# Asset Pricing and the Intertemporal Risk-Return Tradeoff

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**By**


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# **Abstract**

The intertemporal risk-return tradeoff is the cornerstone of modern empirical finance and has been the focus of much debate over the years. The reason for this is because extant literature cannot agree as to the very nature of this important relation. This is troublesome in terms of academic theory given that it challenges the notion that investors are risk-averse agents and is furthermore troublesome in practice given that market participants expect to be rewarded with higher expected returns in order to take on higher risks.

The motivation for this thesis stems from the conflicting and inconclusive empirical evidence regarding the risk-return tradeoff. Through each of the chapters, it sheds new light on possible reasons as to why extant studies offer conflicting evidence and, given the enhancements and innovative approaches proposed here, it provides empirical evidence in support of a positive intertemporal risk-return tradeoff when examining several international stock markets.

The research questions this thesis addresses are as follow. Firstly, is it possible that extant conflicting evidence is manifested in the use of historical realized returns to proxy for investors' forward-looking expected returns? Secondly, can accounting for shifts in investment opportunities (i.e. intertemporal risk) better explain investors' risk aversion and changes in the dynamic risk premium? Thirdly, is it possible that conflicting findings are the result of neglecting to account for the possibility that there exist heterogeneous investors in the stock market with divergent expectations?

The empirical findings can be summarized as follows; firstly, there is a strong possibility that many existing studies cannot find a positive risk-return relation because they are relying on *ex post* historical realized returns as a proxy for investors' forward-

looking expected returns. Secondly, there is evidence in favor of the Merton (1973) notion that there exists intertemporal risk which impacts investors and that this type of risk should be considered. This has been also another reason why extant literature cannot agree on the nature of the intertemporal risk-return tradeoff. Finally, even after accounting for investor heterogeneity, the findings provide support for the Merton (1973) theoretical Intertemporal Capital Asset Pricing Model. Namely, in contrast to existing studies on the matter, there is evidence of fundamental traders over longer horizons and no evidence of feedback traders at such horizons. Although this sheds new light on some of the driving forces behind stock prices, the nature of investors' degree of risk aversion seems to be best supported by the Merton (1973) theoretical Intertemporal Capital Asset Pricing Model.

## Statement of Publication

Some of the arguments made forth in this thesis have been published and have been presented in academic conference presentations. In particular, the argument made about some of the intrinsic limitations behind using *ex post* realized returns to motivate asset pricing theories and to serve as a proxy of investors' required rate of return (see Koutmos, 2010; Koutmos, 2011).

A working paper of the third chapter has been presented at the University of Leicester at the November 2009 UKEPAN Finance Conference on "Global Trends in the Efficiency & Risk Management of Financial Services."

A working paper of the second chapter has been presented at the Eastern Finance Association (EFA) in Savannah, Georgia on April 2011.

# Declaration

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I declare that this thesis is my own and has not been submitted to any other institution for credit or another degree.

# Disclaimer

This thesis is the author's property and, as such, any omissions or errors are my sole responsibility. I retain the right to modify and change the material here or in future research papers or whenever I feel it is necessary.

## Dedication

*To my loving parents, for teaching me*

*the boundless importance of knowledge and love,*

*and for raising me to be a decent person.*

## Acknowledgements

# - Chapter One -

# Introduction

## 1.1. Focus of the Thesis

The intent of this thesis is to investigate empirically the nature of the intertemporal tradeoff between risk and return on the market portfolio. Historically, the risk-return relationship retains a prominent position in the field of asset pricing and is the foundation for much of modern empirical finance. Interestingly, this relationship has inspired much innovative advancement in econometrics such as the autoregressive conditional heteroskedasticity (ARCH) model of Engle (1982) and the generalized ARCH (GARCH) of Bollerslev (1986) and Taylor (1986), which, as is explained later on, enables researchers to model market risk and to see how it varies through time. It also allows researchers to explicitly see its relation with market returns and to observe whether there is a positive risk-return tradeoff.

Despite advancements in econometric sophistication as well as the development of new technology and economic databases which now allow more accessibility to financial data, this field of research is still in a state of flux. In particular, academic research has reached no clear consensus as to the nature of the intertemporal risk-return tradeoff and literature often reports conflicting findings which change with the econometric technique used or with the nature of the data.

The risk-return tradeoff has been such an important issue which motivates much of the work that is related to asset pricing because, from this very relationship, we seek to

answer important questions relating to market efficiency, the predictability of stock returns, and the behavior of market participants. However, in order to empirically test many of these propositions, it is important to examine the tradeoff between risk and return in the stock market because, from understanding this relationship, then we can be at a better position to determine what the driving forces behind stock prices are and whether risk plays a role in investors' decision-making and their portfolio selection criterion. Therefore, given the paramount importance of this relation, it is rather troublesome that literature which empirically examines the nature of the risk-return tradeoff reports mixed findings as to its nature.

Traditionally, theory dictates that the risk-return tradeoff is positive and that rational risk-averse investors demand higher returns in order to take on more risk (see Markowitz, 1952). This proposition has then been developed further and used in order to develop the paradigm that investors are mean-variance optimizers and seek investments which have the highest possible mean returns at the lowest possible variance. In other words, investors are looking for assets that have the highest possible expected returns at the lowest level of risk. Should risk increase, we would also expect investors' expected return to rise commensurate to this risk.

Much of asset pricing has evolved on the basis that risk and return are positively related. In particular, Sharpe (1964) and Lintner (1965) introduce the highly acclaimed Capital Asset Pricing Model (CAPM) which seeks to explain assets' expected returns on the basis of their risk. Although this model was introduced many years ago, it is still explored by researchers today and even used among practitioners as a valuation tool for cost of capital approximations (see Graham and Harvey, 2001).

From the perspective of an investor, it is important to understand the nature of the risk-return relation because it directly impacts their decision-making and their willingness to bear more risk. For example, why would an investor take on more risk if it appears that there is no evidence of a positive risk-return tradeoff? Therefore, this thesis not only attempts to provide some insights into strictly the theory of asset pricing literature, but also raises some practical questions and how they directly influence investors. If we have a better understanding of the nature of the risk-return tradeoff, then this will help investors make better decisions and we can better understand whether the volatility of an asset plays a role in the expected returns of this very asset.

Despite the risk-return tradeoff being the foundation for much of modern empirical finance and a key ingredient in investors' decision-making, the motivation for this thesis also stems from the fact that many studies which investigate this important relation tend to report mixed findings that are oftentimes counterintuitive and inconsistent with the predictions of theory. In particular, since the introduction of the CAPM, other researchers have introduced multi-period models which suggest investors' risk aversion shifts through time in accordance to shifts in market risks and investment opportunities. One such prominent and classical model is the Intertemporal Capital Asset Pricing Model (ICAPM) of Merton (1973). This model, unlike the CAPM of Sharpe (1964) and Lintner (1965), attempts to find the link between risk and return in a multi-period continuous framework where investment opportunities shift stochastically through time. In other words, the ICAPM postulates that risk is time-varying in nature and so is investors' expectations and degree of risk aversion.     From the perspective of investors, such a model may be a more accurate description of reality since, as observation of markets

suggests, market events and investors' perceptions and degree of risk tolerance shift rapidly through time and are never "static" as the CAPM suggest. If the ICAPM is indeed an accurate portrayal of reality, then such a model can prove useful in determining what are the factors which influence stock prices and which drive investors' risk aversion.

Despite the significant theoretical advancements of the Merton (1973) ICAPM, there are still many gaps in the literature which merit attention. More specifically, the literature still cannot agree on the nature of the intertemporal risk-return tradeoff despite the so many advancements that have been made in econometric and time-series modelling. In particular, the proposition that intertemporal risk and return should be positively linked has been explored extensively, as is explained later on, using variations of the GARCH methodology. The evidence is mixed and oftentimes counterintuitive.

In light of extant conflicting findings, this thesis seeks to make a novel contribution by addressing the intertemporal risk-return tradeoff from three different angles. Each of these different angles not only explores the intertemporal risk-return tradeoff but also examines of what relevance the findings are for market participants. Each of these findings and arguments are discussed in turn in the remaining chapters of this thesis.

## 1.2. Objectives of the Thesis

In particular, the following chapters look at the intertemporal risk-return tradeoff from different angles and try to provide explanations as to why existing findings are mixed. For example, the second chapter provides arguments which highlight the limitations with using *ex post* historical realized returns as a proxy for investors' forward-looking

expectation of returns. It contributes to existing literature by providing a forward-looking proxy of expected returns which is derived theoretically from the Gordon (1962) dividend constant growth model, something which, to my knowledge, has not been considered before. In an additional contribution to literature, this chapter finds a positive tradeoff between risk and return in both the short- and long-run. It thus emphasizes that extant conflicting findings may not be the artifact of econometric (miss-)specification of the conditional volatility process but may instead be rooted in the use of realized historical returns as a proxy for investors' forward-looking expected returns.

The third chapter takes on a different approach. It considers a two-factor variant of the seminal Merton (1973) ICAPM and considers why two-factor empirical implementation of this model has been so limited when compared to literature which implements a one-factor variant of the ICAPM whereby conditional volatility is the only explanatory variable that should be able to describe variations in expected returns. In particular, the two-factor ICAPM posits that expected returns are a linear function of their conditional volatility and their conditional covariance with investment opportunities which shift stochastically through time. The empirical challenge, however, with this two-factor model is that it is difficult to identify variables, known as "state factors," which serve as a proxy for investors' opportunity set.

In a contribution to existing literature, the third chapter raises arguments as to why this is the case and why the long-term government bond interest rate may not be an appropriate proxy for the investment opportunity set, despite it being advocated by Merton (1973). This is because this interest rate is, to a large extent, influenced by the activities of Central Banks and may not reflect real economic activity as, say, the

industrial production index. It thus proposes to use a set of macroeconomic factors which have proved to be instrumental in literature in detecting shifts in macroeconomic conditions and in explaining stock market returns. It furthermore implements an econometric technique which allows each of the proposed state factors to be time-varying in nature and evolve as investment conditions in the market shift through time.

Finally, the fourth chapter takes yet a different approach and argues that perhaps we need to incorporate the behaviors of different types of investors since there is ample evidence to suggest that investors do not conform to 'rational expectations' and do not invest on the basis of mean-variance considerations as is advocated by Markowitz (1952). In particular, it incorporates the behavior of three different types of investors; fundamental traders, feedback traders and rational investors who make investment decisions on the basis of mean-variance considerations.

Despite the different approaches each of the following three chapters takes in trying to resolve the intertemporal risk-return puzzle, they are all linked in the sense that they touch on many contemporary issues related to asset pricing and, more specifically, to what the issues regarding the intertemporal risk-return tradeoff are. It is interesting to see how this tradeoff encompasses many other topics in finance theory; for example, the second chapter contains principles related to corporate finance when it derives from the Gordon (1962) dividend constant growth model the earnings-yield as a proxy for investors' required rate of return in the stock market. The third chapter explores evidence from macroeconomic and financial regulatory literature which explores to what extent macroeconomic factors can explain shifts in economic market conditions. The fourth chapter draws on literature from the field of behavioral finance in order to motivate the

methodology used and to show perhaps it is necessary to incorporate the behavior of different investors when examining the risk-return tradeoff.

Overall, the objective of this thesis, through each of the chapters, is to shed light onto why existing studies still cannot agree on the nature of this very important relation. This thesis takes on an international perspective and evaluates the risk-return tradeoff, using the various aforementioned advancements and innovations, in several industrialized markets. The findings lend credible support for a positive intertemporal risk-return tradeoff and that perhaps extant shortcomings in the literature do not stem from empirical irregularities. Therefore, consistent with theory, we are risk-averse investors and demand higher returns per unit of risk that we take in the stock market.

## 1.3. The Main Issues

What are some of the underlying reasons why extant literature cannot agree on the risk-return tradeoff? Perhaps the most widely accepted theory is known as the so-called 'volatility feedback effect (hypothesis)' which was mentioned originally by French, Schwert and Stambaugh (1987) and discussed more elaborately by Campbell and Hentschel (1992). Its arguments are very intuitive and are the core reason why existing studies find a negative or statistically negligible risk-return tradeoff. More specifically, this hypothesis states that negative shocks in stock returns lead to higher future volatility than positive shocks of equal magnitude. This proposition is consistent with the empirical observation that volatility is persistent and, as is described in Mandelbrot (1963) and Fama (1965), an increase in current volatility leads to more volatility in the future. The reason for this is, as Campbell and Hentschel (1992) argue, is because the negative

effects associated with bad news in the stock market are more pronounced than good news and have a larger bearing on investors' investment decisions.

The volatility feedback argument can be used to explain why extant studies find a negative or statistically insignificant risk-return relation; in particular, as Mandelbrot (1963) describes, since volatility is persistent, an increase in volatility today 'signals' that volatility will be higher in the future. This raises investors' required rate of return and the discount factor they use to discount expected future streams of income. If we assume that corporate earnings and dividends are not rising while volatility rises, prices will obviously fall since investors sell off their positions and wait until expected returns rise again to the appropriate level. As investors sell their positions, this will produce declining prices and produce a lower historical mean return leading one to erroneously believe that the expected *ex ante* required rate of return is falling. However, the required rate of return is actually rising commensurate to higher perceived risk (as theory predicts) and hence this is what produces lower prices.

Despite the arguments made by the volatility feedback hypothesis, it seems that extant studies continuously rely on historical realized returns as an unbiased proxy of investors' future expected returns and their required rate of return. The reason they do so is because expected returns, just like expected market risk, are unobservable factors and therefore they rely on various proxies which can describe them. Furthermore, it is convenient to use historical realized returns given that this data is widely available and can easily be derived from stock prices.

However, it is important to note that there are at least three intrinsic shortcomings to using historical realized returns; firstly, current research indicates that the risk

premium is time-varying and, therefore, any inferences drawn concerning *expected* returns using *ex post* returns may be highly sensitive to the sampling period under consideration (see Merton, 1973; Lundblad, 2007). Secondly, we as investors are forward-looking and thus form expectations of the required rate of return on the basis of current volatility, as well as news regarding future volatility in the stock market. This is consistent with the arguments made by Campbell and Hentschel (1992) that future volatility is a function of past news as well as any future news that may disseminate to investors. Finally, as Lundblad (2007) duly indicates, the belief that a long enough sample of historical returns will 'converge,' eventually, to expected returns is misplaced and inaccurate. More specifically, his study finds that nearly two hundred years worth of data is needed in order for us to see historical realized returns converge to investors' expected rate of return.

Another likely reason as to why extant literature documents conflicting findings is because the majority of studies limit their empirical methodology to one-factor GARCH-type models whereby the conditional mean of returns is solely a function of their conditional variance. As is proposed by Merton (1973), perhaps it would be beneficial for researchers to look at what factors may accurately serve as a proxy of the investment opportunity set and consider integrating these factors into their analysis. Such factors, as is described by Merton (1973) and Gerard and Wu (2006), proxy for what is known as 'intertemporal risk.' Such risk reflects the fact that investment opportunities are constantly shifting through time and are constantly affecting investors' portfolios and marginal utility of wealth. As such, expected returns in the stock market may not only be

a function of market volatility but also a function of intertemporal risk, as is suggested by Scruggs (1998) and Scuggs and Glabadanidis (2003).

Finally, another issue which merits attention is that existing studies have not taken into account the possibility that there are heterogeneous types of investors in the stock market. So far, most studies empirically test the Merton (1973) model assuming that all investors have similar expectations and trading behaviors. This, however, may not be the case; in particular, there is a distinguished body of empirical finance literature which has found that there are different types of investors which exhibit different trading patterns. For example, apart from making investment decisions on the basis of mean-variance considerations, there is evidence to suggest that investors engage in trading patterns such as positive feedback trading and trading on the basis of fundamentals (see De Long, Shleifer, Summers and Waldmann, 1990b; Shiller, 2000).

Given that these investors play a significant role in the market, it may be useful to integrate their behavior in econometric models in order to more accurately describe the nature of the risk-return relation. By examining these issues across international markets, we can establish a more global perspective about the intertemporal risk-return tradeoff as well as check the qualitative robustness of the findings.

## 1.4. Contribution of the Thesis

The empirical nature of the risk-return tradeoff is so important in finance that it has even been described as the "first fundamental law in finance..." (see Ghysels, Santa-Clara and Valkanov, 2005). Despite the importance of this relation in finance, the existing literature still cannot provide a concerted description as to its nature. Despite the volatility

feedback hypothesis being cited as a reason why existing studies cannot find a consistent positive risk-return tradeoff, there is still continuous reliance on using *ex post* historical returns as an unbiased estimate of investors' forward-looking expected returns.

Thus far, the literature has not been able to provide a coherent view as to why we cannot find a positive link between expected returns and their conditional variance. Many studies report a statistically non-existent risk-return relation (see French, Schwert and Stambaugh, 1987; Baillie and DeGennaro, 1990; Chan, Karolyi and Stulz, 1992; Harrison and Zhang, 1999; Koulakiotis, Papasyriopoulos and Molyneux, 2006, to name only a few), while others find it to be negative (see Pindyck, 1984; Nelson, 1991; Glosten, Jaganathan and Runkle, 1993; Bekaert and Wu, 2000). Lundblad (2007) finds it to be positive yet does so only when using nearly two centuries worth of data. Only then, after using a long sample, does he find convergence between historical realized returns and investors' expected returns.

In a contribution to existing literature, the second chapter of this thesis argues that the conflicting findings may not stem from empirical methodologies but instead is rooted in the use of historical realized returns as an unbiased estimate of investors' forward-looking risk premium. Sharpe (1978) and Elton (1999) also warn of the problems associated with using *ex post* realized returns to test asset pricing theories and to estimate expected returns. More specifically, Elton (1999) argues that future work in asset pricing should strive to consider alternative ways to measure expected returns instead of focusing on the development of new statistical procedures that continue to rely on *ex post* realized returns.

In light of these arguments and conflicting extant findings, the second chapter explores a variant of the Merton (1973) and provides an innovative proxy for investors' forward-looking risk premium that is derived theoretically from the Gordon (1962) dividend constant growth model. This proxy is the earnings-yield and reflects the required rate of return in the stock market. In terms of forecasting capabilities, the earnings-yield, which is the reciprocal of the familiar P/E ratio that is used by practitioners, has proved to be a good predictor of future returns and economic conditions (see Campbell and Shiller, 1998, 2001). Shiller (2000) argues that the P/E ratio is a strong proxy for future expected returns and finds that when it rises above its long-run average, it signals 'irrational exuberance' in the stock market and a probable likelihood of an imminent correction in stock prices.

Now, in order to form an estimate of the risk premium, traditionally, asset pricing studies compute the spread between *ex post* average stock market returns and the yield on treasuries. The proposed *ex ante* proxy set forth in this chapter consists of the market earnings-yield and the long government bond yield since this reflects the possibility that investors can either invest their money in the stock market or in a risk-free asset. Whereas the earnings-yield reflects the stock market yield, the risk-free yield can be represented by the long-term government yield. In the long-run, there is a positive equilibrium relation between these two yields and any deviations from this signal changes in economic conditions. Such a relation, therefore, serves as a forward-looking measure of investors' risk premium.

The reason why the long-term government yield is used is because this yield may more accurately reflect investors' and households' opportunity costs given that they have

longer trading and investment horizons. As is argued by Chen, Roll and Ross (1986), because investors' discount factor varies with expected dividends, earnings and firms' long-term prospects, the long-term government bond yield more closely reflects this discount factor. As a result, this yield contains a broader range of information regarding macroeconomic conditions which directly impact investors' relative risk aversion and utility of wealth. Finally, as mentioned, there is a growing body of literature that finds a long-run positive relation between the earnings-yield and the long-term government bond yield whereby deviations from this relation may exist in the short-run and serve to signal shifts in economic conditions and market returns (see Lander, Orphanides and Douvogiannis, 1997; Thomas and Zhang, 2008).

This literature has been motivated by what practitioners have called the so-called 'Fed Model,' whereby they use the long-run relation between the market earnings-yield and the long-term government bond yield to estimate future returns and economic conditions. Practitioners dubbed this relation the 'Fed Model' on the basis of a Humphrey-Hawkins report that the Federal Reserve released which talked about the relation between the market earnings-yield and the long-term government bond yield. Although the Federal Reserve does not endorse any trading strategy nor does it try to take any stance in order to avoid speculation among investors, there has been academic research which shows that there is a long-run relation between the market earnings-yield and the long-term government bond yield and that any short-run deviations may be useful in identifying shifts in macroeconomic conditions (see Lander, Orphanides and Douvogiannis, 1997; Thomas and Zhang, 2008).

In a contribution to extant literature, and in a step in the right direction in exposing some of the intrinsic deficiencies with using ex post historical returns as a proxy for investors' forward-looking expected returns, the second chapter makes use of the literature which examines the Fed Model and also of classical literature that has been the backbone of financial theory, such as the Gordon (1962) dividend constant growth model. It derives theoretically and from this model how the market earnings-yield can be used as a proxy for the required rate of return in the stock market. Thus, this contribution is unique because it is firstly emphasizing the limitations to using historical returns and how, according to the volatility feedback hypothesis of Campbell and Hentschel (1992), we are likely to find a negative or statistically insignificant risk-return relation. Furthermore, it illustrates why backward-looking historical returns are an unjustifiable proxy for investors' forward-looking expectations. It thus provides a forward-looking measure and argues that future research, as Elton (1999) maintains, investigating the intertemporal risk-return tradeoff should focus on trying to find methods to test asset pricing theories which do not rely on using historical returns as a proxy for expected returns. The research here is a step in the right direction in trying to accomplish this.

It is important to emphasize that the findings herein are of interest to academics and practitioners alike. From the perspective of academic research, the research herein lends credible support to the notion that we as investors are risk averse and therefore demand higher returns in order to take on higher risks. More specifically, the market earnings-yield, which serves as a proxy for investors' required rate of return in the stock market, varies positively with market volatility both in the short- and long-run when looking at international stock markets. There is also evidence of a positive long-run

relation between the earnings-yield and the long-term government bond yield. This relationship can be justified on grounds that as interest rates rise, the cost of firms' debt also rises and their ability to raise capital is impinged. Thus, the future prospects of the firm become relatively riskier and investors may assign a higher discount rate to its future cash flows (i.e. their required rate of return rises). Secondly, the stock market may simply become a less attractive investment as investors' opportunity cost rises and they move into more "risk-free" investments such as Treasury bills and bonds. Therefore, their required rate of return in the stock market rises commensurate to this risk. Such a relation is also consistent with extant literature which also documents a positive association between the market earnings-yield and the long-term government bond yield (see Gordon, 1962; Bleiberg, 1989; Fairfield, 1994; Greenspan, 1997; White, 2000).

From the perspective of practitioners, the research here provides information about the market earnings-yield and shows how this can shift as market volatility varies through time. In particular, periods of heightened stock market volatility are associated with higher market earnings-yields. This empirical observation is consistent with the findings of Campbell and Shiller (1998, 2001) and Shiller (2000). Namely, the market earnings-yield, as well as its reciprocal – the price-earnings ratio – can serve as an indicator of future market conditions. In particular, when the market earnings-yield is relatively high, it generally corresponds to higher market volatility and that investors' required rate of return has risen. As a result, and consistent with the volatility feedback hypothesis of Campbel and Hentschel (1992), this will lead to a drop in stock prices as investors sell of their positions in the stock market and wait for expected returns to rise to the appropriate level (see Koutmos, 2010; Koutmos, 2011). Thus, a relatively high

earnings-yield serves to signal that returns will be higher in the future because investors' required rate of return has risen and thus future returns must rise to compensate them for increases in market volatility.

These findings are also consistent with the arguments made by Shiller (2000), who argues that a high price-earnings ratio (i.e. low earnings-yield) may be a signal of "irrational exuberance" in the stock market whereby investors are heavily invested in the stock market with an expectation that stock prices will continue to rise in the future. Under a scenario such as this one, investors do not foresee any imminent risks and feel comfortable with their investing and, thus, their required rate of return is low. In a scenario where the market price-earnings ratio is low (i.e. the earnings-yield is high), this may signal that many investors avoid investing in the stock market and stock prices are undervalued (see Shiller, 2000), possibly because of increased risks and market volatility. In such a scenario, their required rate of return (i.e. the market earnings-yield) is high and they demand higher returns to compensate them and in order to invest in the stock market.

Whereas the second chapter considers a single-factor variant of the Merton (1973) ICAPM, which posits that expected returns are solely a function of conditional volatility, the third chapter introduces the two-factor ICAPM. This model posits that expected returns are, in addition to volatility, a function of their conditional covariance with investment opportunities that shift stochastically through time (see Scruggs, 1998; Scruggs and Glabadanidis, 2003). Despite its intuitive predictions and empirical tractability, the two-factor ICAPM has not received as much attention relative to the single-factor ICAPM. This may be due to the fact that, up until now, there has not been

sufficient data which enables researchers to find a link between returns and other macroeconomic or financial factors (see Cochrane, 2001). This may also be attributable to the fact that researchers have not yet chosen factors which may serve as accurate proxies for the investment opportunity set available to market participants.

Merton (1973) suggests using the interest rate as a proxy for the investment opportunity set and, following this guidance, Scruggs (1998) empirically applies a two-factor variant of the Merton (1973) ICAPM using the long-term government bond yield as a proxy for the investment opportunity set, since this yield may accurately reflect the information content of other interest rates as well. In this study, Scruggs (1998) finds a positive intertemporal risk-return tradeoff and attributes extant conflicting findings on the basis that they do not integrate 'intertemporal risk' into their models. This type of risk, as is discussed in greater length in the thesis, is the risk and uncertainty associated with changes in the investment opportunity set (see Merton, 1973; Turtle, Buse and Korkie, 1994; Scruggs, 1998; Gerard and Wu, 2006). Given the importance of proxying for intertemporal risk, there is a body of literature, which is relatively much smaller in size relative to literature that explores the single-factor ICAPM, and argues that the future direction of research needs to concentrate on investigating the importance of intertemporal risk and how this may influence the risk-return tradeoff.

