impact the power of the tests, and thus the tests are repeated using individual stocks as the main test assets in order to get more accurate inferences about the performance of the model.

Table A.2: Fama-Macbeth Cross-Sectional Regression Tests on the 10 Portfolios Double-Sorted on Size and the Book-to Market Equity and on Individual stocks

Test Assets	α	λ_M	λ_{SMB}	λ_{HML}
10 Size/Book-to-Market Portfolios	-0.032	0.042	0.024	-0.0031
	(-1.84)*	(2.09)**	(2.02)**	(-0.19)
Individual Stocks	-0.01	0.015	0.015	-0.0099
	(-2.44)***	(1.52)	(1.28)	(-0.96)
	[-2.31]	[1.28]	[1.27]	[-0.79]
Fama and French Factors		$\overline{R_M - R_f}$	$\overline{SMB}$	$\overline{HML}$
Sample Average Return		1.19%	1.82%	-0.0317%

Notes: Table A.2 present the intercepts and slopes of the Fama-Macbeth cross-sectional regression of monthly excess returns for 10 portfolios double-sorted on size and the B/M ratio and for individual stocks based on their full-sample betas. T-statistics reported in brackets are derived from heteroskedasticity and autocorrelation consistent regression. The t-statistics based on Shanken's (1992) correction are given in square brackets. The results are obtained from the following regression:

$$R_{it} - R_{ft} = \alpha_t + \hat{\beta}_{it}\lambda_t$$

* reflects significance at 10% level
** reflects significance at 5% level
*** reflects significance at 1% level

A.1.2 Results Based on Individual Stocks

Table A.2 reports the results of the Fama-Macbeth cross-sectional regression applied on individual stocks to augment the results of the previous section. The results show that the intercept is negative and significant at the 1% level which contrasts with the assumption of the model that the intercept should be indistinguishable from zero. Thus, this implies that FF3 cannot capture the cross-sectional variation of stock returns in the Egyptian stock market. In addition, the results show that both the magnitude and the significance level of the factor risk premia substantially decrease compared to the results of Section A.1.1. Specifically, both the market and the SMB risk premia are positive but insignificant, whereas, the risk premium of the HML factor is negative and insignificant. The insignificance of the three risk premia provides evidence against the FF3 when applied to the Egyptian stock market during the sample period.

Given the vulnerability of the tests that employ individual stocks as the main test assets to the EIV bias, the Shanken (1992) correction for standard errors is applied. However, since this thesis uses monthly data, the impact of the Shanken correction on the t-statistics is fairly mild and no major changes to the inferences are made.

To sum up, the results presented in Appendix A show that the static FF3 is strongly challenged in the Egyptian stock market. These unfavourable results may be attributed to model misspecification due to ignoring time-variation in risk and risk premia. These results provide an increased interest in testing whether the conditional versions of the FF3 can provide better explanation of the cross-sectional variation in stock returns. Jagannathan and Wang (1996) argue that conditional asset pricing models may hold even if unconditional models do not hold.