Although the study by Scruggs (1998) finds empirical evidence in support of the theoretical postulation that investors are indeed risk averse and demand higher expected returns to take on more risk, this study's shortcomings become evident by Scruggs and Glabadanidis (2003). In particular, the latter implement an econometric model, as is discussed in greater depth, which allows for the covariation between the long-term

government bond yield and investors' expected risk premium to be time-varying. In other words, the investment opportunity set is "dynamic" in the sense that it shifts as market and macroeconomic conditions shift for investors. In fact, such an econometric approach is a closer depiction of economic reality as opposed to the assumption embedded in the methodology by Scruggs (1998), which assumes a constant covariation between investors' market risk premium and investment opportunities. In fact, literature in this regard has found that, for several international markets, the correlation between stock returns and bond returns is time-varying (see Cappiello, Engle and Sheppard, 2006). When Scruggs and Glabadanidis (2003) allow for the conditional covariance between the long-term bond yield and the market risk premium to be time-varying, they find no evidence of a positive risk-return tradeoff. This therefore raises questions about the methodology implemented by Scruggs (1998) and calls for more research into trying and resolve this issue.

In a contribution to extant literature, the third chapter of this thesis considers a two-factor variant of the Merton (1973) ICAPM and discusses some of the limitations behind using the long-term government bond yield to proxy for investment opportunities in the market. More specifically, it argues that researchers need to consider additional economically meaningful factors which can proxy for shifts in the investment opportunity set and the macroeconomy at large. One of the reasons for this is because the interest rate is, to a large extent, a financial variable that is controlled by the actions of Central Banks around the world which conduct monetary and fiscal policies to adjust interest rates and regulate economic activity (see Mishkin, 2005). The argument of considering additional factors that can accurately proxy for the investment opportunity set is also made in the

study by Guo and Whitelaw (2006); in particular, when they discuss why Scruggs (1998) and Scruggs and Glabadanidis (2003) find conflicting results, they state that this result "Does not imply a rejection of… (Merton's ICAPM); rather, it challenges the assumption that bond returns are perfectly correlated with investment opportunities" (p. 1435).

Furthermore, the third chapter seeks to make methodological improvements in the context of modeling the dynamic risk premium and allowing the interaction between the risk premium and the investment opportunity set to be time-varying in nature, as is expected given that investors' risk aversion and risk premium shift with changes in the macroeconomy.

In a contribution to extant literature, the third chapter therefore argues that it will perhaps be of economic value to look at other real economic variables that may accurately describe market and economic conditions and are not as influenced by the decisions of policymakers. In particular, it uses, in addition to the long-term government bond yield, industrial production and slopes in the yield curve given that there is a distinguished body of literature which finds that these factors can describe economic conditions and explain stock market returns.

For example, Chen, Roll and Ross (1986) use industrial production as one of the factors in their empirical Arbitrage Pricing Model in order to explain stock market returns. Other studies also provide support for industrial production as a natural candidate for an economic state factor for its ability to identify cyclical movements in macroeconomic conditions which impact investors' consumption and, ultimately, their utility of wealth function. More specifically, fluctuations in stock market levels are directly linked with shifts in industrial production, evidence suggesting that it may be a

systematic source of risk and can serve as a factor to proxy for the investment opportunity set (see for example Fama, 1981; James, Koreisha and Partch, 1985; Schwert, 1990; Fama, 1990, to name only a few). In addition to this, Artis, Kontolemis and Osborn (1997) actually uses fluctuations in industrial production as a key variable to determine shifts in business cycle regimes for the United States and 11 other industrialized countries. In their study, they find that their chronology of business cycles is strikingly similar to the chronology established by the National Bureau of Economic Research (NBER).

Likewise, the slope of the yield curve has been found to predict with high accuracy impending recessions (see Estrella and Hardouvelis, 1991; Campbell, 1995; Estrella and Mishkin, 1998; Hamilton and Kim, 2002, to name only a few studies). This empirical observation has even become popular among practitioners who frequently reference where we are on the yield curve in order to make inferences about our current economic state as well as future economic activity.

The findings from this chapter are of interest to academics and practitioners alike. From the perspective of academic theory, the findings herein lend credible support to a positive intertemporal risk-return tradeoff in the context of the Merton (1973) ICAPM. These findings hold in international markets and suggest that perhaps conflicting extant findings are an artifact of omitting the second factor in the ICAPM which serves as a proxy for the investment opportunity set. In particular, the following important findings emerge from this empirical chapter: Firstly, as is indicated in the third chapter, there is international evidence of asymmetry in volatility as well as volatility persistence. This is consistent with previous findings (see Mandelbrot, 1963; Fama, 1965; French, Schwert

and Stambaugh, 1987) and is also consistent with the volatility feedback hypothesis of Campbell and Hentschel (1992).

Secondly, when examining the time-series dynamics of each of the proposed proxies for the investment opportunity set, it is interesting to see that their respective conditional variance estimates are a function of past volatility and innovations. In particular, for the long-term government bond yield, its conditional mean is positively linked with its conditional variance. This suggests a positive relation between its returns and its volatility. Furthermore, when examining the time-series properties of industrial production, it is interesting to see that, alike the other two proposed factors, it appears to respond asymmetrically to innovations across many of the market indices in the sample. In other words, negative shocks (declines in industrial production) lead to more volatility than positive shocks (increases in industrial production) of equal magnitude. Such an empirical observation can be supported by existing studies which examine the economic behavior of markets and what implications policy-making has on output and economic performance. In this regard, Neftci (1984), Hamilton (1989) and Artis, Kontolemis and Osborn (1997) argue that industrial production reflects states in the business cycle and, namely, economic ups and downs exhibit asymmetry; whereby industrial production declines more in absolute terms during recessions than it rises during periods of economic prosperity. Such a finding is of interest to academics and practitioners and suggests that there is something similar to the so-called 'volatility feedback hypothesis' present in economic cycles in our market.

A third major finding from this chapter is the observation that intertemporal risk is important and this can consistently be seen to play a significant role across most of the

G-7 markets here in the sample. This finding sheds new light on existing studies. Namely, up until now, studies have not made it clear whether conflicting findings are the result of econometric (miss-)specifications or because of omission of the second factor which serves to proxy for the investment opportunity state. Whereas Scruggs (1998) argues in favor of the two-factor ICAPM, Scruggs and Glabadanidis (2003) report empirical evidence to the contrary. The findings in this chapter, however, provide strong evidence in favor of the notion that intertemporal risk is an important ingredient in determining investors' risk premium in the stock market and may be a possibly strong reason for extant conflicting findings in the literature. It is important to mention here that, given that industrial production shifts asymmetrically through time and, although relatively less pronounced, there is some evidence of the other proxies exhibiting asymmetric behavior, the model used to test the two-factor ICAPM is the BEKK model of Engle and Kroner (1995). This model is advantageous in that it allows the conditional variance and the covariance within the context of the ICAPM to respond asymmetrically to past innovations. Such a model, therefore, can accommodate the asymmetric time-series movements in factors, such as industrial production, and may provide a better description of investors' risk premium in the stock market.

A fourth major finding, consistent with the tests conducted in this chapter, is that the empirical evidence here supports the Merton (1973) theoretical view of the ICAPM without a constant term. This is conducted in this chapter via a likelihood ratio test to see whether restricting the constant to zero is supported. The findings here lend support to the theoretical ICAPM of Merton (1973) and to the second assumption in his seminal paper regarding capital market structure which is the foundation for intertemporal asset pricing;

namely, transactions costs do not exist and there are no taxes or other constraints (see Merton, 1973, p.868). This theoretical proposition has enabled motivation of the ICAPM, although Scruggs (1998) mentions perhaps it will be useful to include a constant term to account for these very market imperfections. Before this thesis chapter, the literature does not give a clear distinction as to whether the Merton (1973) theoretical two-factor model holds with or without a constant. The findings here support the notion of the theoretical ICAPM and the empirical findings show that if we accept the assumptions that Merton (1973) establishes, the proposed state factors do a comparatively better job in explaining variations in investors' intertemporal risk premium relative to the model if we account for a constant term which attempts to capture such market inefficiencies.

Finally, a fifth major finding in this chapter is that it appears that the long-term government bond yield may not be an appropriate proxy for investment opportunities, given that it does not exhibit consistently reliable empirical significance in terms of explaining intertemporal variations in investors' risk premium. This provides support to the argument made in this thesis that the long-term bond yield is a financial variable that is, to a large extent, controlled by the actions of central banks (see Mishkin, 2005) and may not accurately reflect investment opportunities. This may be a contributing reason why Scruggs and Glabadanidis (2003) do not find a positive risk-return relation when focusing on the U.S. market. However, the international evidence here corroborates the view of Guo and Whitelaw (2006, p.1435) that this does not "imply a rejection..." of the ICAPM, and contributes to literature by empirically showing the behavior of the intertemporal risk premium using proposed factors rooted in theory.

From the perspective of practitioners, this chapter of the thesis, apart from investigating the intertemporal risk-return relation, sheds light on what kind of factors investors ought to consider when assessing economic conditions and when trying to explain variations in expected stock market returns. In particular, the empirical findings reported here show strongest evidence for suggesting that shifts in the yield curve describe states in the economy. This finding provides some basis for using the yield curve in order to track market and economic performance and predict future states of the economy. These empirical findings thus provide further support to studies which argue of the economic information content embodied in the yield curve (see Estrella and Hardouvelis, 1991; Campbell, 1995; Estrella and Mishkin, 1998; Hamilton and Kim, 2002, to name only a few).

Finally, the fourth chapter contributes to literature by examining the intertemporal risk-return tradeoff but takes an innovative approach relative to existing studies in the sense that it integrates the trading behavior of heterogeneous types of traders; namely, the behavior of positive feedback traders and fundamental traders. The motivation for this chapter stems from the fact that, until now, empirical literature applies variations of the Merton (1973) ICAPM assuming that investors make decisions on the basis of mean-variance considerations in the context of Markowitz (1952) and that there is no mispricing of assets. A relatively new body of research however finds that, contrary to the equilibrium notion that mispricing is transitory and that markets are efficient (see Malkiel, 2003), there is evidence that identifies many constraints which arbitrageurs face which limit their ability to attack mispricing and, therefore, stock market prices may deviate for some time from their equilibrium value (see De Long *et al.,* 1990a; Shleifer

and Summers, 1990; Shleifer and Vishny, 1997; Shiller, 2000; Abreu and Brunnermeier, 2002 and 2003).

Further to this, the literature cites that there are heterogeneous groups of investors who may drive stock prices away from their equilibrium values. For example, De Long *et al.* (1990b) and Sentana and Wadhwani (1992) cite that positive feedback traders and fundamental traders exist and that their actions, to some extent, drive stock prices. Positive feedback traders are essentially trend chasers (i.e. 'herding investors') and buy (sell) when prices move upwards (downwards). This type of trading may be the result of irrationality, fads, word-of-mouth enthusiasm, overly zealous extrapolative expectations, portfolio insurance strategies such as stop-loss orders, or margin call forced liquidations. Investment behavior or strategies that manifest into this type of trading exert a self-reinforcing influence on prices; fluctuations in price are augmented and independent of any rational valuations placed on fundamentals or other mean-variance considerations regarding the asset's characteristics. This may exacerbate mispricing and allows it to persist. In contrast to positive feedback traders, fundamental investors trade on the basis of fundamentals or some kind of fundamental indicator. It is worth mentioning that the underlying distinction between "rational investors," in the context of Markowitz (1952) and Merton (1973) and fundamental traders is that rational investors make investment decisions on the basis of mean-variance considerations.

In an innovation to extant literature, this fourth chapter, given the extant findings which suggest the presence of heterogeneous investors, explores whether we should integrate this behavior in our models when estimating the intertemporal risk-return tradeoff. So far in the literature, existing studies only have only looked at variants of the

Merton (1973) ICAPM using predominantly GARCH-type frameworks. There has not been an attempt yet to see whether we can better explain the risk-return tradeoff by incorporating the behavior of these heterogeneous investors in our model.

Therefore, this fourth chapter cites a wealth of instances throughout history where investors and market participants can make decisions on the basis of emotions or irrationality and may engage in positive feedback trading in the stock market. It contributes to literature by modelling the trading patterns of three types of investors in several industrialized markets and to see to what extent their behavior is manifested in the time-varying dynamics of stock market returns. Namely, it extends the work of Sentana and Wadhwani (1992) and Cutler *et al.* (1990) and contributes to extant studies by producing a feedback trading framework that models the actions of rational risk-averse expected utility maximizers (i.e. 'smart money' investors, positive feedback traders, and fundamental traders. Thus far, the literature has not tried to see whether conflicting evidence in the intertemporal risk-return tradeoff is the result of neglecting to incorporate these heterogeneous investors' trading behavior.

Fundamental traders believe in mean reversion of stock prices toward a long-run average, or fundamental, value. These traders decrease (increase) their demand for risky assets when prices are high (low) relative to fundamentals. Given some of the findings mentioned in the second chapter regarding fundamental factors, the fourth chapter will consider the spread between the market dividend-yield (D/P) and long-term government bond yield (see Jagannathan *et al.*, 2000), as well as the spread between the market earnings-yield (E/P) and long-term government bond yield (see Lander *et al.,* 1997; Thomas and Zhang, 2008) as measures of fundamental value. Consistent with these studies, these spreads

are useful in estimating the equity premium and predicting future economic conditions. Other authors also find that the market E/P and D/P ratios are useful valuation measures of real stock market performance (see Shiller, 2000; Campbell and Shiller, 2001).

The findings are of interest to practitioners and academics and pave the way for future research into this field. Namely, in terms of explaining the intertemporal risk-return tradeoff, the empirical evidence provided here corroborates the arguments made in the second and third chapters; namely, it provides support for the Merton (1973) theoretical notion that the conditional variance and intertemporal risk are the sole determining factors of investors' risk premium. The evidence from the fourth chapter suggests that integrating the behavior of heterogeneous investors does not help to better explain variations in the intertemporal risk premium. Instead, the findings shed new light which has not been identified before and raises additional insights which merit further exploration. These findings are of interest to practitioners who seek valuation methods for the stock market and for academics who further want to explore into this field.

Firstly, there is empirical evidence here that fundamental traders drive, to some extent, movements in stock prices. This shows that valuation ratios, such as the earnings-yield and dividend-yield, may prove useful to practitioners who want to measure stock market performance and predict future market movements. In particular, the evidence here shows that fundamental traders increase their demand for stock shares when prices are low relative to their fundamental value and vice versa. In terms of gauging fundamental value, the ratios proposed here seem to be good indicators of whether stock prices as over- or under-valued. These results confirm the arguments made in the second chapter and the arguments of other researchers (see Shiller, 1996; Lander, Orphanides and Douvogiannis,

1997; Shiller, 2000; Campbell and Shiller, 1998, 2001; Thomas and Zhang, 2008, to name a few).

A second major empirical finding which merits future research is that it appears positive feedback trading is not statistically evident when exploring monthly frequency data. This result does not imply a rejection of the notion that there exist heterogeneous groups of investors in the stock market, it instead suggests that feedback traders are present but only in the short run. These results are in contrast to those by Sentana and Wadhwani (1992), Koutmos (1997), and Antoniou, Koutmos and Pericli (2005). This of course may be due to the fact that these studies are using daily data. In this case an argument can be made in favor of the notion that positive feedback trading is present in the short run, but it becomes insignificant in the longer run. It is also possible that there are also negative feedback traders so that the net result becomes insignificant over the longer-run and when looking at lower frequency data such as monthly stock market returns. This suggests that high-frequency traders and institutions may drive prices in the short-run but in the longer-run, negative feedback traders and fundamental traders push the prices back to their equilibrium values.

Overall, this thesis explores the intertemporal risk-return tradeoff from different angles and provides plausible explanations as to why existing findings are mixed in the literature. It provides unique contributions and reasons as to why extant studies document conflicting findings. The second, third and fourth chapters, respectively, provide unique contributions and valuable information that have not been explicated before and pave the way for future research into this field. The intertemporal risk-return tradeoff will surely be a contemporary topic for years to come in finance literature. However, now with the

findings of this thesis, there is new evidence and a new approach to explaining why extant findings cannot agree on the nature of the intertemporal risk-return tradeoff.

## 1.5. Limitations of the Thesis

Despite the advancements and contributions in this thesis, there are still issues which merit attention and which will be addressed undoubtedly by more authors to come in the future. Namely, in a recent paper, I investigate the time-varying nature of volatility in various industries within the NYSE, NASDAQ and AMEX, and find that some industries exhibit higher systematic risk for investors relative to others (see Koutmos, 2011). Instead of focusing strictly on the intertemporal risk-return tradeoff in the stock market, future research should also investigate the nature of this important relation across various industries. This is something that I am undertaking in future research projects. The reason why this is important is because different industries have unique risk characteristics given that they produce respective goods and services and consumers exhibit varying degrees of elasticity in terms of their demands towards these goods and services. Thus, investors considering to invest in various industry sectors need to be aware of the risk-return characteristics and how they shift relative to shocks in the aggregate stock market.

Another possible extension of this thesis that can be addressed in a separate study is that it is more difficult, using the innovation outlined in the second chapter, to examine the risk-return relation in a high-frequency setting. For example, suppose we wanted to estimate the intertemporal risk-return tradeoff using minute-by-minute stock price trades. Such a task will not be feasible given that the earnings-yield, which serves as a proxy for the required rate of return in the stock market, is unavailable at such high frequencies.

Traditionally, macroeconomic factors, such as the market earnings-yield, are available on a monthly basis and, as such, the frequency of the data investigated here is also monthly. Future research, therefore, can look into ways of adopting the framework herein to be applied to higher frequency data. This is something that is being undertaken in a separate study and will almost certainly receive attention by other authors as well.

However, it does not go without saying that using higher frequency data is free of theoretical problems; as is argued by Officer (1973) and Cochrane (2001), investors' degree of risk aversion probably shifts along with shifts in other macroeconomic factors as well as shifts in the business cycle. In fact, Cochrane (2001, p.26) maintains that "It is not plausible that risk or risk aversion change at daily frequencies... It is much more plausible that risk and risk aversion change over the business cycle..." In addition to this, higher frequency stock prices are known to be too noisy. Thus, these are some of the challenges which need to be overcome when motivating investigation into the risk-return tradeoff in high-frequency settings and which will undoubtedly be explored in future research.

Finally, the proposed intertemporal risk factors motivated in the third chapter are in no way inclusive of all the risk factors which investors face in this world. Instead, the contribution of this thesis argues that intertemporal risk is indeed time-varying, as is indicated by the empirical tests herein, and that future research ought to focus on indentifying factors which can accurately proxy for shifts in this risk. Given the empirical and theoretical contributions made herein, the findings support the notion that investors are risk averse agents and thus demand higher expected returns to take on higher risks. In some respects, the important contributions herein corroborate the view of Chen, Roll and

Ross (1986, p.384) that "A rather embarrassing gap exists between the theoretically exclusive importance of systematic 'state variables' and our complete ignorance of their identity." With these contributions, there will be more future research into intertemporal asset pricing and, namely, modelling the risk-return tradeoff and measuring investors' risk aversion across various markets, industries, and assets.

## - Chapter Two -

## Risk-Return Tradeoff: A Forward-Looking Approach to Measuring the Equity Premium

## 2.1. Introduction

A fundamental challenge in modern empirical finance is quantifying the intertemporal tradeoff between risk and return on the aggregate stock market portfolio. Although intuition dictates that investors demand higher compensation in order to take on higher risks, the empirical evidence provides mixed conclusions despite recent advancements in the sophistication of modeling techniques (see French, Schwert and Stambaugh, 1987; Chou, 1988; Baillie and DeGennaro, 1990; Harvey, 1991 and 2001; Nelson, 1991; Campbell and Hentschel, 1992; Glosten, Jagannathan and Runkle, 1993; Bekaert and Wu, 2000; Lundblad, 2007). This is problematic from a theoretical standpoint since it defies the predictions of general equilibrium asset pricing models which postulate a positive and linear relation between expected market returns and market risk (see Sharpe, 1964; Lintner, 1965; Merton, 1973). It is furthermore troublesome in practice given that the risk-return tradeoff is an important ingredient in cost of capital estimations and optimal portfolio allocation and risk management decisions (see Graham and Harvey, 2001).

To circumvent the problem that expected returns are not readily observable, the convention in literature has been to use historical realized mean returns as a proxy for investors' risk premium. Dozens of papers utilize this approach to explore the time-series nature of the risk-return tradeoff yet the evidence remains inconclusive, with inferences

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that are highly sensitive to econometric specifications or sampling periods (see Harvey, 1991 and 2001; Nelson, 1991; Campbell and Hentschel, 1992; Bekaert and Wu, 2000; Lundblad, 2007). They justify the practice of using *ex post* mean returns on grounds that, for long enough time horizons, realized mean returns 'converge' to *ex ante* expected returns. Thus, *ex post* mean returns provide an empirically tractable alternative to motivating asset pricing models.

Despite its widespread use however, there are at least two fundamental limitations to using *ex post* realized returns as an estimate of investors' *ex ante* risk premium; firstly, since the risk premium is time-varying and linked to fluctuations in the business cycle, any inference drawn concerning *ex ante* expected returns is naturally determined by the sampling period considered (see Lundblad, 2007). Secondly, investors are forward-looking and estimate future risks on the basis of current volatility and news regarding future volatility. Their resultant discount factor (required rate of return) which they apply to future streams of income therefore adjusts accordingly and may not be reflected in *ex post* realized mean returns (see Paudyal and Saldanha, 1997).

The prevailing hypothesis which attempts to reconcile much of the conflicting aforementioned findings is known as the 'volatility feedback effect,' originally proposed by French, Schwert and Stambaugh (1987) and formalized by Campbell and Hentschel (1992). It states that a negative shock in returns (unexpected drop in price) leads to higher future volatility than a positive shock (unexpected increase in price) which is of equal magnitude. The reason for this is straightforward; since volatility is persistent (see Mandelbrot, 1963), an increase in volatility today 'signals' that volatility will be higher in the future. This raises investors' required rate of return and the discount factor they use to

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discount future streams of income. Assuming that corporate earnings and dividends are not rising, prices will obviously fall since investors sell off their positions and wait until expected returns rise again to the appropriate level. The declining prices produce a lower historical mean return leading one to erroneously believe that the expected *ex ante* required rate of return is falling when, on the contrary, the required rate of return is rising commensurate to higher perceived risk (as theory predicts) and hence to lower prices.[1]

In this chapter I show that the fundamental problem in estimating the time-series relation between risk and return may not be the result of econometric (miss-)specification of the variance, but is rooted in the use of *ex post* realized returns as an appropriate proxy of investors' *ex ante* risk premium. Sharpe (1978) and Elton (1999) also warn of the pitfalls associated with using ex post realized returns to test asset pricing theories and to estimate expected returns. In particular, Elton (1999) maintains that future work in asset pricing should strive to consider alternative ways to measure expected returns instead of focusing on the development of new statistical procedures that continue to rely on *ex post* realized returns. More recently, Lundblad (2007) illustrates that an extremely large time-series of historical market returns is required – nearly two centuries worth of data – in order to see 'convergence' between *ex post* returns and expected returns.

To address the problem more directly, I empirically explore the risk-return tradeoff using a variant of the Merton (1973) intertemporal capital asset pricing model in conjunction with a proxy for expected returns that is 'forward-looking' and can be derived theoretically from the classic Gordon (1962) dividend constant growth model. This proxy is the earnings yield which is the inverse of the price-to-earnings ratio, a time

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[1] This argument can be expressed in the context of a cost-of-capital problem; if a rise in volatility raises investors' required rate of return for bearing systematic risk, this will lead to a higher cost of equity capital for firms and may result in a reduction in investment and output and possibly a rise in future volatility and uncertainty. Thus, realized stock market returns tend to be historically low during recessionary periods since investors' required rate of return (discount rate) rises commensurate to the rise in systematic risks.

honored market valuation measure. The earnings-yield can be thought of in the same way as the yield to maturity on bonds. Consider, for example, why the expected returns on bonds are computed as yields as opposed to the logarithmic first-difference of their price, as is the case when computing returns on stocks. It is because the yield reflects investors' required rate of return and reveals insights about their forward-looking expectations about the state of the economy as well as the prospects for other investments. It is no surprise, therefore, that while historical mean returns in the stock market may slump during recessions and periods of increased uncertainty, the yields on bonds (and their spreads with other bond classes) rises (see Campello, Chen and Zhang, 2008). Bond yields are computed on the basis of forward-looking internal rates of return and their yields rise along with increases in investors' required rate of return (discount factor) and, thus, bonds of firms with higher systematic risk have higher yield spreads in relation to 'safer' bonds. As Campello, Chen and Zhang (2008) argue, averaging *ex post* realized returns only seems to hide investors' conditional forward-looking expectations about future returns and states of the economy.

In terms of forecasting capabilities, the earnings-yield, which is the reciprocal of the familiar P/E ratio that is used by practitioners, has proved to be a sound predictor of future returns and economic conditions (see Campbell and Shiller, 1998 and 2001). In particular, Shiller (2000) identifies that the P/E ratio is a strong proxy for future expected returns and finds that when it rises above its long-run average, it signals 'irrational exuberance' in the stock market and a probable likelihood of an imminent correction in stock prices. Lamont (1998) argues the earnings-yield contains useful information about the future and is a good forecaster of expected returns. Consistent with this argument,

earnings reflect the current state of the economy and, since risk premia on equities covary negatively with current economic activity, investors will demand higher (lower) expected returns during recessionary (expansionary) economic periods. Therefore, since earnings vary with economic activity, current earnings can predict market future returns.

To put things into perspective, conventionally, when asset pricing literature talks about the risk premium, it is referring to the spread between *ex post* average stock market returns and the yield on treasuries. The proposed *ex ante* proxy set forth in this chapter consists of the spread between the market earnings-yield and the long government bond yield since this reflects the possibility that investors can either invest their money in the stock market or in a risk-free asset. Whereas the earnings-yield reflects the stock market yield, the risk-free yield can be represented by the long-term government yield. The difference between these two yields forms a forward-looking measure of investors' risk premium.

A relevant question to ask is why this proposed *ex ante* risk premium uses the long-term government bond yield as opposed to a treasury yield with a shorter-term maturity. There are several reasons for this; firstly, the average investor (household) has a longer holding period horizon and therefore this yield more accurately reflects their opportunity cost of investing their money in the stock market. Secondly, because investors' discount factor varies with expected dividends, earnings and firms' long-term prospects, the long-term government bond yield more closely reflects this discount factor. Thirdly, this yield encompasses a broader range of information regarding macroeconomic conditions which directly impact investors' relative risk aversion and utility of wealth (see Chen, Roll and Ross, 1986). Finally, there is a long-run positive relation between the

earnings-yield and the long-term government bond yield whereby deviations from this relation are transitory and serve to signal shifts in economic conditions and market returns (see Lander, Orphanides and Douvogiannis, 1997; Thomas and Zhang, 2008).[2]

This chapter sheds new light on the time-series relation between risk and return on the market portfolio. In sharp contrast to most existing literature, I find this relation to be both positive and significant for several major international markets both in short- and long-run representations in the context of Engle and Granger (1987). These findings confirm theoretical predictions that investors demand higher compensation in order to hold higher market risk. They also confirm the findings of Lundblad (2007), who finds a positive risk-return tradeoff, yet demonstrates that an extremely large sample – nearly two centuries worth of data – is needed in order for historical realized returns to 'converge' to investors' expected returns.

Market risk is estimated via the asymmetric GJR-GARCH model (see Glosten, Jagannathan, and Runkle, 1993) given its proven ability to capture many of the 'stylized facts' in stock return dynamics such as volatility clustering and the volatility feedback effect which argues that negative market shocks (i.e. bad news) leads to more volatility than positive shocks (i.e. good news) of equal magnitude (see Mandelbrot, 1963; Campbell and Hentschel, 1992).

This chapter further argues that inconsistencies in existing studies are driven by the inability of *ex post* returns to properly estimate investors' expected *ex ante* required rate of return and therefore the problem in existing studies is more fundamental than possible miss-specifications of the conditional variance. Thus, when most studies

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[2] The spread between the market earnings-yield and long-term government bond yield has unofficially been coined as the 'Fed model' by practitioners as a valuation tool for gauging whether the stock market is over- or under-valued and for predicting future returns. Its name originates from a July 1997 Humphrey-Hawkins report which made reference to this spread as an indicator of future market performance. This report can be accessed on-line at http://www.federalreserve.gov/boarddocs/hh/1997/july/fullreport.htm.

estimate a GARCH-in-mean model using stock returns (see Engle, Lilien, and Robins, 1987) they find a weak or negative relation between risk and returns.

The remainder of this second chapter is organized into four main sections: Section 2.2 provides a review of the relevant literature along with the theories and principles leading up to the Merton (1973) ICAPM and why this model is so important. It analyzes the modeling methodologies that have been traditionally used and what others find and why. Section 2.3 introduces a forward-looking approach to measuring investors' required rate of return and the equity premium in the stock market. It does this for several industrialized markets and presents strong evidence of a positive time-series relation between risk and return, as is further explained in Section 2.4. Finally, Section 2.5 concludes the second chapter.

## 2.2. Review of Literature

This section provides readers with an overview of the Capital Asset Pricing Model (CAPM) and how it led to the development of the ICAPM. It discusses what the major underlying theories behind the model are and the empirical findings and limitations of existing research.

### 2.2.1. Birth of the Capital Asset Pricing Model: Theory and Evidence

Markowitz (1952) established the groundwork for modern asset pricing. He formalizes the notion that investors are risk-averse and require higher expected returns to take on additional units of risk. As such, investors select portfolios that maximize expected

returns and minimize the variance of returns (risk). This is referred to as the optimal or "efficient" mean-variance portfolio.

Sharpe (1964) and Lintner (1965) extend the work of Markowitz (1952) to include the key assumption that investors have the ability to lend and borrow at a risk-free rate. Having established the premise that all investors are risk averse and seek to maximize expected returns and minimize variance, Sharpe (1964) and Lintner (1965) make fundamental assumptions regarding investors' preferences and the risk-free asset. Firstly, all investors seek the most efficient investment opportunity (i.e they seek assets with minimal variance and highest possible mean returns). Secondly, there is unrestricted borrowing and lending at the risk-free rate. With these assumptions in place, they mathematically illustrate how to calculate the expected returns of an asset, given its variance. Thus, the expected return of any asset $i$ is formularized as follows by the Sharpe-Lintner CAPM:

$$E(R_i) = R_f + \beta_{iM}[E(R_M) - R_f] \qquad (2.1)$$

The market beta of asset $i$, $\beta_{iM}$, is derived by first computing the covariance of returns between asset $i$ and the returns of the market, then dividing this product by the variance of market returns:

$$\beta_{iM} = Cov[R_i, R_M] / \sigma^2 (R_M) \qquad (2.2)$$

As equations (2.1) and (2.2) indicate, the market beta of asset $i$ influences its expected returns. From a mathematical perspective, beta can rightly be interpreted as a slope because it describes the returns of asset $i$ relative to the returns on the market. Another interpretation is that it measures the sensitivity of the returns of asset $i$ to variations in market returns.

Black (1972) modifies the Sharpe-Lintner version of the CAPM by removing the unrealistic assumption of borrowing and lending at a risk-free. Instead, he assumes investors have the unlimited ability to short sell risky assets. More specifically, the expected return of hypothetical asset $i$, $E(R_i)$, is derived as follows:

$$E(R_i) = E(R_{0m}) + \beta_{iM}[E(R_M) - E(R_{0m})] \tag{2.3}$$

In the Black version of the CAPM, beta is calculated as in equation (2.2). $E(R_M)$ denotes the expected return on the market and $E(R_{0m})$ represents the expected return of a portfolio with zero beta (i.e. no association with returns on the market, $R_M$). $R_{0m}$ has the minimum variance of all portfolios with no sensitivity to returns in $m$. As in the Sharpe-Lintner CAPM, the Black (1972) version is also a static model and does not account for changes in risk or investment opportunities.

The Sharpe (1964), Lintner (1965) and Black (1972) (henceforth SLB) versions of the CAPM reflect the need for economists and investors to effectively quantify the tradeoff between risk and expected returns. This tradeoff is, after all, the building blocks for modern financial theory. The CAPM provides an intuitively straightforward way for calculating expected returns, $E(R_i)$, given a security's or portfolio's risk, $\beta_{iM}$. In plain language, the CAPM posits that the expected return of an underlying asset is linearly associated to the covariance between its returns and returns on the market. A keen observer may question where investor's idiosyncratic investment preferences and risk tolerance comes into play. Although in reality we know that market participants carry dissimilar expectations about the future prospects of markets and have unique degrees of risk aversion, the CAPM assumes market participants to be entirely homogeneous agents. In other words, they all agree on the choice of optimal proportions of risky assets to hold

in relation to risk-free assets. Furthermore, this model is explicitly stating that the expected returns of an asset of interest are only related to its covariance of returns with respect to returns on the market. Therefore, investors only look at this covariance coefficient and do not utilize any other subjective measures for risk.

Since the CAPM assumes investor homogeneity, it means that all market participants agree on how to proportionately allocate their wealth between risky and risk-free assets. In other words, all investors will hold 1/50 of '$\alpha$ shares,' 1/30 of '$\beta$ shares,' and so on. It is a well-established tradition in finance that investors are always faced with the decision of how to allocate their wealth. They can either put their money in a portfolio of risky assets or they can invest all their money in the risk-free asset. Since most investors do some combination of both, we have what is coined in finance as the "two-fund separation theorem." This principle was first discussed by Tobin (1958) and maintains that an investor's decision-making process can be broken down into two elements: The first step involves deciding on the optimal proportions of risky assets to hold independent of an investor's unique preferences and expectations. The second step then accounts for their individual risk preferences and expectations. Given their unique risk preferences, an investor can decide how much to borrow (lend) at the risk-fee rate in order to magnify (reduce) their exposure to risk. In other words, an investor who is risk hungry can borrow funds at the risk-free rate and use the funds (in addition to their current wealth) to invest in risky assets. A risk-averse individual, however, will prefer to invest the majority of their wealth and earn a risk-free rate (essentially becoming a lender) and maybe put a small proportion of their funds in a risky portfolio.

Given however the assumption of investor homogeneity, the CAPM assumes that all investors (i.e. the aggregate market) agree on the proportion of their wealth that they will invest in each respective risky asset which constitutes a risky portfolio of assets. In other words, all investors will, for argument's sake, put 1/50 of their wealth in '$\alpha$ shares,' 1/30 in '$\beta$ shares,' and so forth). It is therefore important to note that, when the market is in equilibrium, which has to hold in order for the CAPM to work, individuals' unique risk preferences do not influence the relative quantity demanded of risky assets (i.e. proportions of '$\alpha$ shares' to '$\beta$ shares'). Therefore, the equilibrium expected returns for an asset are uninfluenced by the subjective preferences of individuals. Instead, only objective measures matter such as variances and covariances.

In the real-world however treating investors as homogenous agents is incompatible with observations of how markets function.[3] One can argue that even the assumption of zero transactions costs or a frictionless market void of inefficiencies is merely a fictitious scenario. Although the assumption that markets are in equilibrium and are frictionless may be unrealistic when you look at markets day-to-day, this is an important assumption economists make when developing models (such as the CAPM). It is perhaps the only way to come to grips with complex economic and financial data, which is influenced by an immeasurable quantity of factors, and to draw meaningful conclusions that can help us to assess risk and return, economic conditions, et cetera. For example, there is no currently available model that can capture the impact weather conditions have on stock returns. In particular, Saunders (1993) and Hirshleifer and Shumway (2003) find evidence that perhaps bad weather influences stock returns. Nor

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[3] The issue of addressing and modeling investor heterogeneity is explored in the fourth chapter of this thesis.

there exists a model that can account for investor behaviors, such as their emotional state (see Ackert, Church and Deaves, 2003) for a review of literature that finds evidence on how investors' emotions drive markets.[4] If there was such a model, it would be most useful to apply when the Dow dropped a record 777 points on September 29, 2008 after the House of Representatives rejected a proposed bailout bill that hoped to remedy the U.S.' financial troubles. But such a model that takes into account *all* factors which can possibly influence the value of a variable of interest simply does not exist.

That is why we have more generalized models that include specifically detectable and testable variables which should theoretically have an impact on whatever it is we are testing for. These models oftentimes assume market equilibrium and zero transactions costs. For example, the Black and Scholes option pricing formula makes certain assumptions such as, among others, no transaction costs or taxes, no arbitrage opportunities (i.e. markets are in equilibrium and there are no mispriced assets), all investors are rational and all market participants have the ability to borrow and lend at a constant risk-free rate (see Black and Scholes, 1973).

Although no model is perfect in an absolute sense, these models do serve as a starting point and allow us to accurately see the relationship one variable has (such as volatility) on another variable (such as the price of an option), ceteris paribus. If one can stomach the assumptions that form the underpinnings for the CAPM, our next question becomes whether this model can successfully and consistently provide an accurate picture of assets' expected returns.

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[4] Dr. Ackert is a visiting scholar at the Atlanta Federal Reserve Bank. This paper can be accessed from the Fed's website at http://www.frbatlanta.org/

Early evidence provided support for the CAPM and the notion of mean-variance efficiency (see Black, Jensen and Scholes, 1972; Fama and MacBeth, 1973; Blume and Friend, 1973). There were some concerns that the Sharpe (1964) and Lintner (1965) version of the CAPM calculated an expected return for zero beta portfolios that were greater than the risk-free rate. However, these concerns were mitigated by the Black (1972) version of the CAPM which removed the risk-free asset from the right-hand side of the equation.

By the late 1970s unfavorable evidence started to emerge. In particular, evidence suggests that firm/portfolio-specific factors (such as size or its price-earnings (P/E) ratio) lead to different expected returns than predicted by the CAPM. These so-called "anomalies" in the literature are well-documented and suggest one cannot consistently and accurately predict an asset's expected returns exclusively relying on its beta. For example, Basu (1977) finds a P/E effect whereby returns on stocks with low P/E ratios yield higher returns than the CAPM predicts. Banz (1981) documents a size effect; when firms' stocks are arranged based on market capitalization (i.e. price per share multiplied by the number of shares outstanding) the smaller firms' stocks yielded a higher average return than predicted by the CAPM (if the market portfolio truly was mean-variance efficient). Others find that if a portfolio is constructed by buying losing stocks (stocks that have experienced price depreciations in the past) and selling winners (stocks that have experienced appreciations) it yields mean returns higher than the CAPM predicts.

Perhaps the most controversial extension of the CAPM is the Fama and French (1993, 1995, 1996) three-factor model which hypothesizes that the expected return on asset $i$, $E(R_i)$, is a linear function of a market factor ($\beta_{iM}$ from the SLB CAPM), a size

factor (Return on small-firm stocks less the return on large firm stocks) and a book-to-market (B/M) factor (Return on high B/M stocks less the return on low B/M stocks).

Though the SLB CAPM provides a sound theoretical framework for its arguments, it makes rather facile assumptions which do not hold in reality. For example, claiming that markets are "frictionless" and void of inefficiencies is as realistic as saying all investors are the same. Despite these shortcomings however the SLB CAPM is taught to business and economics students in universities throughout the world. It is even used by financial managers in order to calculate the cost of capital of a particular project.

Perhaps the CAPM remains such a popular model because it is intuitively straightforward to understand and easy to apply. Furthermore, from a theoretical perspective, it makes sense to assume that higher beta (riskier) stocks are expected to yield higher returns. The lively debate surrounding the CAPM will likely grow in years to come. But any future application of the CAPM in today's hectic financial markets is unlikely to yield fruitful results. Perhaps the biggest blow to the CAPM is its inability to capture shifts in the investment opportunity set. Oftentimes, it is referred to as being a "static" or "single-period" model since it does not have any time dimension. Furthermore, as we know, risk and investment opportunities are changing constantly. The SLB CAPM (as well as the Fama and French three-factor model) cannot capture such changes in risk and changes in the investment opportunities available to investors. Such static models are instead used to capture the cross-sectional relation between certain factors (such as $\beta_{iM}$ or the Fama and French factors) and expected returns. Since the investment environment is constantly changing, we want to use a model that is "dynamic" in nature and can capture the time-varying link between risk and returns.

Such a model should be capable of capturing the changes in risk from period to period. There is evidence to suggest that the risk associated with an asset (when measured using variances and covariances) changes from period to period (see Mandelbrot, 1963; Fama, 1965). It therefore seems appropriate to use a model that can measure these changes. The next section introduces readers to an alternative capital asset pricing model that has such time-varying properties.

## 2.2.2. Modeling the Conditional Mean and Variance in the ICAPM Framework

As is described in Koutmos (2010, 2011 and references therein), market volatility is time-varying as well as investors' expectations and their required rate of return. Therefore, this presents a serious limitation in the sense that the CAPM is a single-period model and does not capture the time-varying moments of stock returns.

Empirical shortcomings in the CAPM prompted efforts to produce a replacement model. Merton (1973) recognized that in an ever-changing investment landscape, investment opportunities and risks are constantly shifting. He formalized this notion and proposed an intertemporal CAPM with time-varying variances and returns. This model is oftentimes referred to as the "conditional," "dynamic" or "intertemporal" capital asset pricing model (ICAPM):[5]

$$E_t[R_{t+1}] = \alpha \;+\; \theta\,\sigma_t^2 \;, \qquad\qquad (2.4)$$

where $E_t[R_{t+1}]$ is the conditional expected excess returns and $\sigma_t^2$ is the conditional variance of the stock market. The parameter $\theta$ denotes the degree of risk aversion and

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[5] The third chapter explores a variant of the ICAPM which includes a second factor that accounts for changes in the investment opportunity set. The specification in Eq. (2.4) depicts the simple relation between risk and return while the third chapter estimates a two-factor version that accounts for changes in the investment opportunity set, as is argued by Merton (1973). However, the specification in Eq. (2.4) serves as an approximation (see Merton, 1980).

should have a positive sign (i.e. as conditional risk increases so should conditional mean returns). $\alpha$ is a constant and in a perfect world with no transaction costs or deviations from market equilibrium should be zero.

Measuring and quantifying uncertainty has always been a central theme in finance. Traditional asset pricing models, for example, suggest that expected returns on an asset are a function of the covariance of the asset's returns and the returns of some benchmark portfolio (such as the market index). In option pricing literature, uncertainty (measured as volatility) is a significant determinant in the pricing of the option. Conditional variances and covariances play yet another important role in the construction of hedge portfolios. From portfolio managers and institutional investors to the average tax-payer saving for retirement, uncertainty is a risk that plays a major role in their decision-making process.

History teaches us that when we downplay, misestimate, or outright ignore risk, it can be disastrous. Take for example the October 1987 stock market crash that impacted not only the U.S. but the rest of the global economy. There are also many facts before the crash that most researchers can agree on.[6] Firstly, it is clear that asset prices in the years preceding the crash were experiencing exorbitant appreciations that were unjustified given those assets' fundamental values (see Anders and Garcia, 1987). Appreciations in price were also instigated by the surges of new large investors (such as pension funds and other institutional investors) who wanted a piece of the action (see Katzenbach, 1987). Yet, although this irrational exuberance was driving up prices, there were other macroeconomic factors at play which many investors at large ignored. This leads to the

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[6] The fourth chapter examines such events in detail and what implications they have for the Efficient Market Hypotheis (EMH) and in asset pricing.

second turning point. There were many macroeconomic factors that, during the months preceding the crash, signaled investors that the economy was going awry. Interest rates were rising on a global level and the trade deficit had increased higher than expected. These factors mixed with fears of high future inflation and put downward pressure on the dollar. To add to these troubles, the House of Representatives decided to eliminate existing tax benefits associated with companies' use of debt to finance mergers [Securities and Exchange Commission Report (1988, p. 3-10)]. Consequently, by eliminating these benefits, investors therefore reduced the probability that certain "undervalued" companies would be considered as takeover targets.

The end result was disastrous. On Monday, October 19, 1987, the Dow Jones Industrial Average (DJIA) plummeted 508 points, an approximately 22% drop in a single day. The U.S.' financial woes also spread globally to other countries. Investors and savers saw their wealth diminish right before their eyes. Unfortunately however, it is usually too late when people start asking questions after a crisis.

Although these are rather infrequent examples they serve to illustrate the importance of effectively evaluating risk and perceiving adverse events before they occur. Of course, no model exists which can capture *all* possible risks such as changes in impending legislation or changes in investors' emotions. They can, however, compare assets' prices with fundamentals – such as earnings – to decipher whether there is "irrational exuberance" in the marketplace or whether assets are fairly priced. Section 2.3 of this chapter discusses the E/P ratio and the Fed Model (i.e. the difference between the E/P ratio and the long-term government bond yield) and whether such measures can capture investors' required rate of return.

Another common way to measure an asset's risk is to compute the variance of its returns (i.e. the dispersion of an asset's returns about its mean returns). Linear asset pricing models, such as the CAPM, estimate an asset's expected returns based on its variance. Calculating an asset's variance is easy to do and tells us a quick story about how volatile the asset's price is. The higher the asset's return variance (i.e. the more dispersed its returns are about its historical mean), ceteris paribus, the riskier that asset tends to be. However, since the ICAPM is time-varying and takes into account changes in risk, how then do we calculate the conditional variance, $\sigma_t^2$ and what types of models can we use to achieve this?

### 2.2.3. Using Time-Series Techniques to Capture Stock Return Dynamics

When examining some of the properties of stock returns, there are several 'stylized facts' which appear time and time again. In particular, there is evidence that supports the notion of volatility "clustering" or "pooling" whereby large changes in volatility tend to be followed by more large changes and small changes tend to be followed by small changes (see Mandelbrot, 1963; Fama, 1965). This is oftentimes referred to as "volatility persistence" and is discussed in greater detail in section 2.2.4 of this chapter. Since volatility is not constant (i.e. it is time-varying) an appropriate model needs to be used. A linear model, such as the CAPM, in the form

$$y_t = \beta_1 + \beta_2 x_2 + \beta_3 x_3 + u_t$$
$$\text{where } u_t \sim N(0, \sigma^2) \tag{2.5}$$

is not appropriate to use when attempting to model the time-varying behavior of volatility. Volatility, like many other financial time-series data, is heteroskedastic (i.e. the disturbance terms are not constant) whereas linear regression models assume them to

be constant and normally distributed.  However, empirical evidence shows that financial assets' returns are not normally distributed but are leptokurtic (i.e. exhibit fat tails and excess peakedness about the mean).

It is a stylized fact in the literature that investors' perceptions in the marketplace and their willingness to trade off between returns and risk are non-linear. This is why some of the input variables in options pricing formulas are also non-linear (see Campbell, Lo and MacKinlay, 1997). Historical volatility is the simplest form of modeling volatility and basically involves calculating the variance (or standard deviation) of returns over some specified historical period. This then becomes an estimate for future volatility and is oftentimes used as an input for options pricing formulas. Evidence suggests, however, that more sophisticated time-series models should be used to improve the accuracy of our volatility estimates (see Akgiray, 1989; Chu and Freund, 1996).

Figure 2.1 graphs the daily percentage of stock returns of the S&P 500 index from January 1993 through January 2007 and illustrates the concept of volatility "clustering." As can be seen, large (small) changes in assets' prices of either sign, positive or negative, tend to be followed by subsequent periods of large (small) changes.  Put another way, tranquil periods tend to be followed by more tranquil periods and periods of economic disarray tend to be followed by more periods of economic volatility.

Figure 2.1: Evidence of Volatility Clustering
Daily S&P 500 Returns for January 1993 – January 2007
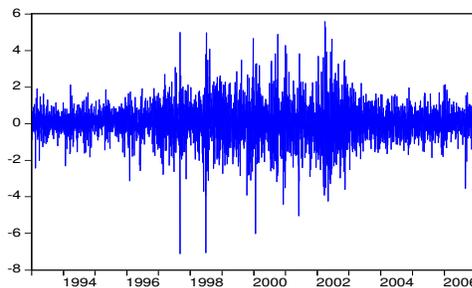
For example, from 1993 through the end of 1996 and from 2003 through the beginning of 2007, the market appears to experience a prolonged period of tranquility as opposed to the volatility it experienced in 1997 through 2002. In between volatile times, one can easily note that volatility appears to happen in small bursts. The technical term for this is "autoregressive conditional heteroskedasticity." That is why we see small outbursts of volatility over a short time interval. This is the very notion of volatility clustering. If therefore the volatility today is a function of (i.e. is conditional on) past volatility, it is also clear that a linear model is inappropriate to use in order to model volatility since linear models assume homoskedasticity.

Engle (1982) thus proposes an Autoregressive Conditional Heteroskedasticity (ARCH) model which defines the conditional variance today as a function of past squared errors. It is important to interject at this point and explain the role of the error term, $u_t$. Oftentimes in the literature, $u_t$ is also referred to as "news" or "innovations." We know that the error term can essentially take negative or positive values, but what does this mean in the context of financial markets? To answer this question we need to understand the fundamental driving forces behind assets' price movements. Economists approach this question by assuming that any expected variations in assets' returns simply reflects fundamental risks whereas unexpected movements reflects the arrival of news (see Engle and Ng, 1993). Therefore, although $u_t$ may represent the error term (i.e. the degree to which a predictive model's output differs from an actual realized value) from a strictly econometric sense, it represents the impact news has on the conditional variance. This is explained more in section 2.2.4 and offers interested readers an illustration using a hypothetical firm.

Engle's seminal ARCH model formularizes the impact news has on volatility and defines the conditional variance, $\sigma_t$, at time $t$, as depends on $q$ lags of squared residuals (or innovations). This is known as the ARCH($q$) model:

$$\sigma_\tau^2 = \alpha_0 + \alpha_1 u^2_{t-1} + \alpha_2 u^2_{t-2} + \alpha_q u^2_{t-q} \qquad (2.6A)$$

Or, equivalently, this can be rewritten as follows:

$$\sigma_\tau^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i u^2_{t-i} \qquad (2.6B)$$

The ARCH model of Engle in equations 2.6A and 2.6B provides a clear formula for computing the conditional variance using past squared residuals. However, this model does have its limitations. Since the conditional variance, $\sigma_\tau^2$, must be positive, the coefficients within the model should also be positive. For example, all the coefficients in equation 2.6A ($\alpha_0$, $\alpha_1$, $\alpha_2$,…,$\alpha_q$) need to be non-negative in order for the conditional variance estimate to be positive. A negative conditional variance calculation at any time would be  nonsensical. More generally, the non-negatively constraint for the ARCH($q$) model in equation 2.6A can be expressed as follows: $\alpha_i \geq 0$ $\forall$ $i = 0, 1, 2,…,q$. The reason for this non-negativity constraint is because if, for example, one or more of the coefficients is negative, then for a relatively large lagged squared innovation, the conditional variance output may also take a negative value.

Another problem with the ARCH($q$) model is specifying the value of q (i.e. how many lagged squared innovations should our model have?). To answer this question researchers typically tend to exploit the likelihood ratio test, among other tests (see Gourieroux, Holly and Monfort, 1982). It does not go without saying however that these tests do have their pitfalls and there is no precise approach to determining the value of q.

Engle (1982) attempts to elude this problem by subjectively specifying an ARCH(4) process. However, in this model, each successive lagged squared innovation contributes a declining weight on the conditional variance computation:

$$\sigma_\tau^2 = \gamma_0 + \gamma_1(0.4u_{t-1}^2 + 0.3u_{t-2}^2 + 0.2u_{t-3}^2 + 0.1u_{t-4}^2) \tag{2.7}$$

If equation 2.6A or 2.6B were an unrestricted ARCH(4), then there would be five parameters that need to be estimated. However, in the case of Eq. (2.7), only $\gamma_0$ and $\gamma_1$ need to be estimated. Engle (1982) recognized the problem that if q is too large (i.e. there are too many lagged squared innovations in a model) then the specified model may not be parsimonious. Furthermore, the more parameters there are that need to be estimated, the more likely it is that the non-negativity constraint will be breached.

To overcome these problems, Bollerslev (1986) and Taylor (1986) independently formulated a generalized autoregressive conditional heteroskedasticity (GARCH) model. Under such a model, the estimated conditional variance is dependent on its own previous squared lags and lagged squared innovations:

$$\sigma_\tau^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{2.8}$$

This equation is a GARCH(1,1) model and represents the simplest form of the GARCH class family of models. In this case, $\sigma_\tau^2$ is known as a one-period ahead estimate since it reflects all relevant past information. As is explained further on in this chapter, any volatility at time *t-1* will have an impact on volatility at time *t* (i.e. any volatility yesterday will influence investors' perceptions of volatility today. Likewise, any volatility at time *t+1* is conditional on volatility at time *t* (i.e. volatility that investors perceive tomorrow is conditional on the volatility today). This is precisely what the

GARCH methodology attempts to capture and, since it takes into account lagged squared innovations, it also considers the impact news has on volatility.

The GARCH(1,1) model can be expanded into a GARCH($p,q$) whereby the conditional variance is dependant on $q$ lags of squared innovations and $p$ lags of the conditional variance:

$$\sigma_\tau^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \ldots + \alpha_q u_{t-q}^2 + \beta_1 \sigma_{t-1}^2 +$$
$$\beta_2 \sigma_{t-2}^2 + \ldots + \beta_p \sigma_{t-p}^2 \qquad (2.9A)$$

$$\sigma_\tau^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \qquad (2.9B)$$

GARCH models have several important advantages over their ARCH counterparts. Firstly, they capture the premise that volatility tends to cluster together and any volatility tomorrow is conditional on volatility today. Secondly, GARCH models are also more parsimonious and are less likely to breach non-negativity constraints. Evidence suggests that GARCH-type models consistently outperform their ARCH counterparts and offer more accurate measures of volatility. Akgiray (1989) finds that GARCH models outperform ARCH models, exponentially-weighted moving average models, and historical variance models in out-of-sample forecasting. Therefore, researchers tend to use these models instead of ARCH models when estimating the conditional volatility. GARCH(1,1) models are typically used since they are parsimonious and effective in capturing the volatility clustering that asset returns exhibit. It is therefore uncommon for studies to compute conditional variances using higher order models that include more lagged terms of the conditional variance.

Having determined how to compute the conditional variance given past innovations and volatility, let us now turn our attention to how we calculate conditional returns. The notion that expected returns are positively associated with risk is the foundation of modern finance. One way to formularize this concept is by allowing the return on an asset to be partially linked to the conditional variance. Engle, Lilien and Robins (1987) propose an ARCH-in-mean specification whereby the conditional variance enters directly into the conditional mean equation. However, since GARCH models are more widely used than their ARCH counterparts, researchers typically utilize GARCH-in-mean models:

$$
\begin{aligned}
r_t &= \alpha_0 + \theta\sigma_{t-1} + u_t, \quad u_t \sim N(0,\sigma^2_t) \\
\sigma^2_t &= \alpha_0 + \alpha_1 u^2_{t-1} + \beta\sigma^2_{t-1}
\end{aligned}
\tag{2.10}
$$

In Eq. (2.10) the coefficient of risk aversion is represented as $\theta$ and, consistent with theory, should be positive. Therefore as risk, $\sigma_{t-1}$, increases we would also expect conditional returns, $r_t$, to increase accordingly. Instead of using the square root form of the conditional variance, $\sigma_{t-1}$, many studies just enter the conditional variance term, $\sigma^2_{t-1}$, directly into the conditional mean equation. In addition, other studies calculate the conditional mean using a contemporaneous conditional variance term, $\sigma^2_t$, instead of the lagged term, $\sigma^2_{t-1}$.

The GARCH(1,1)-in-mean models are typically used because they provide a parsimonious framework for capturing volatility clustering and for examining the conditional risk-return tradeoff. However, as this chapter explains later on, negative and positive innovations appear to have an asymmetric impact on the conditional variance computation. In plain language, a negative piece of news about a company or the market

will lead to more volatility than a positive piece of news. In order to operationalize this observation, researchers have proposed asymmetric GARCH models which can respond asymmetrically to positive and negative innovations.

It is a stylized fact in the literature that negative innovations lead to more volatility than positive innovations. This is discussed in greater depth in section 2.2.4 of this chapter. But consider a hypothetical economy where the Federal Reserve is considering to either (a) cut interest rates by half a percent or, conversely, (b) increase interest rates by half a percent. These are both big decisions and their impact on markets needs to be addressed. In the former scenario, this would be perceived as good news for households, businesses and financial intermediaries (such as banks) seeking loans and wishing to make investments. Although it is good news, it will lead to volatility in the market as different investors react differently to this news. Some market participants may even perceive this with caution, since it may lead to an expansion of credit to credit "unworthy" persons and malinvestments by large organizations. If the Fed decides to raise interest rates unexpectedly, this will immediately be perceived as bad news and may amplify the effects of volatility. If the Fed does nothing, then volatility should decrease because there are no surprises. Of course, this is a basic and realistic scenario of good and bad news and how the market may react. The key point to note is that a large piece of news will inevitably lead to volatility. If it happens to be bad news, it will even amplify the effects of volatility. So now the question is, how can GARCH-type models capture this?

Nelson (1991) proposes an exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model which responds asymmetrically to positive and negative innovations:[7]

$$log(\sigma_t^2) = \alpha_0 + \alpha_1|z_{t-1}| + \alpha_2 z_{t-1} + \beta log(\sigma_{t-1}^2), \qquad (2.11)$$

where, $z_t = \varepsilon_t / \sigma_t$ and is the standardized residual. The conditional variance, $\sigma_t^2$, is described as a non-linear function of past residuals and its own past value (i.e. $\sigma_{t-1}^2$). The EGARCH specification is log-linear in nature, whereby the term $\alpha_2 z_{t-1}$ serves to capture asymmetric shocks to the volatility process in the sense that if $\alpha_2$ is negative and significant, then negative shocks in the market (i.e. negative innovations) are responsible for intensifying volatility more than positive shocks (i.e. positive innovations). The converse is true if $\alpha_2$ were positive and statistically significant. Finally, a statistically negligible value for $\alpha_2$ implies that negative and positive shocks exert the same impact on the conditional volatility process.

The EGARCH specification is advantageous in the sense that estimates for $\sigma_t^2$ are always positive values, regardless of the values for the coefficients. Therefore it is not necessary to impose non-negativity constraints, as may typically be required when working with the conventional ARCH and GARCH models discussed earlier.

Although the proposed EGARCH specification is relatively more complex, it appears to enhance some shortcomings in the pure GARCH specification. For example, pure GARCH models are incapable of capturing asymmetries and impose parameter restrictions in order to avoid a negative conditional variance (thereby restricting random

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[7] The third chapter of this thesis considers the two-factor EGARCH specification and describes in more detail how it applies and what inferences can be drawn from it. Koutmos (2011) considers the EGARCH specification described in Eq. (2.11) and how it applies to U.S. industry portfolios and what economic benefit can be drawn from applying this model.

oscillations in $\sigma_t^2$ for all $t$ periods) (see Nelson, 1990). The proposed EGARCH appears to respond to some of these shortcomings. It is important to note that in his original proposal of the model, Nelson (1991) assumed that the errors are structured in terms of a Generalized Error Distribution (GED). Most empirical applications of the EGARCH however use conditionally normal errors, as is indicated by most studies cited in section 2.2.4 in this chapter.

Whereas the EGARCH redefines the variance process, Glosten, Jagannathan and Runkle (1993) introduce an asymmetric GARCH that extends the pure GARCH specification expressed in equations 2.9A and 2.9B by adding an indicator variable. Oftentimes, their model is referred to as a "GJR-GARCH" and can be expressed as follows:

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

$$\text{where } I_{t-1} = 1 \text{ if } u_{t-1} < 0$$
$$= 0 \text{ otherwise} \qquad (2.12)$$

The $\gamma$ coefficient represents the indicator variable and increases conditional volatility in the presence of negative innovations. Evidence suggests that the GJR-GARCH specification adequately reflects asymmetric innovations in the conditional variance estimate and provides for a good estimation technique in comparison to other models (see Brailsford and Faff, 1996). Therefore, the GJR-GARCH is widely employed by researchers and is also used in this chapter.

Despite there has been much work in the area of volatility modeling, this still remains a growing field in finance and is a hotly debated topic in terms of which models work best for which applications. As access and availability to new data increases, we expect to see more results in the future and new innovations in the range of volatility

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estimation techniques. As Cuthbertson and Nitzsche (2004, p. 664) jokingly put it, there are more variations of the GARCH process "than there are varieties of breakfast cereals..." This is certainly true over the last few years as more and more data became available and new ideas started to receive empirical investigation. According to the study by Bollerslev, Chou and Kroner (1992), they find that over two hundred papers utilize such models to make empirical inferences. Given that their study was published almost two decades ago, this figure has surely grown since then. But what it does show is how important these models are in finance literature and in asset pricing at large. They are considered a breakthrough in econometrics since they have been so successful in capturing many properties which show up in financial data such as, for example, stock and bond returns and even exchange rates.

As is discussed in Koutmos (2011), these models can also be used to find which industries (and perhaps various assets) are sensitive to shifts in aggregate stock market volatility and what implications this has for the industry. It is also important to know the volatility persistence of assets in order to see how they behave as stock market conditions change. Finally, GARCH-type volatility models can be used to estimate risk and to perhaps gain insights as to future expected volatility. Therefore, instead of being used solely by academics for research, these models are also very useful for practitioners and other researchers who wish to examine financial data.

### 2.2.4. Evidence on the Intertemporal Risk-Return Tradeoff

This section examines the ICAPM of Merton (1973), what other researchers find when they apply this model, and what some of the established hypotheses are regarding the

nature of the risk-return tradeoff. It examines each of the competing hypotheses in turn and their strengths and limitations.

### 2.2.4.1. The ICAPM and Existing Hypotheses

The Merton (1973) ICAPM in Equation (2.4) hypothesizes a positive time-series relationship between conditional risk and return:

$$E_t[R_{t+1}] = \alpha + \theta \sigma_t^2$$

where $E_t[R_{t+1}]$ is the conditional expected excess returns and $\sigma_t^2$ is the conditional variance of the stock market. The parameter $\theta$ denotes investors' degree of risk aversion and should have a positive sign, consistent with theory. $\alpha$ is a constant and in a perfect world with no transaction costs or deviations from market equilibrium should be zero.

Yet, empirical findings investigating this dynamic tradeoff are inconclusive. Many studies document a negative or statistically insignificant risk-return relation. These findings are at odds with our notion that we are rational risk-averse individuals and require higher returns to take on an additional unit of risk. Few papers document a positive and significant relationship.

It seemingly appears as though different econometric methodologies and different sets of data (i.e. samples from different countries, different ranges and frequencies of data), yield different outcomes in our risk-return tradeoff calculations. GARCH modeling is the standard workhorse in literature for deriving conditional mean-variance estimates. Yet researchers ascertain different results when they change their data samples or the size and frequency of those samples. This striking piece of evidence leads us to question the validity of past results.

In light of these findings, there are three widely accepted explanations as to why studies find a negative or weak intertemporal risk-return relationship. The first theory, dubbed as the "volatility feedback effect," offers us a plausible explanation of the culprit (see Campbell and Hentschel, 1992). Consistent with this hypothesis, a rise in volatility leads to an increase the required rate of return. This results in a decline in the price of assets. Thus, a researcher interested in modeling the conditional mean-variance relation needs to proceed with caution. Irrespective of the methodology they select to model this relationship using historical returns can misrepresent the true relationship between risk and return. In other words, as volatility increases (i.e. our conditional variance forecast is rising), historical average returns are falling because the required rate of return is increasing. GARCH models will therefore capture a negative or non-existent risk-return tradeoff when, in fact, the required rate of return is rising.

The notion of volatility feedback is contingent on the observation that volatility is persistent, as is graphically illustrated in Figure 2.1). As Mandelbrot (1963, p. 418) observes:

"…large changes tend to be followed by large changes – of either sign – and small changes tend to be followed by small changes…"

In other words, a large piece of news about a company or the market will lead to more pieces of news. This will increase volatility as well as the required rate of return. For sake of argument, let us consider a large piece of good news concerning a hypothetical company. Suppose that it announces a substantial increase in next period's dividends.

This will increase expected future volatility and raise the required rate of return. Although this is good news concerning the company, it will lead to reductions in its stock price. This reduction in stock price stems from the increases in expected volatility. In effect, the rise in volatility diminishes the impact of the good news. A large negative piece of news regarding the market or a particular company will only magnify the volatility feedback mechanism and lead to more severe downward movements in price. In the case of small pieces of news, expected future volatility will decline and prices will tend to rise. In the unlikely case where no news arrives, prices will rise. This is because, as Campbell and Hentschel (1992) indicate, "no news is good news."

The seminal study by Campbell and Hentschel (1992) also offers an explanation to why studies produce conflicting results. In particular, they find that stock price movements are directly linked to future expected volatility. As expected volatility rises, so will the required rate of return. This in turn leads to a decline in price leading one to believe that the required rate of return is falling. The problem with existing studies is clearly expressed in their paper. More specifically, they caution researchers of the limited power GARCH models have and their inability to capture volatility feedback. For example, asymmetric GARCH models can very well be used to capture the statistical description of asymmetric volatility in the presence of good or bad news. Yet, these models do not provide an economic explanation of volatility feedback. More specifically, GARCH modeling is incapable of describing movements in the required rate of return. Instead, volatility feedback is discussed passively when interpreting estimates from GARCH models. This leaves much room for improvement in the literature. The tendency to relate historical returns with volatility forecasts will produce spurious conclusions

about the true risk-return tradeoff. Effort needs to be directed to examining how the required rate of return responds to changes in volatility from model estimates.  By doing so, we can effectively address the volatility feedback argument and determine why existing studies cannot agree on the nature of the intertemporal risk-return tradeoff.

The so-called "leverage hypothesis (effect)" is a second explanation that attempts to rationalize why there exists a negative or insignificant risk-return tradeoff. The leverage effect, first discussed by Black (1976) and Christie (1982), differs from the volatility feedback hypothesis largely in the causality of volatility. The volatility feedback argument claims that changes in conditional volatility create return shocks. The leverage effect, however, argues that return shocks bring about changes in conditional volatility.  For instance, let us suppose that a hypothetical firm experiences a reduction in its stock price. This entails a reduction in its equity value and an increase in its financial leverage.  Investors' uncertainty surrounding the future prospects of the firm's equity also rises, thereby leading to increased volatility. Thus, changes in leverage (resulting from declines in a stock's price) impacts conditional volatility estimates. At this point I interject and clarify the meaning of the leverage effect and how its meaning is used in other studies.  It is not uncommon in the literature for authors to ascribe any asymmetric relation between an underlying asset's returns and volatility as a "leverage effect."  This term has become loosely synonymous for this asymmetry even if the underlying asset has nothing to do with leverage, such as an exchange rate.  For purposes of this thesis, however, the leverage effect applies only to changes in a firm's financial leverage.

The underpinnings for the so-called leverage hypothesis originate from early studies that examine firms' capital structure. Modigliani and Miller (1958) argue that the

total asset of the firm is the entire firm. If the firm has both equity and leverage in its capital structure, then its value is the equivalent of the sum of these two components. Any securities issued simply represent different methods of separating ownership of the firm's total asset. Miller (1991) explains this proposition and analogizes a firm's decision of issuing debt relative to equity with that of a farmer who has a giant tub of whole milk they want to sell. The farmer can either sell the whole milk as is, or, they can separate the cream from the whole milk and sell it for a higher price. The Modigliani-Miller proposition asserts that, if there was no cost for separation, then the cream plus the skim milk is equivalent to the price of the whole milk. The dilemma facing the farmer is analogous to a firm's decision of whether it should issue debt or equity. By increasing the proportion of debt (cream), there is a proportionate reduction in outstanding equity (milk). Consider a firm has both debt and equity in its capital structure. Bondholders' claim on the firm is limited to the face value of the bonds. Therefore, any volatility associated with the firm is absorbed by the stockholders. If the firm decides to increase its leverage (decrease outstanding equity), this will entail more risk for each individual shareholder and lead to increased volatility in share price.

The leverage hypothesis offers a possible explanation to why returns and volatility are systematically and asymmetrically linked. Since equity is less than the total value of the firm, while bondholders' claims are limited to the face value of the bonds, any ups or downs that the firm experiences are absorbed by the stockholders. If the total value of the firm increases (decreases), the returns on the stock will be proportionally higher (lower) than the returns of the whole firm. Thus, the stock of a levered firm is more volatile than the rest of the firm. Now consider if the levered firm experiences a

considerable drop in return. Since debt is fixed, the firm's leverage will increase as equity volatility increases. Conversely, there should be an opposite effect if there is a rise in return of a firm.

Although an intuitively compelling hypothesis, it is exposed to criticism. In particular, it has no practical application to firms with little or no financial leverage. Naturally, any study examining the so-called leverage hypothesis and its impact on volatility requires debt valuation measures. These are oftentimes problematic to obtain in practice, especially at higher frequencies. Black (1976) and Christie (1982) find that financial leverage partly explains the asymmetric relation between returns and volatility. Schwert (1989) finds that financial leverage inadequately captures movements in market volatility. Cheung and Ng (1992) find that the leverage effect is stronger for small firms than it is for relatively larger firms (i.e. the asymmetric link between volatility and returns is stronger for small firms than it is for larger firms). Nonparametric tests in their study show that the strength of the leverage effect changes over time. This suggests that parameter estimates may vary depending on sample period selection. Duffee (1995) corroborates the findings of Cheung and Ng (1992) that smaller firms exhibit a much stronger positive contemporaneous relationship between returns and volatility than do relatively larger firms. His study further finds that this contemporaneous relationship is even stronger for firms that are ultimately delisted from the stock exchange. Therefore, there is a survivorship bias in favor of the leverage hypothesis.

Figlewski and Wang (2000) characterize the leverage effect as merely a "down market effect." More precisely, they find that when leverage changes as a result of changes in a firm's outstanding debt or shares, then volatility remains unaffected. If,

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however, leverage changes as a result of negative stock price movements, then we begin to see movements in volatility. On the flip side, the leverage hypothesis does not hold when there is a positive change in stock price. Hence, they characterize the so-called leverage effect as being nothing more than a "down market effect" because we only begin to see a link between volatility and leverage during market downturns. Furthermore, any changes in volatility as a result of stock price declines are transitory. These findings present three fundamental weaknesses in the leverage hypothesis: Firstly, if the leverage hypothesis were to be true, then the sources for the leverage changes should be irrelevant. Secondly, the leverage hypothesis is associated with falling stock prices rather than just leverage in isolation. The leverage hypothesis is nearly non-existent when stock prices rise. Thirdly, changes in volatility supposedly instigated from the leverage hypothesis are transitory. However, a change in the level of a firm's leverage should, supposedly, result in a permanent shift in volatility. Empirical tests show that this is not the case and that changes to volatility are short-lived. These findings show that leverage may have little or no direct connection with changes in volatility.

Finally, some studies offer a trading-based explanation for the negative conditional mean-variance tradeoff (see Avramov, Chordia and Goyal, 2006). They contend that the leverage hypothesis and the volatility feedback argument may not hold when examining data with higher frequencies. For example, when considering a data sample at the daily frequency, the volatility feedback argument and leverage hypothesis may not be manifest since asset prices should follow a martingale at shorter time horizons (see Sims, 1984; Lehmann, 1990). In other words, any price deviations from the asset's

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fundamental value will be transitory since the flow of information is random (i.e. markets are efficient).

Trading-based explanations have examined the impact trades have on conditional volatility. Empirical investigation reveals that there is a relationship between level of trades and the conditional variance of assets' prices (French and Roll, 1986). Avramov, Chordia and Goyal (2006) extend this research to show that there is indeed a relationship and that, depending on the type of trade, conditional volatility increases or decreases. More specifically, there exist two types of investors: Contrarian (also known as informed) traders and herding (also known as non-informed or liquidity-driven) traders. Contrarian investors sell their positions when returns are positive (i.e. traders who buy low and sell high). Herding investors, on the other hand, sell their positions when returns are negative (i.e. they buy high and sell low). Herding investors are irrational traders that cause increased volatility and move prices away from their fundamental values. Contrarian traders decrease conditional volatility and move prices closer to their fundamental values. Thus, depending on the type of trading, conditional variance increases or decreases accordingly.

Avramov, Chordia and Goyal (2006) argue that the trading activity of these two types of agents causes the asymmetric link between realized returns and volatility. Consistent with the rational expectations hypothesis, market participants' forecasts for the future outlook of the market are contingent on all currently available information. Thus, following periods of unexpected negative stock returns, herding investors sell their positions (for fear of negative future returns) and induce market volatility. Contrarian traders buy during market downturns and reduce market volatility by pushing prices back

to their fundamental values (see Friedman, 1953; Hellwig, 1980; Wang, 1993). Trading activity is defined as the number of sell transactions that occur each day. In their study, they find that when the lagged unexpected return is negative, selling activity from herding traders is responsible for next period's increase in volatility. When the lagged unexpected return is positive, selling activity from contrarian traders leads to a reduction in next period's volatility. To differentiate between rational (contrarian) and irrational (herding) investors, they employ a methodology implemented by Campbell, Grossman and Wang (henceforth CGW) (1993). In their model CGW (1993) show that informed (uninformed) trades are unrelated (related) to changes in future price. Therefore, contrarian investors have no bearing on the autocorrelation in stock returns while uninformed sell trades lead to downward pressure on prices. The results of Avramov, Chordia and Goyal (2006) are robust to different measures of the conditional variance at the daily frequency.

The trading-based hypothesis delivers empirically powerful results and provides evidence that trades are a source of volatility. However, the usefulness of this proposition is called into question. Whereas most research tends to explore the asymmetric relation between volatility and returns using lower frequencies (i.e. such as monthly data), Avramov, Chordia and Goyal (2006) derive their hypothesis using daily data. However, it may be implausible to make the argument that an investor's perceived risk aversion changes from day-to-day. Perhaps risk changes along with changes in other macroeconomic variables (see Officer, 1973) or is contingent upon an investor's unique expectations. Research shows that investors have dissimilar expectations and one cannot safely assume that they share identical estimates of future outcomes (see Miller, 1977).

Perhaps changes in risk aversion are attributable to a combination of these factors. Thus, it may be unfeasible to see movements in risk aversion at such high frequencies as those used in the study by Avramov, Chordia and Goyal (2006). In fact, Cochrane (2001, p. 26) maintains that

> "It is not plausible that risk or risk aversion change at daily frequencies, but fortunately returns are not predictable at daily frequencies. It is much more plausible that risk and risk aversion change over the business cycle, and this is exactly the horizon at which we see predictable excess returns."

To counter these arguments, this study makes use of monthly data (see section 2.4). Nonetheless, trading-based hypotheses have received attention in the literature. Some researchers extend these trading-based theories to see how futures trading impacts volatility. Empirical tests show that changes in stock market volatility are not statistically attributable to the level of futures trading (see Santoni, 1987; Davis and White, 1987; Edwards, 1988a and 1988b; Antoniou, Holmes and Priestley, 1998, to name only a few). In fact, Antoniou, Holmes and Priestley (1998) further report that the observed asymmetry between volatility and returns cannot be the result of solely the so-called leverage hypothesis. There are yet other factors responsible such as noise and feedback trading.

The volatility feedback, leverage, and trading-based hypotheses, have all spawned much research interest in the conditional risk-return tradeoff. Efforts examining this relationship predominantly use historical realized rates of return to produce conditional

mean-variance estimates. Oftentimes, results regarding the dynamic risk-return tradeoff are idiosyncratic to particular methodologies or data sets. These observed outcomes vary as researchers change the specifications in their models or the range and frequency in their data sets, casting doubt on their conclusions.

This chapter focuses on addressing the volatility feedback argument. The leverage hypothesis runs into empirical and theoretical roadblocks when examining leveraged firms. Furthermore, it has no way of explaining the asymmetric risk-return link in firms with little or no leverage. The trading-based hypothesis may be a significant improvement over the leverage hypothesis but also has shortcomings. Namely, it may be unjustified to use high frequency data (such as daily returns) since investors' risk aversion does not change from day-to-day. It is more reasonable to assume that investors' degrees of risk aversion changes together with shifts in macroeconomic factors. Despite their shortcomings, the leverage- and trading-based hypotheses are a step in the right direction and a basis for future research. However, testing these hypotheses is beyond the scope of this chapter. Instead, this chapter addresses the notion of volatility feedback and the importance of trying to capture the required rate of return. Existing literature addresses the notion of volatility feedback passively when interpreting results. For example, studies that document a weak or negative intertemporal risk-return relation allude to volatility feedback as the likely culprit. As the required rate of return is increasing, prices will fall leading to lower historical average returns. Section 2.3 of this chapter stresses the importance of capturing movements in the required rate of return to address the intertemporal risk-return puzzle. In any event, there exists much literature

devoted to this topic and, although conflicting at times, it is a good starting point for discussion and merits consideration for future research endeavors.

### 2.2.4.2. An Investigation of Extant Findings

Studies usually examine the intertemporal risk-return link by means of univariate or multivariate GARCH-in-mean models, where the conditional mean is linearly related to the conditional variance. Findings are mixed, with some studies reporting a negative or weak intertemporal mean-variance tradeoff while others find it to be positive. Many of these studies are at odds with our notion that we are risk-averse investors and require higher returns to take on additional units of risk.

French, Schwert and Stambaugh (1987) find an insignificant risk-return relation when they use past daily returns to compute the conditional monthly variance. They conclude that "Future work in this area is called for," and that "Other variables that could affect expected risk premiums should be integrated into this analysis" (p. 27). Baillie and DeGennaro (1990) use GARCH-in-mean models to test the relationship between mean returns on a portfolio and its conditional variance. They replace the normal distribution assumption in their model specification with a fatter-tailed t-distribution. They find no evidence of a conditional risk-return relationship. Chan, Karolyi, and Stulz (1992) implement a bivariate GARCH-in-mean model to estimate the conditional relationship between excess returns of U.S. equities with their conditional variance. They find that expected returns on the U.S. market have no link to its conditional variance, but have some relation to the conditional volatility of the foreign index.

Harrison and Zhang (1999) argue that conflicting evidence on the dynamic risk-return tradeoff may be due to model misspecification. Instead of using a GARCH-in-mean model the way most studies use, they use Monte Carlo integration to form the conditional mean and conditional variance of the returns. It has been argued that parametric models, such as the GARCH model, may lead to specification error and produce spurious results (see Galant, Rossi and Tauchen, 1992). However, in their study they find a statistically significant and positive relation at long holding horizons, such as one or two years, but an insignificant relation at shorter holding horizons, such as one month.

Goyal and Santa-Clara (henceforth GS) (2003) take a different approach to examining the intertemporal risk-return puzzle. They use a much larger sample size and they try to identify the link between average stock variance (idiosyncratic risk) and returns on the market. Consistent with traditional financial models, however, we should be focusing on market risk and not idiosyncratic risk. Nonetheless, they base their decision on the fact that investors and households do not necessarily hold diversified portfolios (see Barber and Odean, 2000; Goetzmann and Kumar, 2001). In fact, research shows that the median household invests in 2.61 stocks. Some investors simply include stocks in their portfolio that they are familiar or "comfortable" with and downplay the important benefits associated with diversification (see Huberman, 2001). Others prefer to invest in stocks of companies that they work for (see Benartzi and Thaler, 2001). Apart from holding undiversified portfolios, GS (2003) base their decision on other market factors and inefficiencies such as transactions costs, taxes and privileged information, all of which influence investors' selection criteria. They further argue that investors hold

non-tradable assets which add "background risk" to their portfolio and, should those assets increase in risk, investors are less willing to hold a market portfolio of traded stocks (unless there is a rise in the expected return of the market). So long as the risk of the non-tradable assets correlates with the individual stocks' total risk, we begin to see a tradeoff between returns on the market and idiosyncratic risk. To measure returns on the market, they use a value-weighted portfolio on New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and Nasdaq stocks from 1963:08 to 1999:12. Their findings indicate a positive link between average idiosyncratic risk and returns on the market. They find no relationship between conditional risk and return in the market portfolio.

Bali, Cakici, Yan and Zhang (2005) refute the findings of GS (2003), claiming that their results are not robust across different sample periods and portfolios. For example, if one were to replicate their procedure and extend their data sample, originally from 1963:08 to 1999:12, to 1963:08 to 2001:12, the relation between idiosyncratic risk and market returns diminishes. In addition to different sample periods distorting their results, Bali, Cakici, Yan and Zhang (2005) argue that the conclusions of GS (2003) do not hold if they were to exclude Nasdaq stocks from their value-weighted portfolio to calculate idiosyncratic risks. Thus, they argue, their results are not only nullified if one were to change sample periods, but also if you were to compare idiosyncratic risk across different portfolios. Though they managed to find weaknesses in the study by GS (2003), they too could not find a positive risk-return tradeoff in the market.

Other researchers look to international markets to explore the intertemporal risk-return link. Theodossiou and Lee (1995) use the GARCH-in-mean model to test the

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conditional risk-return tradeoff in ten industrialized countries using three specifications for the conditional mean-variance relationship: The linear, the square-root, and the log-linear specifications, yet cannot obtain positive results in any of the ten countries under consideration. Koulakiotis, Papasyriopoulos and Molyneux (2006) study nearly all the same countries that Theodossiou and Lee (1995) examine, but instead use the asymmetric EGARCH of Nelson (1991) to capture the effects of positive and negative innovations. They too cannot find a statistically significant risk-return relation. Other researchers investigating the Chinese market (see Lee, Chen and Rui, 2001), emerging markets (see De Santis and Imrohoroglu, 1997; Shin, 2005), and other international markets around the world (Balaban, Bayar and Kan, 2001), also find that the conditional risk-return relationship is not statistically different from zero.

There exist yet other studies that document a negative, and at times statistically significant, conditional mean-variance tradeoff. Pindyck (1984) documents a negative relation between market returns and volatility and finds support for the volatility feedback argument. As volatility increases, the required rate of return on equities increases and leads to an immediate drop in stock prices. Campbell (1987), Turner, Startz and Nelson (1989) and Nelson (1991) all use different methodologies and data sets, yet also find a negative intertemporal risk-return link. In particular, Nelson (1991) uses the EGARCH-in-mean specification, which captures negative and positive innovations, yet finds a negative relation. Glosten, Jaganathan and Runkle (1993) use their GJR-GARCH to capture the asymmetric impact positive and negative news has on the conditional variance. Even after using dummy variables to control for the so-called "January effect," they find a negative conditional risk-return link.

Whitelaw (1994) integrates four financial variables in order to estimate the conditional first and second moments of stock returns: The spread between Baa and Aaa bonds, the commercial paper-Treasury spread, the one-year treasury yield and the dividend yield on the S&P 500. These variables were selected from a universe of regressors for their proven predictive abilities. However, a natural concern with this method of selection is the possibility of data snooping biases. Whitelaw (1994) defends the use of these variables on theoretical grounds for their consistent empirical performance. Research shows that these variables are good predictors of the mean and variance of market returns (see Breen, Glosten and Jagannathan, 1989; Fama and French, 1989; Kandel and Stambaugh, 1989 and 1990; Keim and Stambaugh, 1986, to name only a few studies). For example, the spread between commercial paper and the treasury yield is a good predictor of stock market volatility as well as real economic activity (see Stock and Watson, 1989; Bernanke, 1990). The treasury yield curve, by itself, is used by economists and central banks as a method for predicting future economic activity (see Estrella and Hardouvelis, 1991; Campbell, 1995; Estrella and Mishkin, 1998; Hamilton and Kim, 2002, to name only a few). Whitelaw (1994) finds that, for shorter time horizons, expected returns are positively related to the default spread and the dividend yield but are negatively related to the one-year treasury yield. Since the dividend yield and the default spread may very well proxy for variations in the risk premium, they are positively linked to expected returns. The fact that expected returns are negatively related to the one-year treasury yield is consistent with the theory of money demand outlined by Fama (1981) and Kaul (1987). However, even with the inclusion of these variables as

predictors of the mean and variance of market returns, his study finds a negative intertemporal risk-return tradeoff.

Bekaert and Wu (2000) document a negative conditional mean-variance link when examining the Japanese stock market index. To motivate their study, they cite the two competing hypotheses responsible for the asymmetric conditional mean-variance relation (i.e. the leverage hypothesis and volatility feedback argument). They find that, although much work has been done examining each of these hypotheses in isolation, these hypotheses have not been examined and compared simultaneously. More specifically, no study examines volatility asymmetry at the market level and at the firm or portfolio level. Most studies examining the leverage hypothesis typically use data from individual firms or a portfolio of firms and calculate their gross volatility. Gross volatility is typically applied in studies investigating individual firms whereby regression analysis is used to find a link between some measure of volatility and returns in the preceding month (see Black, 1976; Christie, 1982; Duffee, 1995). Literature investigating the volatility feedback hypothesis tends to use market level data and produces conditional mean-variance forecasts using GARCH-type models. Therefore, it appears there are two separate strands of literature which use distinct data sets and methodologies. In order to unify these two strands of literature and to test which hypothesis perseveres, Bekaert and Wu (2000) test both these hypotheses simultaneously using the Japanese market index along with various levered portfolios of stocks.

Their sample ranges from January 1, 1985 to June 20, 1994 and includes firms from the Nikkei 225 index. To avoid survivorship biases from skewing their results, they select firms that have been actively listed in the Nikkei 225 index over the entire sample

period. These stocks must also have debt data available throughout the sample period. Stocks that do not fulfill these requirements are discarded from the study. Bekaert and Wu (2000) create three portfolios of stocks with varying degrees of financial leverage; a high, medium and low levered portfolio. Along with these levered portfolios, they also examine volatility asymmetry in the Nikkei 225 index. Findings in their study indicate that leverage variables are significantly associated to changes in conditional volatility estimates. Nonetheless, their explanatory power on conditional volatility estimates appears to be dwarfed by the volatility feedback mechanism. The conditional mean-variance asymmetry is most pronounced as a result of market shocks (i.e. shocks in the GARCH specification). These shocks best explain this asymmetry in the market and in the high and medium leverage portfolios. Financial leverage, however, seems to play a slightly larger role for the low leverage portfolio. Bekaert and Wu (2000) take their analysis one step further and test the findings of Cheung and Ng (1992), who find that volatility asymmetry is much stronger for small U.S. stocks. They extend this line of research and sort Japanese equities on the basis of their average market capitalization over the sample period. They find that the degree of volatility asymmetry is not necessarily contingent upon the size of a firm. For example, larger firms may exhibit stronger volatility asymmetries than their smaller counterparts. All in all, neither size nor leverage can solely be used to decipher the degree and direction in conditional volatility shifts.

Other studies change the methodologies or assumptions in their models, yet continue to find this relationship to be negative. Harvey (2001) contrasts linear from non-parametric methods for estimating conditional expectations. Results in his study

indicate that the conditional mean-variance relation depends on the specification that the researcher imposes on the conditional variance. The rationale behind using nonparametric techniques is to model the returns of securities which have complex embedded options. By doing so, it is not necessary to assume that the data fall into a class of parametric distributions. This paper focuses on four applications where nonparametric regression techniques can be used: Firstly, it may be able to model the behavior of a market timer. A market timer shifts funds into market sensitive stocks during market upturns (to magnify returns) and into market insensitive stocks during market downturns (to minimize losses). Secondly, the use of nonparametric density estimation techniques may be a useful approach to model returns in the recreation industry portfolio. The returns of this portfolio are nonlinearly related to the returns on the market. By using the nonparametric density estimation technique, it may be possible to model these complex nonlinearities. In the third scenario mentioned, the nonparametric density estimation technique may be used to model portfolios for hedging securities. Many pass-through securities by the Federal National Mortgage Association contain embedded options which make them more complicated and nonlinear when compared to other securities. The nonparametric method gives researchers some ability to model these nonlinearities.

Empirical tests indicate that the use of nonparametric regression techniques does not lead to improved forecasts of market returns, suggesting that the use of linear techniques is well-grounded. For example, when examining the conditional mean, a higher $R^2$ coefficient is obtained when looking at the NYSE value-weighted portfolio. This means that the linear estimation technique may provide a better "fit" for the data. In terms of the conditional mean-variance relationship, his results indicate that if the

conditional variance estimator uses the same information as the conditional mean, a negative relation between the two is likely to transpire. Furthermore, market participants demand a large expected return per unit of risk during market downturns and a lower expected return per unit of risk during market upturns.

Although intuitively straightforward, research examining the intertemporal risk-return tradeoff produces these mixed results. This study finds that if the same information used to produce the conditional variance is used to estimate the conditional mean, it is likely that a negative conditional mean-variance relation will materialize. Another argument of this paper is that, although we can produce accurate estimates of volatility using an asymmetric GARCH model, it is groundless to treat the conditional mean estimate as a proxy for the required rate of return. Harvey (2001) finds that investors demand more returns during market slumps (when volatility is higher). Yet, the conditional risk-return tradeoff he finds is negative. The use of nonparametric density estimation methods may very well be used to model the returns of securities with complex embedded options. Yet, as section 2.3 of this chapter argues, this may not resolve the theoretical shortcomings of using conditional mean estimates as proxies for investors' required rate of return.

Koopman and Uspensky (2002) use a stochastic volatility-in-mean model (SVM) derived from Monte Carlo simulation methods to examine the intertemporal relation between stock index returns and volatility. They study this relationship in three major stock markets: The U.K., the U.S. and the Japanese stock markets. A fundamental difference between stochastic volatility (SV) models and GARCH models is in the way that the variance forecast is estimated. GARCH models produce conditional variance

forecasts using all information available up until that of the previous period. They are deterministic models whose forecast is based on past squared innovations and lags of the conditional variance. SV models contain a second error term that impacts the direction of the conditional variance forecast. A simple SV model may define volatility as a logarithmic first-order autoregressive process:

$$y_t = \mu + u_t\sigma_t \ , \ \ u_t \sim N(0,1)$$

$$\log(\sigma_t^2) = \alpha_0 + \beta_1\log(\sigma_{t-1}^2) + \sigma_\eta\eta_\tau \tag{2.13}$$

$\eta_\tau$ is a stochastic variable that is independent of $u_t$ and has a distribution $N(0,1)$. Use of SV models has much useful application for option pricing studies. They allow researchers to relax the assumption that volatility is constant throughout the life of an option (see Black and Scholes, 1973). SV models are, however, disadvantageous in the sense that they are relatively more complex than their GARCH counterparts and require more work in order to estimate the model parameters (see Harvey, Ruiz and Shephard, 1994).

Koopman and Uspensky (2002) defend their use of SV models on grounds that, although relatively more complex than GARCH models, many advances have been made to facilitate their use. GARCH models are advantageous in the sense that, since the model is devised using the distribution of a one-step ahead prediction error, maximum likelihood estimation is easier to perform. SV models are much more difficult to estimate by using maximum likelihood. More specifically, there are generally two methods for estimating SV models: A researcher can either attempt to create the entire likelihood function to estimate the SV model. Doing so is a complex process and requires much effort. Alternatively, they can simply approximate the likelihood function or just avoid

this matter altogether.  However, there has been a recent trend towards trying to develop techniques in order to calculate the entire likelihood function.  In their study, Koopman and Uspensky (2002) utilize a Monte Carlo likelihood estimation approach functionalized by Shephard and Pitt (1997) and Durbin and Koopman (1997).  Koopman and Uspensky (2002) estimate an SV model whereby volatility is one of the key variables that direct movements in the conditional mean.  This is strikingly similar to an ARCH-in-mean model, where the conditional mean is linked to the conditional variance.  However, whereas the ARCH-in-mean model attempts to decipher the relation between expected returns and expected volatility, the SVM model seeks to simultaneously predict the ex ante tradeoff between volatility and returns, as well as capture the volatility feedback effect.

Findings using the SVM framework suggest a negative, albeit statistically insignificant, risk-return tradeoff for all stock index series. Koopman and Uspensky (2002) then compare these results with those obtained using GARCH-in-mean models, which happen to find a weak but positive relationship.  The GARCH-in-mean results in their study corroborated the weak conditional risk-return relation that other researchers have found.  The results from their SVM models again point to the theoretical pitfalls of using historical realized returns to address the volatility feedback argument.  SVM models may be more sophisticated than their GARCH-in-mean counterparts, but may not be a solution to the problem.

Other more recent studies in the literature use a variety of methodologies and different data samples yet ascertain a negative conditional risk-return relation.  Brandt and Kang (2004) implement a latent vector autoregressive (VAR) process.  They defend

their decision to use this model on the basis that it provides a flexible statistical framework to examine the contemporaneous and intertemporal risk-return relation without the necessity of using exogenous variables. In addition to not having to specify exogenous variables (since all are endogenous), there are several other advantages that make VAR models attractive to researchers. First of all, they give researchers flexibility and allow a variable of interest to depend on more factors rather than just its own lags or some combination of stochastic terms. VAR models received attention for their ability to provide better forecasts than other traditional large-scale structural models (see Sims, 1980). Other research has shown that VAR models are superior to other traditional models in terms of forecasting macroeconomic variables, such as the unemployment rate and gross national product (GNP) (see McNees, 1986). Despite their flexibility and their empirical capabilities, VAR models also have their disadvantages. Firstly, they are a-theoretical and require no theoretical information about the nature of the variables in order to establish a specification of the model. Another drawback to using VAR models is there may be too many parameters that have to be estimated. For example, if there exist $n$ equations, an equation for each of the $n$ variables and with $q$ lags for each variable in each equation, then $(n + nq^2)$ parameters need to be computed. Hence, if $n = 4$ and $q = 4$, then 68 parameters need to be estimated. If a researcher is to implement a VAR methodology using a small sample size they may find that degrees of freedom will rapidly be spent, meaning that standard errors will be large and confidence intervals may be wide.

Brandt and Kang (2004) investigate the time-series relation between the conditional moments using a latent VAR methodology. The first equation in their model

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describes properties in the conditional mean. The second equation in their model describes the conditional variance and nests the standard SV model that other researchers have used (see Wiggins, 1987; Andersen and Sorensen, 1994; Jacquier, Polson and Rossi, 1994; Kim, Shephard and Chib, 1998, to name only a few]. Their study examines movements in the conditional mean and variance from business cycle to business cycle. They find that as the economy moves from a peak to a trough, conditional volatility increases immediately. The conditional mean remains relatively flat, increasing only slightly at times. In conclusion, Brandt and Kang (2004) find a negative and statistically significant conditional mean-variance relation.

Perhaps one of the most recent studies that examine the conditional risk-return tradeoff on an international level is the study by Li, Yang, Hsiao and Chang (2005). They apply the GARCH-in mean and E-GARCH-in-mean methodology to the twelve largest stock markets. Their sample period for all markets ranges from January 1980 to December 2001. They motivate their study by discussing the two well-known hypotheses for why the conditional risk-return tradeoff may be negative: The volatility feedback hypothesis and leverage effect. Li, Yang, Hsiao and Chang (2005) acknowledge much work already exists which tries to capture the conditional mean-variance relationship. However, they argue that perhaps researchers should consider the use of flexible semi-parametric specifications of the conditional variance in order to examine this relationship. GARCH-in-mean models are sensitive to model misspecification and, in order for the model to be estimated properly, its parameters need to be correctly identified (see Bollerslev, Chou and Kroner, 1992). Other researchers have expressed their reservations surrounding GARCH models and their ability to produce accurate

conditional mean-variance forecasts. For example, Nelson (1991) warns that GARCH models impose parameter limitations which may be violated by coefficient estimates. Because GARCH models are restrictive, we are also restricting the nature of the conditional variance process. Jones, Lamont and Lumsdaine (1998) express a similar concern. They argue that GARCH modeling may result in inferior estimates of volatility if a researcher does not correctly specify their model.

Given these concerns, Li, Yang, Hsiao and Chang (2005) choose to take two approaches to study the conditional mean-variance tradeoff. Firstly, the EGARCH-in-mean method is utilized, since it has the ability to respond asymmetrically to positive and negative innovations. Then, for sake of comparison, a flexible semi-parametric GARCH-in-mean model is used. Both of these approaches are utilized to study the same sample period for all twelve stock markets. Findings in their study emphasize how sensitive estimated conditional risk-return relationships are to the different techniques in which volatility is forecasted. More specifically, they find that, when a parametric EGARCH framework is employed, the conditional mean-variance tradeoff is more or less statistically negligible. Ten of the twelve countries under scrutiny exhibit a positive relation, but its significance is not statistically different from zero. When a flexible semi-parametric specification for the conditional variance is used, the conditional risk-return tradeoff is negative in most of the sample markets. In fact, for six of the twelve markets, a negative and statistically significant relation was estimated.

This study made a strong point about the restrictive nature of GARCH models and a possibility that these restrictions may be a problem. It also shows how sensitive conditional risk-return tradeoff estimates are to the presence (or absence) of parameter

restrictions.  However, as their results indicate, this is not the source of the problem.  The study by Li, Yang, Hsiao and Chang (2005), alike other studies, alluded to volatility feedback as the culprit for why so many researchers document different results.  For some countries, they even found this relationship to be negative and statistically significant.  Despite changing from a "rigid" to a more flexible statistical framework, the qualitative nature of their results did not change.  Even when using a more flexible semi-parametric approach, Li, Yang, Hsiao and Chang (2005) did not find a positive conditional risk-return tradeoff as financial theory dictates.  Instead, shifting from a parametric to a semi-parametric method only seemed to change the significance of their test statistics.  The parametric approach yielded an insignificant conditional tradeoff while the semi-parametric approach estimates the relation to be negative and statistically significant.

It seems implausible, therefore, to blame the properties of GARCH models on the reason for the insignificant or negative tradeoff that researchers find.  It is well-recognized in the literature that deriving volatility forecasts is a difficult task.  Akgiray (1989) recognized that the time-series of market returns show signs of second-order dependence (i.e. the probability distribution of returns at time $t$, $R_t$, is not entirely independent of future period's returns, $R_{t+n}$).  However, he contends that conditional heteroskedasticity models work best for capturing the properties of return series data since they allow for autocorrelation between the first and second moments of the return distribution.  In a comparison test, he finds that GARCH models accurately predict volatility and outperform their ARCH counterparts, exponentially-weighted moving averages and historical mean models for estimating monthly volatility in the U.S. market.

West and Cho (1995) approach a similar conclusion when working with dollar exchange rate volatility. Pagan and Schwert (1990) consider a range of GARCH-type models and their ability to produce accurate estimates. They compare the GARCH and EGARCH models to several non-parametric models in an effort to see which performs better. Their findings show that parametric models fare better than their non-parametric counterparts during out-of-sample prediction experiments. More specifically, non-parametric techniques may result in too much variability in estimates of the conditional variance.

Perhaps, a conclusion that all researchers can agree on is that estimating volatility is problematic and, whatever the econometric or theoretical model a researcher elects to use, it will certainly have its advantages and disadvantages. This led Brailsford and Faff (1996) to characterize the forecasting of volatility as a "notoriously difficult task." Their study examined the daily returns of the Australian stock market index. They find that the asymmetric GJR-GARCH model works best for forecasting volatility and for capturing positive and negative innovations. However, overall, they find that simple ARCH-type models are most effective in capturing movements in volatility while relatively more sophisticated models, such as non-linear and non-parametric models, afford substandard forecasts. Dimson and Marsh (1990, p.420) corroborate the findings of Brailsford and Faff (1996) that simpler models may be a superior alternative to complex models: "For those who are interested in forecasts with reasonable predictive accuracy, the best forecasting models may well be the simplest ones." Furthermore, they urge fellow readers to take heed to results generated by volatility models, suggesting that a stipulated model may not capture the true dynamics of a particular data set.

For example, a researcher may very well select to use a particular model that, given the nature of their data sample, happens to provide support for the hypothesis under consideration. Dimson and Marsh (1990) warn that such data snooping can misleadingly show a relationship between variables where one does not exist, or happens to exist only under certain conditions (which may be elusive to the researcher but are disregarded in their discussion). Data snooping has long been a concern in the field of finance as well as other social sciences. It is no surprise, therefore, that researchers may prefer one model over another simply because it provides a better fit for their data (see Leamer, 1978). Merton (1987) expresses concern that, although data snooping is recognized, it tends to go largely ignored.

Given these concerns in the research profession, it is important for readers not to focus exclusively on the values of test statistics or $R^2$ coefficients, but to evaluate a study based on its theoretical motivations and whether or not its arguments make fundamental sense. To mitigate such concerns in this thesis, market return data is utilized going back as far as possible up until the current period. Extraordinary events, such as wars or stock market bubbles, were not removed or filtered out of the sample. This is because they offer valuable information concerning movements in the conditional mean and conditional variance forecasts.

Apart from data snooping issues, the findings just presented also show that parametric restrictions are not necessarily to blame for the insignificant or negative conditional risk-return relation as Li, Yang, Hsiao and Chang (2005) hypothesized. Although use of semi-parametric methods may aid researchers in uncovering the properties of other time series, it is not a solution to the volatility feedback hypothesis.

Furthermore, there already exists much evidence that supports GARCH modeling as a technique for effectively and accurately estimating volatility. Oftentimes, use of parametric methods surpasses forecasts of semi-parametric or non-parametric techniques.

Although the study by Li, Yang, Hsiao and Chang (2005) may encourage future use of semi-parametric methods to explore other topics concerned with the conditional mean-variance tradeoff, it is of no service to us in addressing the volatility feedback argument. Especially when there is evidence that standard GARCH models sufficiently and efficiently predict volatility.

It is important to note that up to now, this chapter has examined studies that have found either a negative or statistically negligible conditional risk-return relation. However, there exist yet other studies that actually find this relation to be positive. Using different theoretical and econometric approaches, some researchers maintain that this tradeoff is indeed positive and statistically significant.

Chou (1988) examines weekly data in the U.S. from 1962 to 1985 and, using the GARCH-in-mean model, finds the conditional risk-return relation to be positive. Bollerslev, Engle and Wooldridge (1988) implement a multivariate GARCH process to estimate the conditional mean and the conditional covariance of returns on T-bills, bonds and stocks with excess returns on the market. They find the conditional mean-variance relation to be small, yet statistically significant. Their study suggests that perhaps other factors should be included when estimating the conditional distribution of returns, such as innovations in consumption. Sheikh (1993) incorporates implied volatility derived from call options into his research to examine the conditional risk-return tradeoff. His study finds that implied volatility is positively and significantly related to movements in

forecasted return volatility and would serve as an appropriate forecast for conditional risk.

Implied volatility estimates the volatility of an asset's price based on a number of factors (i.e. interest rates, strike price of the underlying asset, number of days until expiration, to name only a few variables). Implied volatility is thus distinguishable from historical volatility because the latter is calculated from realized historical prices. Implied volatility is advantageous in the sense that it is forward-looking (i.e. implied volatility increases when investors are bearish and declines when they are bullish). When examining returns on individual stocks with their corresponding lagged implied volatilities, Sheikh (1993) finds them to be positively related. However, when using the same procedure for the S&P 100 index, he does not find a statistical relationship between returns and lagged values of implied volatility.

In an effort to resolve the intertemporal puzzle, Scruggs (1998) employs a conditional two-factor model. To motivate the construction of his empirical model, Scruggs (1998) includes the return on long-term government bonds as a second factor in the ICAPM of Merton (1973). When doing so, Scruggs finds a positive and significant intertemporal risk-return relation. He justifies the inclusion of the long-term government bond rates on the basis that investors are always shifting their investment preferences and hedging against any possible undesirable changes in the markets. Merton (1973, p. 879) supports the use of interest rates as an instrumental factor in determining the pulse of the economy: "One should interpret the effects of a changing interest rate in the forthcoming analysis in the way economists have generally done in the past: namely, as a single (instrumental) variable representation of shifts in the investment opportunity set."

Scruggs (1998) defends use of the long-term bond yield on grounds that it accurately captures shifts in investment opportunities. Furthermore, other studies are well aware of the forecasting properties of long-term and short-term government bond yields, the spreads between long- and short-term interest rates and the spread between high- and low-grade bonds as instrumental "indicators" of market performance and changes in risk. Therefore, these factors have been incorporated in multifactor asset pricing models to examine the conditional risk-return relation (see Chen, Roll and Ross, 1986; Shanken, 1990, to name only a few). The properties of long-term government bond yields are covered in more depth in section 2.3 of this chapter.

Deviating from the traditional ARCH approach, Ghysels, Santa-Clara and Valkanov (2005) implement a mixed data sampling (MIDAS) estimator to forecast the monthly variance using historical daily squared returns. Their findings suggest a positive and significant conditional risk-return tradeoff. They uphold that the risk-return tradeoff is the "first fundamental law of finance," yet are perplexed as to why studies offer conflicting results. Using daily aggregate stock market data from the U.S. market, from January 1928 through December 2000, they claim to find a positive conditional risk-return relation that is robust in sub-samples and to asymmetric specifications in the variance process.

They begin their study with the Merton (1973) ICAPM formula expressed in Equation (2.4):

$$E_t[R_{t+1}] = \alpha + \theta \, \sigma_t^2,$$

where $\theta$ is the coefficient of risk aversion and $\alpha$, in a 'perfect' economy absent of transactions costs and market inefficiencies, is zero. To estimate returns on the left-hand

side they use monthly data, since daily returns may be too noisy. On the right-hand side, they use daily lagged squared returns. They also extend the MIDAS methodology to allow negative and positive innovations to asymmetrically impact the dynamics of the conational variance forecast (i.e. negative and positive daily squared returns have different weightings on the conditional variance).

Their approach is comparable to that of French, Schwert and Stambaugh (1987), previously discussed in this literature review, whereby the monthly variance is computed using a "rolling window" approach. The rolling window approach calculates an estimator for the conditional variance by taking the sum of the daily squared returns of the previous month(s). French, Schwert and Stambaugh (1987) used a one month rolling window, yet calculate an insignificant coefficient for the risk aversion parameter, $\theta$. Ghysels, Santa-Clara and Valkanov (2005) find that when they increase this rolling window from one month to three or four months, they calculate $\theta$ to be 2.6, which is consistent with theory that we are risk-averse. To test their results, they also break their sample into two subparts of approximately equal size: 1928 through 1963 and 1964 through 2000. Their results indicate a positive and statistically significant coefficient of risk aversion for both of the sub-samples. Leon, Nave and Rubio (2007) also extend the work of Ghysels, Santa-Clara and Valkanov (2005) and implement the MIDAS forecasting technique to examine the conditional risk-return tradeoff in European equity indices. They examine daily returns from the Eurostoxx50 (Europe's Blue-chip index), CAC (French stock index), DAX (German stock index), Ibex-35 (Spanish stock index) and the FTSE100 (British stock index) from January 1988 through December 2003.

Their findings indicate a positive and significant coefficient of risk aversion for all their samples.

Instead of focusing on econometric models to provide support for the intertemporal risk-return tradeoff, Lundblad (2007) approaches this issue from a theoretical perspective. His study claims that the data samples of previous studies, which conclude a negative or insignificant relation, are plagued with small-selection biases and the problem in detecting a positive relation does not originate from volatility specification. When using nearly two centuries of data from the U.S. stock market, he finds the risk-return tradeoff is indeed positive. By using such an expansive data set, a researcher is able to capture the impacts of several pronounced macroeconomic occurrences which contain important information about equity prices during times of increased uncertainty. This claim contrasts sharply with the arguments of most other researchers, who hypothesize that the problem may be in the specification of the model. To corroborate his findings, Lundblad (2007) uses a variety of specifications for the conditional variance and ascertains qualitatively similar results.

**2.2.4.3. Some Final Thoughts on Intertemporal Risk-Return Literature**

The existing findings just presented show how fundamental the conditional risk-return tradeoff is in modern financial theory. It is no surprise, therefore, that so much effort is devoted in order to decipher this relationship. Despite the vast body of literature, however, not enough attention has been given to why researchers' studies yield these mixed results. The literature just examined attempts to resolve the puzzle using a variety of methodologies while ignoring the possible theoretical shortcomings for using historical realized returns as a measure for the required rate of return. For example, using SV, VAR or MIDAS modeling techniques instead of GARCH models may prove useful in identifying trends and the dynamics of volatility through time, but such models may not provide an economically sound answer to the volatility feedback argument. For example, Lundblad (2007) makes the argument that small samples are to blame and not specifications in the conditional variance process. Ghysels, Santa-Clara and Valkanov (2005) claim that, although MIDAS modeling has yielded a positive conditional tradeoff, this tradeoff changes as the rolling "window" length of previous months changes. French, Schwert and Stambaugh (1987) used a one month rolling window and found no evidence of a positive coefficient of risk aversion. Ghysels, Santa-Clara and Valkanov (2005) extended the window length from one month to three and four months, and find it to be significantly positive.

The volatility feedback argument hinges on the observation that volatility is persistent. In other words, a large piece of news about the market, good or bad, typically leads to more pieces of news and increases future volatility. In cases of good news, volatility is, to some degree, relatively less pronounced. In the event of bad news,

volatility is more pronounced. Consistent with the volatility feedback argument, if future volatility increases as a result of the arrival of negative news, then the required rate of return investors demand should also increase. Prices will fall as perceived risk (volatility) increases. However, a researcher using realized returns as a benchmark for the required rate of return will observe that returns are falling. This is no surprise, since prices are falling. However, it is theoretically unjustifiable to extend this observation and claim that the required rate of return is also falling. This is the very reason why so many studies happen to find a negative or weak intertemporal risk-return relation. The central argument of the volatility feedback hypothesis is that the required rate of return should increase. Thus, it is imperative that a proxy for the required rate of return is established and its movements are compared to movements in volatility estimates.

As researchers change the frequency of their data or the range of their samples, results vary. Results also vary as they take on different econometric approaches. However, these approaches may not be an adequate solution. Perhaps one thing most of the above studies have in common is that they use historical realized returns to compute and compare the conditional mean with the conditional variance. Therefore, when the conditional mean of returns falls as conditional volatility rises, it is misconstrued as a negative relation between the required rate of return and risk.

The volatility feedback, trading-based and leverage hypotheses are all a step in identifying reasons for changes in volatility. Perhaps all three hypotheses play some role in the asymmetric link between conditional risk and returns. This will undoubtedly be an interesting topic for future research. For purposes of this chapter, the volatility feedback argument will be addressed. As mentioned, the leverage hypothesis is rather difficult to

apply at times and may result in biased results. For example, there are many firms that have an insufficient, or non-existent, amount of financial leverage. Yet, these firms experience an asymmetric mean-volatility relation.

In addition, it has been found that changes in leverage may not necessarily induce changes in volatility. For example, there appears to be a link between volatility and leverage only when there is a decline in a firm's stock price. Conversely, the leverage effect does not seem to hold when a firm's stock price appreciates. The trading-based hypothesis makes the claim that trades, and depending on the type of trade (i.e. informed opposed to non-informed) are responsible for the asymmetric risk-return relation. However, in order to derive this claim, daily data needs to be used. Typically, studies use monthly data to explore the intertemporal risk-return tradeoff. By doing so, we are capturing fluctuations in the business cycle and other macroeconomic variables. Making the claim that investors' degree of risk aversion changes daily may be unrealistic.

Given these findings and criticisms, the leverage and trading-based hypotheses are beyond the scope of this thesis. Instead, this chapter aims to offer a plausible solution to the volatility feedback hypothesis and to effectively capture the required rate of return. By doing so, we can then see how the required rate of return commoves with fluctuations in conditional volatility estimates. The stock indices of eight major international countries will be investigated in order to compare my results with that of other studies which look at international markets.

It thus seeks to address the current gap in the literature of using *ex post* historical realized returns to make *ex ante* inferences regarding investors' forward-looking expectations. Namely, is it possible that extant conflicting findings result from the use of

historical realized returns as a proxy for investors' required rate of return? As it stands now in the literature, this gap has not been addressed and is a strong reason for why the findings are mixed and inconclusive.

## 2.3. Modeling Risk and the Required Rate of Return

Given the empirical results cited above, the main question is whether there exists a positive intertemporal link between risk and the required rate of return. Extant studies examining this relationship should not be using historical returns to derive conditional mean-variance forecasts. Volatility feedback will distort findings and lead to a negative or weak intertemporal risk-return tradeoff. GARCH-type models are limited in the sense that they cannot capture the required rate of return and need to be used carefully. This study explores the intertemporal risk-return tradeoff by focusing on how to effectively quantify risk and the required rate of return. Previous studies are inclined to using multi-factor models to examine variations in expected returns. For example, Fama and French (1996) use a three factor model that attempts to predict movements in the return of a portfolio in question using three variables: Returns on the market, the returns of small stocks subtracted by the returns on big stocks and the returns of high book/market stocks minus the returns on low book/market stocks. Other researchers have used macroeconomic variables in an effort to forecast returns in the market such as labor income (see Jagannathan and Wang, 1996). Chen, Roll and Ross (1986) use inflation and industrial activity as predictive variables, while Cochrane (1996) uses investment growth.

Although macroeconomic variables are much easier to theoretically motivate, there use has drawn concerns. As already mentioned, there are concerns of data mining

and data selection biases, whereby researchers simply select variables or models that yield empirically favorable results. This very practice led Fama (1991) to characterize the ICAPM as a "fishing license." The ICAPM, however, is not such an extensive model. Therefore we should not be "fishing" for variables that empirically yield desirable results. Instead, we need to include variables that are theoretically justifiable and can help us explain the cross-sectional and time-series link between conditional risk and returns. Cochrane (2001, p. 171) expresses a similar concern:

"The CAPM and multiple factor models are obviously very artificial. Their central place really comes from a long string of empirical successes rather than theoretical purity."

Instead, Cochrane (2001) argues that, when examining the ICAPM, researchers need to integrate variables that can help to explain variations in returns (p. 444):

"Though Merton's theory says that variables which predict market returns should show up as factors which explain cross-sectional variation in average returns, surprisingly few papers have tried to see whether this is true…"

The seminal paper by Kane, Marcus and Noh (1996) makes a similar argument. It attempts to rationalize why historical realized returns present empirical difficulties in deciphering the intertemporal relation between risk and return. They argue that existing findings are inconclusive and offer conflicting evidence because historical realized

returns are backward-looking. We should instead be focusing on a forward-looking measure for returns, such as the E/P ratio.

These very issues are a motivation for the construction of this chapter and an attempt to tackle the volatility feedback argument. However, an immediate question that may arise is whether integrating the Fed model, let alone the E/P ratio, is a theoretically justifiable proposition.

As previously discussed in this chapter, data mining is a concern and can misrepresent the truth. We therefore need to include variables that we can justify on theoretical grounds and avoid including variables simply because they tell us a good story. Merton (1973) argues that researchers should only include instrumental variables that capture changes in the investment opportunity set and which can help to explain the time-series and cross-sectional variation in returns, something which few papers have attempted to do and is a motivation for this chapter.

An integral piece of this chapter, therefore, is the discussion of the so-called Fed model and its constituents, and whether they can justifiably be considered to help answer the intertemporal risk-return puzzle. There are two variables that constitute the Fed model: the market earnings-yield, E/P, and the 10-year government bond yield. To be more exact, the Fed model is the spread between these two variables (i.e. the E/P ratio minus the 10-year risk free rate). Before discussing the Fed model's role in this analysis, it needs to be made clear why the E/P ratio is useful and what role it plays here in this thesis and in the intertemporal risk-return tradeoff literature. Most studies investigating this tradeoff focus on GARCH methodologies or emphasize the use of different parameterization techniques to produce volatility forecasts. What role can the E/P ratio

possible play in this literature? There are three reasons why this ratio serves as a proxy for the required rate of return and why it can help to answer the volatility feedback argument. However, we first need to understand the problem with using historical realized returns.

As mentioned, volatility feedback distorts findings and results in an insignificant or even negative conditional mean-variance relation. During periods of increased volatility, prices fall leading to a negative historical mean return. This is then misconstrued as a negative (or insignificant) conditional risk-return tradeoff. This is exactly the problem. However, as already mentioned, volatility is persistent. Hence, any volatility today will have a bearing on volatility tomorrow. A potential problem in existing research is the use of historical realized average returns as unbiased estimates of the future required rate of return. Simple reflection however reveals that this is unjustified. If an investor perceives higher future volatility (e.g. a large piece of negative news regarding dividends in the near future), this will then result in an increase in the future required rate of return and an immediate drop in prices. The declining prices will produce a lower historical average return, misleading one to believe that the required rate of return is falling. In order to capture movements in the required rate of return, we need to use a proxy that is "forward-looking."

To illustrate what is meant by "forward-looking," let us consider literature examining the term structure of interest rates, a common valuation method for bonds and fixed income assets. When considering the expected return on bonds, it is incorrect to calculate the rate of change on the bond's price, $P$, from the previous period, $t$-$1$, to the current period, $t$ [i.e. $\ln(P_t/P_{t-1})$].

Although this is used to calculate the historical rates of return on the prices of equities, it is inappropriate to use for bonds. Instead, yield-to-maturity (YTM) is used by practitioners and academicians to measure the relative value and return of the underlying instrument:

$$P_t = \sum_{i=1}^{n} CFi /(1+r)^{I} \qquad (2.14)$$

Where $P_t$ is the price of the bond, $CF_i$ is the cash flow due at period i, and r is the internal rate of return (IRR) that equates future expected cash flows of the bond to its current market price. Calculating the YTM provides an accurate method for valuating fixed income assets and can help us to understand an underlying asset's intrinsic properties. For example, bonds that are perceived as being relatively "riskier" investments should offer investors a higher return (YTM). Amihud and Mendelson (1991) find, ceteris paribus, that YTM is higher for assets which have lower liquidity and make it harder for investors to cash out. Other studies examining the term structure of interest rates argue that bond yields can tell us valuable information about the possible future state of the economy (see Estrella and Hardouvelis, 1991; Campbell, 1995; Estrella and Mishkin, 1998; Hamilton and Kim, 2002, to name only a few).

Alike term structure studies, we need to also adopt a forward-looking approach to tackle the volatility feedback argument. Any volatility today will have an impact on volatility tomorrow. As Campbell and Hentschel (1992) indicate, stock price movements today are directly linked to future expected volatility. If investors perceive future volatility, prices will fall since the required rate of return is rising (i.e. volatility feedback effect). Thus, comparing historical realized returns (which are backward-looking) with

volatility forecasts will likely produce spurious results. We need a forward-looking measure of the required rate of return that can accurately capture variations in the future risk premium. The E/P ratio will serve as this proxy.

An E/P ratio is the ratio of earnings to share price. It is the inverse of the well-known PE multiple (or "P/E ratio") that analysts use to value stocks and markets and to check whether stocks are reasonably priced. For example, analysts usually construe a low E/P ratio (i.e. a high PE ratio) as signs that an asset may be overvalued and that investors are expecting a firm to produce higher earnings in the future (i.e. the "price" in the E/P ratio is too high and the "earnings" are too low). When the E/P ratio is low, it is usually followed by a correction in the stock's price. The opposite is usually true in the case of a high E/P ratio. Since this chapter is concerned with the intertemporal risk-return tradeoff of market indices, it calculates the E/P ratio from a market's overall index (such as the S&P 500 for the U.S. market). Calculating an E/P ratio for a market is similar to calculating it for individual firms – average earnings per share of the firms in the index divided by their average price. In this case, the "average" is the weighted average that is proportional to each firm's market capitalization.

Many studies exist supporting the use of the E/P ratio as an indicator of future market performance and claim that it has the ability to forecast future returns reliably and consistently. The E/P ratio and its predictive power has even drawn the interests of central bankers who are responsible for implementing monetary and fiscal policies that impact the overall financial health of the economy.

Before presenting evidence, it is important to understand how the E/P ratio works. Since earnings are in the numerator and price is in the denominator, this ratio compares

stock prices relative to fundamentals. Furthermore, stock prices should reflect the fundamental value of the firm and be positively related to expected returns. Consistent with the mispricing view, when the E/P ratio is low, it warns investors that stocks are overpriced and may entail low returns in the near future. The converse is true when the E/P ratio is high. A good question to ask is why some literature focuses on the PE multiple while others talk about the E/P ratio. After all, one is simply a reciprocal of the other. Usually practitioners and academicians talk about the E/P ratio when valuing markets for two reasons. Firstly, the P/E ratio will approach an infinite value should earnings approach zero and, second, because the E/P ratio is linearly linked to growth in earnings as well as interest rates (see Beaver and Morse, 1978; White, 2000; Jain and Rosett, 2006). This allows researchers to easily compare the level of the E/P ratio with interest rate levels which is the basis of the Fed model.

The expectation that deviations in E/P ratio should be "corrected" in the future is based on the well-established premise of mean reversion (i.e. the value of a variable may fluctuate but should eventually gravitate towards its mean value). For example, markets can reasonably expect that prices of a stock should not drift away from their historical values and from fundamental measures of value (such as earnings). If they do, such deviations should only be transitory. Now let us consider the E/P ratio. Should prices drift too far from earnings – a fundamental measure of a firm's value – we can expect to see the price adjust accordingly to bring the ratio back to normal historical levels. For sake of argument, consider a bull run in a firm's stock price that has nothing to do with changes in its fundamental value. Such a price increase will only be temporary as the price "corrects" in the future to restore the E/P to its normal historical level. In December

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3 of 1996, two Economists, Professor Campbell and Professor Shiller, testified before the Federal Reserve Board that mean reversion applies to the E/P ratio and has the power to predict future stock performance (see Shiller, 1996; Campbell and Shiller, 1998 and 2001). Namely, a low E/P ratio signals market downturns and low future returns while a high E/P ratio signals high future returns.

One may naturally ask, why not use dividends as a fundamental measure of value? The reason dividend-price (D/P) ratios are used sparingly and may not be as effective as the E/P ratio is because their value is strongly influenced by changes in corporate financial policies such as stock repurchases. For example, a company may wish to save taxes during a fiscal period and, as an alternative, repurchase stocks from shareholders. This means that any future dividend payments will be distributed to fewer shareholders. If a firm continues to do this, it will effectively reduce the number of shareholders and increase the growth rate of its dividends-per-share.

All in all, there is mounting evidence in support of the E/P ratio as a predictor of future market performance. Very early research has identified the E/P ratio as a proxy for market performance (see Fama and French, 1988a; Campbell and Shiller, 1988a). More recently, with new estimation techniques and a wider range of data, evidence in support of the E/P as a forecasting variable has strengthened. Shiller (2000) warns that a high P/E (low E/P) signals "irrational exuberance" in the marketplace. Shen (2000) finds that E/P ratios are positively linked to growth in future returns while low E/P ratios signal trouble.[8] Dudney, Jirasakuldech and Zorn (2004) find that E/P ratios are also very valuable because they incorporate other pieces of information that impact investors'

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[8] Pu Shen is an economist at the Federal Reserve Bank of Kansas City. This paper can be accessed through the bank's website: www.kc.frb.org

future outlook of the market. Other evidence supports the observation that the E/P ratio responds positively to changes in inflation (i.e. as inflation increases, so does the E/P ratio) (see Modigliani and Cohn, 1979; White, 2000, to name only a few). Thus, as inflation rises, the required rate of return demanded by investors also rises.

Given the forecasting properties of the E/P ratio and its ability to read the market's "pulse," it is no surprise that it plays such a large role in the so-called Fed model. The Fed model is the spread between the E/P ratio and the 10-year government bond yield. This model gained prominence when it was mentioned in a monetary policy report on July 1997 by the Federal Reserve to Congress detailing the nation's economic outlook (see Greenspan, 1997). Although it is not officially endorsed by any central bank, it serves as a valuation method for markets among practitioners and it accurately and reliably forecasts future economic conditions.

The question is why does the Fed model look at the spread between the E/P ratio and the 10-year government bond yield (i.e. E/P minus the 10-year risk-free rate)? Theoretically, studies normally decompose the required rate of return into two parts: The risk-free rate and the risk premium. From a practical perspective, this makes sense. For example, as an investor, you can either put your money in the equity market or you can put it in a risk-free asset. If the yield on a risk-free government asset exceeds the yield of a risky portfolio of stocks, then there is no reason to put your money in the portfolio of stocks. Implicitly stated, the Fed model judges the stock market to be "fairly" valued when the E/P ratio equals the long-term government bond yield. The 10-year government bond yield is used in the Fed model for two reasons: Firstly, since the

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average investor typically invests in stocks over the long-term, the E/P ratio is more likely related to the yield on long-term bonds.

Secondly, since the price of a stock is contingent on dividends that will be received in the future (after applying the appropriate discount rate), long-term interest rates are naturally more related to this discount rate than short-term yields. Another question may be why are 10-year government bond yields used instead of other long-term corporate debt instruments? One of the advantages of the 10-year government bond yield is that it incorporates a wide range of macroeconomic factors. Firm-specific debt instruments also incorporate information regarding the prospects of a specific firm and may not be relevant information regarding aggregate market conditions [e.g. an automobile manufacturer's bonds may be influenced by a massive recall or a defect in their products].

To see the Fed model in action, let us consider what happens when there is a disparity between the E/P ratio and the 10-year government yield. The E/P ratio is similar to the yield on the 10-year bonds in the sense that it shows average earnings per dollar invested in a stock or portfolio of stocks. The bond yield shows what interest income you get per dollar invested in bonds. If the bond yield is higher that the E/P ratio, it means that stocks are over-valued and a market correction will likely ensue. Shen (2000) finds that decreases in the E/P ratio relative to the long-term risk-free rate result in a reduction in future returns. Maio (2007) confirms that the yield spread accurately forecasts future returns. Furthermore, if one were to implement a trading strategy using the predictive power of the yield spread, they would be successful and produce a much higher Sharpe ratio than if one were to passively hold the market index. These very same

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findings corroborate a claim by Lander, Orphanides and Douvogiannis (1997) who maintain that formulating a strategy using the yield spread will earn higher returns than if one were to just hold the market.[9] These findings are echoed in many other empirical findings that argue that the Fed model is a reliable predictor of the future outlook of the market (see Wong, Chew and Sikorski, 2002; Thomas and Zhang, 2008).

Apart from its predictive capabilities and use in the Fed model, however, the E/P ratio can theoretically be justified as the required rate of return because it can be derived from the Gordon (1962) Constant Growth Model:

$$P_t = \frac{d_{t+1}}{k - g} \tag{2.14}$$

where

$P_t$ = price at time $t$

$d_{t+1}$ = dividends at time $t+1$

$g$ = long-term growth rate

$k$ = the required rate of return

Dividends at time $t+1$ can be calculated based on a firm's earnings at time $t+1$, $E_{t+1}$, as well as it retention rate (RR). More specifically,

$$d_{t+1} = E_{t+1}*(1\text{-RR}) \tag{2.15}$$

Substituting equation (2.15) in the numerator of equation (2.14), we derive the following:

$$P_t = \frac{E_{t+1}*(1 - RR)}{k - g} \tag{2.16}$$

Through algebraic manipulation, we can take $E_{t+1}$ to the left-hand side:

$$\frac{P_t}{E_{t+1}} = \frac{1 - RR}{k - g} \qquad (2.17)$$

We know from theory that growth, g, is the return on equity (ROE) multiplied by the retention rate, RR. When the market is in equilibrium, ROE is equivalent to the required rate of return, k. Although individual firms may temporarily deviate from equilibrium, overall, in a steady state economy, ROE equals k:

$$\frac{P_t}{E_{t+1}} = \frac{1 - RR}{k - ROE * RR} \quad \text{or, if k = ROE,}$$

$$\frac{P_t}{E_{t+1}} = \frac{1 - RR}{k - k * RR} = \frac{1 - RR}{k * (1 - RR)} \qquad (2.18)$$

Through algebraic manipulation, we can effectively show that

$$\frac{P_t}{E_{t+1}} = \frac{1}{k} \qquad (2.19)$$

Therefore, since the earnings-yield is the reciprocal of the PE multiple, we can now show that the earnings-yield is equivalent to the required rate of return:

$$\frac{E_{t+1}}{P_t} = k \qquad (2.20)$$

Since the numerator is at time *t+1* and the denominator is at time *t*, this is commonly referred to as the "forward" E/P ratio. In the case of this study, since I used monthly data, *t* is on a monthly basis.

Due to the fact that the constant growth model makes several assumptions, we expect Equation (2.20) to hold as an approximation. A more realistic representation would be

$$\frac{E_{t+1}}{P_t} = k + \upsilon_\tau. \qquad (2.21)$$

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Now, let us consider a version of the Merton (1973, 1980) ICAPM:

$$k = r + \theta\sigma_\tau^2 \qquad\qquad (2.22)$$

From combining equation (2.21) and (2.22), we get the following:

$$\frac{E_{t+1}}{P_t} = r + \theta\sigma_\tau^2 + \upsilon_\tau \qquad\qquad (2.23)$$

On the left-hand side we have the required rate of return and on the right-hand side we have the 10-year government bond yield, r, and an error term, $\upsilon_\tau$.

The above equation is consistent with the views of Sharpe (1978), Elton (1999) and Lundblad (2007) which argue of the need to stop relying on historical realized returns as a proxy of investors' required rate of return. On the left-hand side we have the earnings-yield, which has the power to forecast future returns. The 10-year government bond yield was also mentioned by Merton (1973) as an instrumental variable but, as we can see, serves a very important role in the Fed model.

The proposed model in equation (2.23) is also comparable to that of the two-factor approach implemented by Scruggs (1998) in the sense that the 10-year government yield serves as an important factor and determinant in investors' required rate of return and investment decision-making. However, the fundamental difference between his study and the proposed model in this chapter is the use of the forward earnings-yield as a proxy for the required rate of return. Furthermore, the study by Scruggs (1998) employs a two-factor version of the Merton (1973) ICAPM whereby the long-term government bond yield serves as a proxy for the investment opportunity set, as is discussed in greater depth in the third chapter.

In order to produce conditional variance estimates, this chapter uses an asymmetric GJR-GARCH(1,1)-in-mean method where the conditional mean is related to

the conditional variance (see Glosten, Jaganathan and Runkle, 1993). More specifically, $\sigma_\tau^2$ is estimated using the percentage change in price of each market index. Therefore, $\ln\left[\dfrac{P_t}{P_{t+1}}\right]$ = constant + $\upsilon_\tau$, where the error term follows a GARCH process. The GJR method is used since it effectively captures negative and positive innovations and may provide better volatility estimates than standard GARCH models (see Brailsford and Faff, 1996).

It is expected that the coefficient of risk aversion in Equation (2.23), $\theta$, will be positive and statistically significant. In other words, as $\sigma_\tau^2$ increases, so should the required rate of return. The 10-year government bond yield should also be positively related with the earnings-yield since, as the risk-free yield increases, so should the required rate of return in risky assets. Many studies exist which document a positive relation between long-term bond yields and the E/P ratio (see Gordon, 1962; Bleiberg, 1989; Fairfield, 1994; Greenspan, 1997; White, 2000).

## 2.4. Discussion of Data and Results

As mentioned previously, this chapter aims to test empirically the existence of a conditional risk-return tradeoff. The data used for this purpose are solely collected from DataStream, a well-respected source of financial and economic data used by practitioners and academicians alike. It is important that the data came from a single source and I avoided splicing together data from different sources such as, for example, adjoining data from DataStream with data from the International Monetary Fund (IMF), the National

Bureau of Economic Research (NBER), or other research divisions within various Central Banks.

The frequency of the data is monthly and it covers eight industrialized countries, namely, those of Australia, Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States. The reason for selecting this cross-section of countries is to test the proposition that the earnings-yield serves as a proxy for the required rate of return and to see whether there exists a positive relation between the market earnings-yield and market volatility among these industrialized nations. It might be the case that globalization has led developed countries' markets to behave similarly and, as such, the market earnings-yield may serve to capture investors' required rate of return in these respective markets. Apart from robustness among this cross-section of G-7 countries, it is important to see whether in fact the market earnings-yield responds positively to increased market volatility in these various markets. The choice of data frequency is dictated by the fact that some of the variables used are available only monthly.

Table 2.1 reports the markets covered and the sample period for each market whereby the sample ranges are dictated by data availability for all the given variables needed to complete this study. The particular variables used for each market are, the national stock market index, the dividend yield, the price to earnings ratio and the yield to maturity on the 10-year government bond. The price to earnings ratio is used to calculate the earnings yield.

**Table 2.1: Sample Ranges for Each Market Index**

| COUNTRY | EXCHANGE | SAMPLE PERIOD | NUMBER OF OBSERVATIONS |
|---------|----------|---------------|------------------------|
| Australia | Sydney | January 1973 – December 2006 | 408 |
| Canada | Toronto | January 1973 – December 2006 | 408 |
| France | Paris | January 1988 – December 2006 | 228 |
| Germany | Frankfurt | August 1984 – December 2006 | 269 |
| Italy | Milan | January 1986 – December 2006 | 252 |
| Japan | Tokyo | June 1985 – December 2006 | 259 |
| UK | London | December 1966 – December 2006 | 481 |
| USA | New York | January 1968 – December 2006 | 468 |

Note: This study uses monthly data and explores eight major stock markets; namely, the Australian, Canadian, French, German, Italian, Japanese, English and American stock exchanges.

The unconditional return series for each market is calculated by taking the natural logarithmic difference of the respective market's price level at time *t* and *t-1* and multiplying by 100. That is, $R_t = 100*[\ln(P_t) - \ln(P_{t-1})]$, where $P_t$ is the price level of the stock market index at time *t*. Dividends are also factored into each index's return series by adding in the appropriate market's monthly dividend-yield. All stock market indices are broadly based and value-weighted (i.e. stocks in each index are assigned weights proportional to their market capitalizations).

Table 2.2 presents several preliminary statistics on the earnings-yield, historical annualized returns and long-term government bond yields for each market. It appears that the UK, Australia, Canada and France (in that sequence) had the highest historical average E/P ratios. Japan's E/P ratio is historically the lowest when compared to that of other countries and also exhibits the least variability whereas in the U.K., U.S., Canada

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and Australia, the E/P has a relatively higher standard deviation. Skewness and kurtosis calculations indicate that the E/P is positively skewed and leptokurtic compared to the normal distribution. This is not surprising considering that market E/P ratios are a weighted average of all its stock constituents and, on average, companies have positive earnings. Therefore, we would expect them to be positively skewed.

**Table 2.2: Preliminary Statistics**

| | Australia | Canada | France | Germany | Italy | Japan | UK | USA |
|---|---|---|---|---|---|---|---|---|
| **Mean** | | | | | | | | |
| Earnings yield | 7.4821 | 7.4758 | 7.3500 | 6.0010 | 5.6947 | 2.3429 | 7.8249 | 6.8010 |
| Historical annual return | 14.1262 | 10.8509 | 11.8012 | 11.3327 | 9.2829 | 3.1367 | 13.1536 | 10.1268 |
| Long-term interest rate | 9.6316 | 8.4128 | 6.2393 | 5.9079 | 7.6886 | 3.3138 | 8.4584 | 7.5152 |
| | | | | | | | | |
| **Standard Deviation** | | | | | | | | |
| Earnings yield | 2.6719 | 2.9238 | 1.7782 | 1.4093 | 1.2754 | 0.5821 | 3.3085 | 2.9451 |
| Historical annual return | 20.7846 | 16.5233 | 17.6837 | 20.3126 | 22.2814 | 20.4604 | 20.0733 | 15.3017 |
| Long-term interest rate | 3.3013 | 2.8466 | 2.0518 | 1.5443 | 3.1900 | 1.9164 | 3.3023 | 2.4548 |
| | | | | | | | | |
| **Skewness** | | | | | | | | |
| Earnings yield | 0.8866 | 1.0236 | 0.0093 | 1.0658 | 0.3028 | 0.4536 | 1.5629 | 0.7885 |
| Historical annual return | -1.7143 | -1.1916 | -0.6226 | -1.3066 | -0.2683 | -0.1535 | 0.9189 | -0.5371 |
| Long-term interest rate | 0.1277 | 0.3845 | 0.3666 | 0.2112 | 0.1444 | 0.3829 | 0.3041 | 0.9635 |
| | | | | | | | | |
| **Kurtosis** | | | | | | | | |
| Earnings yield | 3.2691 | 2.9962 | 2.1452 | 3.5095 | 4.0481 | 2.5306 | 6.7203 | 2.7037 |
| Historical annual return | 16.4906 | 9.2025 | 3.8134 | 7.3322 | 4.4950 | 3.5494 | 22.6994 | 5.3159 |
| Long-term interest rate | 1.6618 | 2.9000 | 1.7854 | 2.2036 | 1.3756 | 1.7830 | 2.0404 | 3.6392 |
| | | | | | | | | |
| **Minimum** | | | | | | | | |
| Earnings yield | 4.0580 | 3.4360 | 3.5242 | 3.8580 | 2.6942 | 1.1520 | 3.5822 | 2.0995 |
| Historical annual return | -46.8811 | -32.7745 | -17.6523 | -33.0690 | -27.6521 | -17.2490 | -34.6271 | -21.5996 |
| Long-term interest rate | 4.6500 | 3.6600 | 3.1633 | 3.0883 | 3.2943 | 0.5310 | 3.3200 | 3.3300 |
| | | | | | | | | |
| **Maximum** | | | | | | | | |
| Earnings yield | 16.8091 | 16.2700 | 11.3984 | 11.0590 | 10.5983 | 7.0841 | 25.9290 | 14.5461 |
| Historical annual return | 22.7897 | 13.3733 | 13.1672 | 15.1990 | 21.1279 | 20.4557 | 55.9477 | 17.1135 |
| Long-term interest rate | 16.4500 | 17.3200 | 10.4500 | 10.8000 | 13.8300 | 10.3000 | 16.0700 | 15.3200 |

Note: The sample ranges of these statistics are found in Table 2.1. This table reports descriptive statistics on the major variables considered here. Namely, it reports the mean, standard deviation, skewness, kurtosis, minimum and maximum for the market earnings-yield, the historical annual returns and long-term government yield for each of the respective markets in the sample.

Countries with the highest E/P ratios also appear to have the highest historical mean stock market returns. Japan, for instance, with the lowest E/P ratio also had the lowest historical mean stock market returns. Variability in historical returns seems to be highest for the Italian market and lowest for the U.S. market. When measuring skewness and kurtosis, all return series appear to be negatively skewed and highly leptokurtic relative to the normal distribution. This is expected considering that market returns show evidence of autoregressive conditional heteroskedasticity (see Figure 2.1 in section 2.2.3 for example) and is consistent with previous findings that they are not normally distributed (see Mandelbrot, 1963; Fama, 1965).

Finally, the mean long-term government bond yield has been historically lowest for the Japanese market relative to other markets. This is expected considering that the Japanese central bank has kept interest rates artificially low to encourage spending and investment. This yield is most variable in the U.K., U.S. and Italian markets, in that order. For all markets the long-term government bond yield is positively skewed and leptokurtic relative to the normal distribution.

Following Glosten, Jagannathan and Runkle (1993), the asymmetric GJR-GARCH(1,1)-in-mean is used to calculate the conditional mean-variance tradeoff using each respective country's market returns. This can be expressed as follows:

$$r_{t=}c + \theta\sigma^2_\tau + \varepsilon_\tau \qquad\qquad (2.24a)$$

$$\sigma^2_\tau = \alpha_0 + \alpha_1\varepsilon^2_{\tau-1} + \alpha_2 u^2_{\tau-1}I_{t-1} + \beta\sigma^2_{\tau-1} \qquad\qquad (2.24b)$$
$$\text{where } I_{\tau-1} = 1 \text{ if } \upsilon_{\tau-1} < 0$$
$$= 0 \text{ otherwise}$$

The conditional mean, $r_t$, is specified in equation (2.24a) and is linearly dependant on the conditional variance, $\sigma^2_\tau$. The coefficient of risk aversion is represented by

θ and, consistent with theory, should have a positive sign. The conditional variance at time $t$ is expressed in equation (2.24b) as a function of past squared residuals (i.e. innovations), $\varepsilon^2_{\tau-1}$, and squared lags of the conditional variance, $\sigma^2_{\tau-1}$. Squared residuals are used as proxies for shocks to volatility. The GJR-GARCH model is asymmetric since the "indicator" variable, $I_{t-1}$, captures any incremental impact due to negative innovations. For example assuming that $\alpha_1$ and $\alpha_2$ are positive, it can be seen from equation (2.24b) that a positive residual will increase volatility by $\alpha_1$ whereas a negative residual will increase volatility by $\alpha_1 + \alpha_2$.

Studies find that lower order GARCH models, such as the GJR-GARCH(1,1) process, are sufficient in terms of modeling conditional heteroskedasticity (see Bollerslev, Chou, and Kroner, 1992). The model is estimated in EVIEWS7 and the maximization technique used is based on the algorithm suggested by Berndt, Hall, Hall and Hausman (1974). Furthermore, I assume the error term is drawn from a normal density distribution (see Hentschel, 1995) and by maximizing the likelihood function over the sample period, which can be expressed as

$$\mathcal{L}(\theta) = -(1/2)\ln(2\pi) - (1/2)\ln(\sigma^2_{M,t}) - (1/2)(\varepsilon^2_{t-1}/\sigma^2_{M,t})$$

Conditional risk-return relationships for each country index are reported in Table 2.3. Results indicate that market returns for each index are conditionally heteroskedastic. Therefore, current volatility is a function of past squared residuals and past values of the conditional variance. Volatility persistence, measured by $\beta$, is highest for Australia followed by Canada, Great Britain, United States, France, Japan, Italy and Germany, in

descending order. Consistent with theory, we expect the coefficient of risk aversion, $\theta$, to have a positive sign. In other words, as conditional risk rises, we expect to see an increase in conditional returns. Results show that the sign is negative for half of the countries and positive for the remaining half. However, for all markets, $\theta$ is not statistically different from zero suggesting a non-existent conditional risk-return tradeoff.

**Table 2.3: Asymmetric GARCH-M**

| | Australia | Canada | France | Germany | Italy | Japan | UK | USA |
|---|---|---|---|---|---|---|---|---|
| c | 1.4033 | -0.2428 | 2.6965 | 1.9939 | -0.0785 | 1.2649 | 0.7074 | 0.4961 |
| | (3.646)** | (-0.238) | (1.895) | (1.705) | (-0.084) | (1.175) | (1.486) | (1.012) |
| $\theta$ | -0.0084 | 0.0591 | -0.0587 | -0.0250 | 0.0238 | -0.0279 | 0.0162 | 0.0192 |
| | (-0.756) | (1.319) | (-1.032) | (-0.721) | (1.001) | (-0.829) | (1.004) | (0.7136) |
| $\alpha_0$ | -0.0460 | 0.0609 | 6.4356 | 18.8174 | 10.5526 | 12.1244 | 3.9675 | 3.9556 |
| | (-1.267) | (0.276) | (2.522)** | (2.866)** | (2.111)** | (2.397)** | (3.497)** | (4.160)** |
| $\alpha_1$ | 0.0205 | 0.1512 | -0.1138 | -0.0128 | 0.2862 | -0.0972 | 0.0103 | -0.0217 |
| | (11.064)** | (4.129)** | (-3.026)** | (-0.1238) | (3.241)** | (-2.438)** | (0.253) | (-0.6156) |
| $\alpha_2$ | -0.0313 | -0.1555 | 0.2564 | 0.3000 | -0.1392 | 0.3086 | 0.2278 | 0.3211 |
| | (-11.811)** | (-4.271)** | (2.377)** | (1.876) | (-1.026) | (2.602)** | (2.924)** | (4.545)** |
| $\beta$ | 0.9950 | 0.9456 | 0.7174 | 0.2996 | 0.5250 | 0.5927 | 0.7462 | 0.6547 |
| | (1276.519)** | (67.738)** | (5.689)** | (1.277) | (3.232)** | (3.527)** | (13.984)** | (10.612)** |

*Note:* This table reports findings for the GJR-GARCH(1,1)-in-mean estimation for the returns of each of the stock indices. Namely, it estimates the following equation: $r_t = c + \theta\sigma^2_\tau + \varepsilon_\tau$ and $\sigma^2_\tau = \alpha_0 + \alpha_1\varepsilon^2_{\tau-1} + \alpha_2 u^2_{\tau-1} + \beta\sigma^2_{\tau-1}$. (**) and (*) denote significance at the 5% and 10% significance level, respectively. The conditional mean, $r_t$, is linearly dependant on the conditional variance, $\sigma^2_\tau$. The coefficient of risk aversion is represented by $\theta$ and, consistent with theory, should have a positive sign.

These findings are consistent with Campbell and Hentschel (1992) and the findings of many other authors discussed in the Literature Review section of this chapter (section 2.2.4). These findings are also consistent with the notion of volatility feedback which states that if volatility is priced, increases in volatility raise the required rate of

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return on stocks leading to an immediate drop in stock price. This chapter argues that the earnings-yield should serve as a proxy for the required rate of return and should be regressed against conditional volatility (see section 2.3 for arguments and a formal proof).

Before proceeding to investigating the presence of a conditional risk-return tradeoff I test for stationarity in the earnings yield, the long term rate and the volatility series obtained earlier using the GJR-GARCH model. The tests used are the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) (see Dickey and Fuller, 1981; Phillips and Perron, 1986). The ADF technique estimates the regression:

$$\Delta y_t = a + \phi y_{t-1} + \sum_{t=1}^{k} b_s \, \Delta y_{t-s} + \upsilon_\tau \qquad (2.25a)$$

and then proceeding to test the null hypothesis, $H_0$: $\phi = 0$ against the alternative hypothesis, $H_1$: $\phi < 1$. The PP technique is another test for stationarity and involves estimating the following regression:

$$\Delta y_t = a + m*(t - T/2) + \phi y_{t-1} + \upsilon_\tau \qquad (2.25b)$$

and testing the null hypothesis, $H_0$: $\phi = 0$ against the alternative hypothesis, $H_1$: $\phi < 1$, where T is the number of observations. Standard errors from the PP regression equation are computed using the Newey-West method in order to correct for serial correlation in the data (see Newey and West, 1987).

In both the ADF and PP methods, failing to reject $H_0$ indicates that a unit root is present in the series and that first-differencing is necessary to induce stationarity. Results in table 2.4 suggest that the earnings-yield and long-term interest rate contain a unit root for all market indices and are therefore non-stationary.

If a non-stationary series, $y_t$, needs to be differenced $d$ times before it is stationary, then it is said to be integrated of order $d$:

$$Y_t \sim I(d)$$

Applying the first-difference, $\Delta$, to $y_t$ $d$ times before it becomes stationary (i.e. converting an $I(d)$ series to an $I(0)$ series with no unit roots) can be expressed as:

$$\Delta^d y_t \sim I(0)$$

**Table 2.4: Unit Root Tests**

| | Australia | Canada | France | Germany | Italy | Japan | UK | USA |
|---|---|---|---|---|---|---|---|---|
| **Augmented D-F test statistic** <br><br> **Phillips-Perron test statistic** | | | | | | | | |
| Earnings | (-2.3727) | (-3.3247) | (-2.4236) | (-2.8628) | (-3.1401) | (-3.1325) | (-3.1210) | (-2.6496) |
| Yield | (-2.4508) | (-2.6349) | (-2.3493) | (-2.7465) | (-3.3592) | (-3.2661) | (-2.9255) | (-2.5235) |
| Long-term | (-2.1535) | (-2.9895) | (-3.1161) | (-2.8774) | (-2.8251) | (-1.9431) | (-2.4205) | (-2.3684) |
| interest rate | (-2.2191) | (-2.8507) | (-2.8110) | (-2.1036) | (-2.5225) | (-2.2114) | (-2.3813) | (-2.1649) |
| Volatility | (-4.6041)** | (-6.2375)** | (-5.9611)** | (-12.7497)** | (-7.3008)** | (-6.4900)** | (-7.3406)** | (-8.9218)** |
| | (-4.3590)** | (-6.2205)** | (-5.8738)** | (-12.7422)** | (-7.0655)** | (-8.4618)** | (-7.2464)** | (-8.9089)** |

Note: Data ranges for each country index are specified in Table 2.1. The first and second number in each cell represents the test statistic from the augmented Dickey-Fuller and Phillips-Perron unit root tests, respectively. The asymptotic critical value for the augmented Dickey-Fuller and Phillips-Perron tests at the 5% significance level is -3.42. (**) denotes significance at the 5% level and (*) denotes significance at the 10% level.

Since the earnings-yield and the long-term government bond yield contain one unit root they only need to be first-differenced to induce stationarity. This is true for all countries. As table 2.4 indicates, conditional volatility is $I(0)$ for all markets. As is expected, in all instances, the ADF and PP methods yield qualitatively similar results.

As discussed, the volatility feedback effect produces a negative or statistically negligible relationship between conditional risk and returns. As such, the earnings-yield,

as explained in section 2.3, will serve as a proxy for the required rate of return.  As volatility rises we expect to see a rise in E/P, the required rate of return.

In table 2.5, E/P is regressed against conditional risk, $\sigma^2_\tau$, and the long-term government bond yield, *LT_IR*, as is described in Eq. (2.23) and takes the following form:

$$\frac{E_{t+1}}{P_t} = \beta_0 + \beta_1 \sigma_\tau^2 + \beta_2 \, LT\_IR + \upsilon_\tau \qquad (2.26)$$

The long-term government bond yield serves as the long-term risk-free rate.  Now, if we were to rearrange the above equation and move the long-term government bond yield to the left-hand-side and treat it as a regressand, we would get the following:

$$\frac{E_{t+1}}{P_t} - LT\_IR = \beta_0 + \beta_1 \sigma_\tau^2 + \upsilon_\tau$$

Now, the left-hand-side of the above equation looks very much like the so-called "Fed Model" with one substantial difference. In the equation above, the difference between the long-term rate and the earnings yield is a function of risk. As such, this can be thought of as a "Risk-Adjusted Fed Model".

Much literature finds evidence in support of the Fed Model (see Lander, Orphanides and Douvogiannis, 1997; Thomas and Zhang, 2008; and references therein). Namely, they find that this model is a good predictor of future returns and future market conditions, and that there exists a long-run relationship between E/P and the long-term government bond yield. None of these studies however account for risk. Given that the earnings yield and the long term government yield have unit roots the regression above can be interpreted as a long-run equilibrium relationship, assuming that the error term is stationary.

Table 2.5 provides a summary of results when E/P, the required rate of return, is regressed against $\sigma_\tau^2$ and the *LT_IR*. The results indicated that there exists a positive and statistically significant relationship between the required rate of return, E/P, and conditional risk, $\sigma_\tau^2$ with the exception of the Italian and the German markets. In fact, this relationship is significant at the 1% level.  Therefore, as volatility tends to rise, we can expect a rise in E/P.  This is now consistent with theory and the notion of volatility feedback, whereby increases in volatility lead to an increase in the required rate of return. In the German market the relation between E/P and  $\sigma_\tau^2$ is positive but statistically significant at the 10% level. For the Italian market findings are counterintuitive; E/P and $\sigma_\tau^2$ are inversely related and this relation is statistically significant at the 1% level.  This implies a negative tradeoff between conditional risk and the required rate of return.

**Table 2.5: Cointegrating Regressions**

|  | Australia | Canada | France | Germany | Italy | Japan | UK | USA |
|---|---|---|---|---|---|---|---|---|
| $\beta_0$ | 2.5732 | 0.9453 | 2.4680 | 8.0938 | 5.3656 | 2.0060 | 1.3017 | -0.5422 |
|  | (8.677)** | (1.698) | (5.961)** | (24.502)** | (24.897)** | (18.231)** | (4.393)** | (-1.782) |
| $\beta_1$ | 0.0727 | 0.0701 | 0.0477 | 0.0046 | -0.0164 | 0.0149 | 0.0401 | 0.0221 |
|  | (7.356)** | (3.310)** | (4.349)** | (1.742) | (-5.056)** | (5.518)** | (12.807)** | (3.919)** |
| $\beta_2$ | 0.2850 | 0.5845 | 0.5776 | -0.3825 | 0.1311 | -0.0519 | 0.6099 | 0.9163 |
|  | (6.017)** | (14.159)** | (13.654)** | (-7.525)** | (5.478)** | (-2.902)** | (19.729)** | (25.858)** |
| E-G test | -4.188** | -3.581** | -2.2925 | -2.609 | -3.813** | -2.625 | -5.017** | -3.233* |

Note: This table reports results of the following regression: E/P = $\beta_0$ + $\beta_1\sigma^2_\tau$ + $\beta_2$(LT_IR) + $u_t$ using data ranges from Table 2.1.The Engle-Granger (E-G) test is reported in the last row of the table. Critical values for the E-G test can be found in MacKinnon (1991) and are -4.00, -3.37, and -3.02 for the 1%, 5%, and 10% level of significance, respectively. This regression represents the long-run relation between risk and investors' required rate of return, proxied for using the market earnings-yield. The coefficient $\beta_1$ and represents investors' degree of risk aversion.

The coefficient $\beta_2$ is statistically significant for all market indices at the 1% level, suggesting that the *LT_IR* is related to E/P. For the Australian, Canadian, French, Italian, British, and American markets, this relationship is positive. On the other hand, in the German and Japanese markets this relationship is negative. This would provide preliminary support for the "Risk-Adjusted Fed Model" provided as I mentioned earlier that the error term is stationary. To answer this question I utilize the Engle-Granger methodology (see Engle and Granger, 1987).

The Engle-Granger methodology entails two steps. Firstly, a regression with the I(1) variables needs to be estimated. This has already been performed in the first three rows in table 2.5. E/P, the required rate of return is on the left-hand-side, and $\sigma_\tau^2$ and *LT_IR* are on the right-hand-side of the equation, as is indicated in Eq. (2.26):

$$\frac{E_{t+1}}{P_t} \; = \; \beta_0 \; + \; \beta_1\sigma_\tau^2 \; + \; \beta_2 \, LT\_IR \; + \upsilon_\tau$$

The second step is to apply a stationarity test to the residuals, $\upsilon_\tau$, to determine whether or not they are stationary. The appropriate critical values for the Engle-Granger test are given in MacKinnon (1991). To complete this step, the ADF test is applied to the residual series for each market.

Testing for cointegration (i.e. a long-run equilibrium relationship) between E/P and *LT_IR* is the equivalent of measuring whether there exists a linear combination of these I(1) series that is stationary. This approach is unique in providing new insights into the intertemporal risk-return tradeoff. Consistent with the Engle-Granger procedure, the two I(1) series are cointegrated only if $\upsilon_\tau$ is a stationary process. Results in the last row of table 2.5 report these statistics and find that in four of the eight market indices, namely Australia, Canada, Italy and the U.K., cointegration is present. More specifically, signs

of this cointegration are statistically significant at the 1% level for Australia and the U.K. and at 5% for Canada and Italy.  For the U.S. market, this statistic is significant at the 10% level. For the remaining country indices (i.e. France, Germany and Japan), cointegration is not statistically present.

Although E/P and the long-term government bond yield are 'tied together' in the long-run, in the short-run, they may drift apart from one another. It is possible to model this and 'correct' for this disequilibrium using an error correction representation.[10]  This so-called disequilibrium term, *EC*, is the residual series from the long-run equilibrium regression in Eq. (2.26). It is thus called a disequilibrium term, or an "error correction" term, because it captures deviations from the long-run equilibrium.

The so-called *Granger representation theorem* argues that a vector autoregressive model with cointegrated I(1) variables is misspecified if the data are differenced (see Engle and Granger, 1987, p. 259). However, the model becomes well-specified once adding in lagged disequilibrium terms as explanatory variables which serve to 'correct' any deviations from long-run equilibria. Such a model is referred to as an *error correction model* and is expressed in table 2.6 (Panels A through D).

The error correction model is a dynamic representation of the short-run relation of first-differences of the I(1) cointegrating variables E/P and the *LT_IR*.  Taking first-differences of these variables induces stationarity (i.e. they are now I(0)) and are expressed as $\Delta\left(\dfrac{E}{P}\right)_t$ and $\Delta(LT\_IR)_t$, respectively.  In addition to including the lagged error correction term, *EC*, it is also of interest to see whether a lead-lag

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[10] Since the seminal work by Engle and Granger (1987), cointegration and error correction representations have become a powerful tool in time-series econometrics.  Most modern econometrics texts cover the foundations necessary to apply these concepts (see Hamilton, 1994; Enders, 1995; Cuthbertson and Nitzsche, 2004, to name only a few authoritative sources).

relationship is evident between first-differences of the E/P and the *LT_IR*. The seminal

study by Granger (1988) posits this very question and argues that if a pair of I(1)

variables are cointegrated, then there must be 'causation' in some direction. For example,

consider a time-series of jointly stationary variables $\{x_t\}$ and $\{y_t\}$ that are cointegrated. It

is possible that lags of one variable may better help explain variations in another. More

specifically, variable *x* is said to *Granger cause y* if, when included as a lagged

explanatory variable, it better helps predict movements in *y*.

**Table 2.6: Short-Run Regressions**
**PANEL A: Data from Table 2.1**

|  | **Australia** | **Canada** | **France** | **Germany** | **Italy** | **Japan** | **UK** | **USA** |
|---|---|---|---|---|---|---|---|---|
| $\beta_0$ | 0.0590 | -0.3057 | -0.3706 | -0.2644 | -0.0367 | -0.2703 | -0.1335 | -0.2039 |
|  | (1.002) | (-2.642)** | (-3.507)** | (-7.953)** | (-0.616) | (-9.417)** | (-2.682)** | (-6.049)** |
| $\beta_1$ | -0.0023 | 0.0135 | 0.0137 | 0.0075 | 0.0013 | 0.0079 | 0.0039 | 0.0099 |
|  | (-1.289) | (2.757)** | (3.628)** | (10.373)** | (1.047) | (10.057)** | (3.637)** | (7.567)** |
| $\beta_2$ | 0.3109 | 0.3186 | 0.3773 | 0.2474 | 0.2377 | 0.0046 | -0.0302 | 0.2795 |
|  | (4.180)** | (4.860)** | (3.068)** | (2.492)** | (2.733)** | (0.124) | (-0.399) | (4.402)** |
| $\beta_3$ | -0.0474 | -0.0224 | -0.0425 | -0.0385 | -0.0761 | -0.0453 | -0.0345 | -0.0232 |
|  | (-3.087)** | (-1.932) | (-1.810) | (-2.325)** | (-3.100)** | (-2.454)** | (-2.300)** | (-2.149)** |

Note: This Panel reports results from the following regression: $\Delta\left(\dfrac{E}{P}\right)_t = \beta_0 + \beta_1\sigma^2_\tau + \beta_2\,\Delta(LT\_IR)_{t-1} + \beta_3(EC)_{t-1} + u_t$. It seeks

to decipher the nature of the time-series risk-return relation using the earnings-yield as a measure for investors' required rate of return in the stock market. (\*\*) and (\*) denote significance at the 5% and 10% level, respectively. The data ranges can be found in Table 2.1

**Table 2.6 {Continued}**
**PANEL B: Data from Table 2.1**

|  | Australia | Canada | France | Germany | Italy | Japan | UK | USA |
|---|---|---|---|---|---|---|---|---|
| $\beta_0$ | -0.0620 | 0.1127 | 0.0576 | 0.0147 | 0.0783 | 0.0775 | -0.0579 | 0.0305 |
|  | (-1.501) | (1.288) | (0.982) | (0.703) | (1.785) | (1.537) | (-1.981)** | (1.220) |
| $\beta_1$ | 0.0017 | -0.0052 | -0.0030 | -0.0008 | -0.0028 | -0.0028 | 0.0017 | -0.0016 |
|  | (1.368) | (-1.418) | (-1.443) | (-1.767) | (-3.000)** | (-2.006)** | (2.726)** | (-1.623) |
| $\beta_2$ | -0.0176 | -0.1150 | 0.0123 | -0.0155 | -0.0311 | 0.0764 | -0.1151 | -0.0742 |
|  | (-0.491) | (-3.161)** | (0.346) | (-0.473) | (-0.680) | (0.824) | (-4.288)** | (-2.289)** |
| $\beta_3$ | -0.0016 | 0.0194 | -0.0025 | -0.0048 | -0.0135 | -0.0208 | 0.0406 | 0.0198 |
|  | (-0.144) | (2.220)** | (-0.198) | (-0.461) | (-0.740) | (-0.663) | (4.437)** | (2.530)** |

Note: This panel reports results from the following regression: $\Delta(LT\_IR)_t = \beta_0 + \beta_1\sigma^2_\tau + \beta_2\,\Delta\left(\dfrac{E}{P}\right)_{t-1} + \beta_3(EC)_{t-1} + u_t$. It seeks

to determine whether there is any so-called 'Granger causality' from shifts in E/P to shifts in the long-term government bond yield. (**) and (*) denote significance at the 5% and 10% level, respectively. The data ranges can be found in Table 2.1

**Table 2.6 {Continued}**
**PANEL C: January 1988 – December 2006**

|  | Australia | Canada | France | Germany | Italy | Japan | UK | USA |
|---|---|---|---|---|---|---|---|---|
| $\beta_0$ | 0.0465 | -0.2553 | -0.3706 | -0.4126 | 0.1116 | -0.2777 | -0.0414 | -0.1278 |
|  | (0.984) | (-2.315)** | (-3.507)** | (-9.014)** | (1.489) | (-8.481)** | (-1.129) | (-3.265)** |
| $\beta_1$ | -0.0027 | 0.0113 | 0.0137 | 0.0119 | -0.0029 | 0.0082 | 0.0011 | 0.0065 |
|  | (-1.200) | (2.342)** | (3.628)** | (10.370)** | (-1.619) | (9.174)** | (1.095) | (3.743)** |
| $\beta_2$ | 0.2175 | 0.1247 | 0.3773 | 0.1986 | 0.2984 | 0.0009 | 0.1312 | 0.1266 |
|  | (3.383)** | (1.845) | (3.068)** | (1.874) | (3.346)** | (0.016) | (1.636) | (1.423) |
| $\beta_3$ | -0.1151 | -0.0376 | -0.0425 | -0.0369 | -0.0786 | -0.0429 | -0.0236 | -0.0332 |
|  | (-3.563)** | (-2.125)** | (-1.810) | (-2.207)** | (-3.141)** | (-2.026)** | (-1.537) | (-1.668) |

Note: This Panel reports results from the following regression: $\Delta\left(\dfrac{E}{P}\right)_t = \beta_0 + \beta_1\sigma^2_\tau + \beta_2\,\Delta(LT\_IR)_{t-1} + \beta_3(EC)_{t-1} + u_t$. It seeks

to decipher the nature of the time-series risk-return relation using the earnings-yield as a measure for investors' required rate of return in the stock market. (**) and (*) denote significance at the 5% and 10% level, respectively. The data ranges from January 1988 through December 2006 for all stock markets.

**Table 2.6 {Continued}**
**PANEL D: January 1988 – December 2006**

|  | Australia | Canada | France | Germany | Italy | Japan | UK | USA |
|---|---|---|---|---|---|---|---|---|
| $\beta_0$ | -0.0099 | -0.0318 | 0.0576 | 0.0467 | -0.0570 | 0.0614 | -0.0231 | 0.0207 |
|  | (-0.1943) | (-0.288) | (0.982) | (1.598) | (-1.014) | (1.454) | (-0.756) | (0.696) |
| $\beta_1$ | -0.0011 | 0.0002 | -0.0030 | -0.0016 | 0.0008 | -0.0021 | 0.0000 | -0.0020 |
|  | (-0.472) | (0.0414) | (-1.443) | (-2.191)** | (0.552) | (-1.828) | (-0.036) | (-1.507) |
| $\beta_2$ | -0.0720 | -0.1015 | 0.0123 | -0.0132 | -0.0634 | 0.0230 | -0.1216 | 0.0309 |
|  | (-1.079) | (-1.552) | (0.346) | (-0.376) | (-1.318) | (0.311) | (-2.208)** | (0.620) |
| $\beta_3$ | 0.0562 | -0.0024 | -0.0025 | -0.0020 | -0.0213 | -0.0077 | 0.0131 | 0.0090 |
|  | (1.677) | (-0.140) | (-0.198) | (-0.191) | (-1.132) | (-0.291) | (1.026) | (0.589) |

Note: This panel reports results from the following regression: $\Delta(LT\_IR)_t = \beta_0 + \beta_1\sigma^2_\tau + \beta_2\Delta\left(\dfrac{E}{P}\right)_{t-1} + \beta_3(EC)_{t-1} + u_t$. It seeks

to determine whether there is any so-called 'Granger causality' from shifts in E/P to shifts in the long-term government bond yield. (**) and (*) denote significance at the 5% and 10% level, respectively. The data ranges from January 1988 through December 2006 for all stock markets.

The error correction representation described in table 2.6 therefore 'corrects' for disequilibrium in the short-run and examines whether Granger causality is present. The following two regression equations are therefore considered for each stock market index:

$$\Delta\left(\frac{E}{P}\right)_t = \beta_0 + \beta_1\sigma^2_\tau + \beta_2\Delta(LT\_IR)_{t-1} + \beta_3(EC)_{t-1} + u_t \qquad (2.27A)$$

$$\Delta(LT\_IR)_t = \beta_0 + \beta_1\sigma^2_\tau + \beta_2\Delta\left(\frac{E}{P}\right)_{t-1} + \beta_3(EC)_{t-1} + u_t \qquad (2.27B)$$

Both regressions contain the lagged disequilibrium term, $EC_{t-1}$, and estimate the degree of Granger causality between first-differences of the E/P and the LT_IR. The first regression Eq. (2.27A) estimates the short-run relation between risk, $\sigma^2_\tau$, and the required

rate of return, $\Delta\left(\dfrac{E}{P}\right)_t$. The lagged error correction term, $EC_{t-1}$, serves to 'correct' any

deviations from the long-run equilibrium expressed in Eq. (2.26). Depending on whether or not the coefficient for $\Delta(LT\_IR)_{t-1}$ is significant will allow us to detect the presence of Granger causality. The second regression, Eq.(2.27B), is comparable to the first one except that $\Delta(LT\_IR)_{t-1}$ is on the left-hand-side and $\Delta\left(\dfrac{E}{P}\right)_{t-1}$ serves as an explanatory variable. Its purpose is to find whether Granger causality also works in the other direction.

For both equations, the size of the coefficient for the error correction term tells us how quickly the adjustment to long-run equilibrium occurs following a market shock. For instance, if this coefficient is significantly large in either direction, reversion to long-run equilibrium will be relatively quick. A priori, we should expect to see two things. Firstly, the error correction term is expected to be significant since cointegration tests in table 2.5 lend support for the Fed model that E/P and the long-term government bond yield are tied together in the long-run. If in the short-run they diverge from equilibrium, then the error correction term is expected to play a significant role. Secondly, we should continue to see a positive short-run tradeoff between risk and the required rate of return.

Table 2.6 consists of four panels. The first two (A and B) describe the error correction representation for each country using the full sample sizes as summarized in table 2.1. The second two panels (C and D) use the sample range January 1988 through December 2006, for a total of 228 monthly observations, for all country indices. The purpose for this is to compare results across different countries during the same time period so that the economic environment is the same across all markets. It turns out that the largest common sample is January 1988 through December 2006. Furthermore, it is of interest to see whether the relation between conditional risk and the required rate of

return, E/P, is robust to different sample periods. Existing literature finds that the relation between risk and return is not particularly robust across different sample ranges [see Section 2.2.4 of this chapter for examples].

In panel A we see that the short-run relation between conditional risk, $\sigma^2_\tau$, and the required rate of return, $\Delta\left(\frac{E}{P}\right)_t$, is positive and significant at the 1% level for Canada, France, Germany, Japan, the U.K. and U.S. For Italy, as in the long-run regression in table 2.5, the sign is negative but no longer statistically significant. For Australia the sign is positive and significant in the long-run regression however, for the short-run, it is not statistically different from zero. The coefficient $\beta_2$ is positive and significant for all countries except Japan and Britain, suggesting a positive causality from the lagged difference of the long-term government yield to the differenced E/P. Thus, if the long-term government yield jumps up today, we can anticipate increases in E/P tomorrow. It can also be said that in this case the changes in the long-term government bond yield Granger-cause changes in the earnings yield.

The coefficient $\beta_3$ estimates what role the lagged error-correction term, $EC_{t-1}$, plays in 'adjusting' for short-run disequilibria. Results indicate that in all market indices, except Canada and France, this coefficient is significant. This provides support that a long-run equilibrium relation exists between E/P and the *LT_IR*, as the Fed model purports.

Panel B checks if there is any causality from $\Delta\left(\frac{E}{P}\right)_{t-1}$ to $\Delta(LT\_IR)_t$ and is therefore the reason why they are positioned on the right- and left-hand-side of Eq. (2.27B), respectively. Test statistics for the coefficient $\beta_1$ signify that conditional

volatility is significant and negative for Italy and Japan, and is significantly positive for the U.K. market. Granger causality from the differenced lagged E/P to the differenced long-term government yield is only statistically present in the Canadian, U.K. and U.S. markets. For all these cases the test statistic is negative implying that if E/P increases today we can anticipate a fall in the LT_IR tomorrow, and vice versa. The coefficient for the lagged error correction term, $\beta_3$, is significant for the U.S., U.K. and Canadian markets.

At this point, it is worthwhile mentioning that although the error correction term is not significant for every single country index, it still provides some support that the Fed model holds in the long-run and there is an equilibrium relation between E/P and the long-term government bond yield. Research in this field is relatively nascent when compared to studies examining the conditional risk-return tradeoff and findings are mixed. Some findings argue there is indeed a long-run equilibrium relation [see section 2.3]. Others, such as Estrada (2006), find that too few country indices seem to provide support for this model.

Panels C and D repeat the error correction representation, as in panels A and B, but sample ranges for all market indices is from January 1988 through December 2006. The purpose of truncating the sample and re-estimating short-run relations is to see whether the relation between $\sigma^2_\tau$ and $\Delta\left(\dfrac{E}{P}\right)_t$ changes significantly. The lagged error correction term, $EC_{t-1}$, is significant for half the countries in panel C but for none in panel D. It can be seen from the coefficient $\beta_2$ that $\Delta(LT\_IR)_{t-1}$ Granger causes movements in the differenced E/P for three out of the eight countries. In panel D we only see

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Granger causality from $\Delta\left(\dfrac{E}{P}\right)_{t-1}$ to $\Delta(LT\_IR)_t$ in only one country index. More importantly, these results show that, even with the truncated sample, we still observe a positive and significant link between risk and E/P in five of the eight market indices. In Italy and Australia (as in panel A) this relation is not statistically different from zero. The only difference is in the U.K., where in panel A it was positive and significant and now it turns out to be insignificant.

All in all, the above results make two important findings. Firstly, cointegration tests do provide some support for the Fed model. Secondly, they provide evidence in favor of a positive tradeoff between risk and the required rate of return, E/P. This relationship is positive in the long-run (as expressed in table 2.5) and in the short-run when E/P is differenced into an I(0) series (as shown in panel A in table 2.6). Furthermore, this positive tradeoff is robust across a different sampling period (as shown in panel C in table 2.6).

It is important to perform the Engle-Granger cointegration analysis in order to see what the intertemporal risk-return tradeoff looks like in the short- and long-run. This cointegration framework allows for a tractable approach to measuring how the market earnings-yield (i.e., the required rate of return) responds to shifts in market volatility. The short-run regressions are advantageous because they are corrected via the disequilibria term which serves to measure the 'speed' by which adjustment back to long-run equilibrium takes place. This approach and the findings herein contribute useful insights into the intertemporal risk-return tradeoff, which is the underlying theme of this thesis. The approach used here for estimating this important tradeoff is also unique and is useful in future research which may focus on specific industries or other sectors of the market.

## 2.5. Concluding Remarks

The volume of literature examining the conditional mean-variance tradeoff is enormous. It appears as though different econometric methodologies or the use of different data samples results in contradictory delineations of the intertemporal risk-return tradeoff. The Merton (1973) ICAPM posits a positive and significant time-series relationship between conditional risk and conditional returns. Nonetheless, many studies find the relationship to be negative or simply non-existent. This contradicts our notions that we are rational risk-averse investors.

Of the three well-established hypotheses attempting to rationalize these findings, the volatility feedback argument appears to be the most prominent and the most widely cited hypothesis. There exist many arguments against the other two hypotheses (i.e. the leverage effect and trading-based hypothesis) and, therefore, examination of these two is beyond the scope of this thesis. Instead, it is found that extant studies finding a negative or insignificant relation cite volatility feedback as the culprit, but take no additional measures to correct for this. Namely, the volatility feedback hypothesis maintains that declines in price result from increases in volatility since the required rate of return demanded by investors increases. Volatility is persistent and, therefore, volatility today will have an impact on volatility tomorrow. GARCH-type models serve well in the formation of conditional mean and conditional variance forecasts. Yet, it is theoretically unjustified to use a conditional mean series as a proxy for the required rate of return. Historical returns, in the presence of increased volatility, will show up as negative average returns. This is misleading and will illustrate a negative or insignificant tradeoff. It is important to understand that these returns are backward-looking and, if volatility is

persistent, we need a forward-looking proxy for returns. Few studies have taken Merton's (1973) cue and actually included instrumental variables that take into account changes in the investment opportunity set. This shortcoming was the motivation for the third chapter.

In spirit with Sharpe (1978) and Elton (1999) who warn of the pitfalls associated with using ex post realized returns to test asset pricing theories and to estimate expected returns, this chapter uses the E/P ratio as a proxy for the required rate of return.  Its foundation is rooted in the Gordon (1962) DDM.  In particular, it uses E/P as a measure of investors' forward-looking required rate of return in the stock market. The E/P ratio has been explored in a variety of other contexts, as is described in the Literature Review section of this chapter, yet has not been considered when evaluating the conditional risk-return tradeoff. As section 2.3 demonstrates, the E/P ratio can theoretically be derived as a proxy for investors' required rate of return.

What is unique about this chapter is that it incorporates two strands of literature. The first strand is literature on the intertemporal risk-return tradeoff and the second strand is on the so-called Fed Model which uses the spread between the E/P ratio and the long-term government bond yield to predict future movements in the economy. The Fed model has raised the eyebrows of central bankers who use this model to assess market conditions and has also been used by practitioners. Finally, academic research is now considering the Fed Model and whether there is any merit to this market valuation tool.

The findings in this chapter are very interesting and provide a strong contribution to existing studies and to our understanding of the intertemporal risk-return tradeoff. Firstly, there is much criticism for using *ex post* realized returns as a proxy for investors' expected rate of return. This is because investors' discount factor (i.e. their required rate

of return) changes along with changes in market conditions and volatility. If there is an increase in volatility today (at time *t*), it signals that volatility will be higher tomorrow (at time *t+1*), this principle is consistent with the volatility feedback hypothesis which states that increases in volatility lead to more volatility in the future (see Campbell and Hentschel, 1992). When this happens, investors discount expected cash flows at a higher discount factor and this leads to a reduction in stock prices. These falling historical prices lead to declining returns leading one to believe that expected returns are falling. However, the opposite is true, it is because the required rate of return is rising and that is the reason for the falling prices. So far, extant studies have not addressed this issue from the perspective advocated here in the second chapter of this thesis.

Given therefore that investors are forward-looking, this chapter makes the point that researchers must consider alternative proxies to measuring their required rate of return instead of continuously relying on *ex post* historical rates of return. Koutmos (2010) makes this argument and highlights reasons why there is a deficiency in existing techniques and why future work in this area is called for.

When the E/P ratio is used as a proxy for the required rate of return, seven of the eight markets under scrutiny provide support for a positive and significant intertemporal risk-return tradeoff. Cointegration tests also indicate the presence of a relationship between the 10-year government bond yield and the E/P ratio, further providing support for the Fed model. By integrating two seemingly disparate strands of literature, as well as drawing on theory from corporate finance and valuation of firms, this chapter shows a positive intertemporal risk-return link and provides additional insights as to the forecasting power and use of the market earnings-yield.

## - Chapter Three -

## Modeling the Conditional Risk Premium Using a Dynamic Two-Factor

## Model: Evidence from the G-7

## 3.1. Introduction

Dynamic models have produced conflicting results on the nature of the conditional risk premium. Some studies find positive and significant results, others negative and significant results and yet others insignificant results. Recent research has focused on the types of models used and the possible misspecification bias (see Guo and Whitelaw, 2006; Scruggs, 1998; Scruggs and Glabadanidis, 2003). This issue is very important in empirical finance given that investors' risk aversion and expectations varies through time as investment opportunities and market conditions fluctuate. Whereas the second chapter investigated the intertemporal risk-return tradeoff in a model which uses the market earnings-yield as a proxy for investors' required rate of return, this third chapter explores a two-factor variant of the Merton (1973) ICAPM which accounts for intertemporal risk. These issues are important in their own right and distinctive in terms of the approach taken to address them. In other words, the approach taken in the second chapter of addressing the potential pitfalls of using historical returns as a proxy for the required rate of return required re-visiting some of the theory behind the Gordon (1962) dividend constant growth model in order to derive the earnings-yield as a proxy for the required rate of return in the stock market. This third chapter now addresses the importance of integrating intertemporal risk in the two-factor version of the Merton (1973) ICAPM. The

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theme here is again the intertemporal risk-return tradeoff but it is now being examined from a different perspective.

Scruggs (1998) argues that the conflicting results are due to model misspecification. Citing Merton (1973), Scruggs (1998) shows that the investment opportunity set is stochastic. As such, the conditional market return will be a linear function of its conditional variance as well as its conditional covariance with investment opportunities. The first component is called the risk component and the second component is called the hedging component. Most studies do not account for the second component and this may be responsible for the conflicting empirical findings. Scruggs (1998) uses the long-term bond rate as a proxy that describes the state of investment opportunities in the economy. Using data from the US, and a bivariate EGARCH model he finds that the conditional risk premium is positive and statistically significant. In a related study, Guo and Whitelaw (2006) find that the coefficient of relative risk aversion is positive using the dynamic two factor model of Merton (1973). This study also uses data from the US and it applies instrumental variables econometric techniques to model risk. They conclude that the second factor (hedging component) is very important and its omission is partly responsible for the contradictory results.

In this chapter I rigorously examine the issue of the dynamic risk premium in the context of the two-factor model of Merton (1973) and in view of the finding of these recent studies. The contributions to the literature will be as follows: Firstly, it is important to realize that the debate has been limited to US data. In this chapter I plan to investigate the presence of a dynamic risk premium in the stock markets of the Group of 7 (G-7)

industrialized nations. It may be that globalization has led markets to behave in a similar manner or, it is possible that there are important national idiosyncrasies.

Secondly, and perhaps more importantly, the use of the long-term rate as a proxy for the opportunity set by Scruggs (1998) may not be necessarily the best choice for all countries. I plan to use in addition the industrial production index as a proxy for the opportunity set. The reason is that the long-term rate is highly correlated with decisions from policymakers by Central Banks. For example, the Federal Open Market Committee (FOMC) will meet at schedule time to decide whether, through the use of open market operations, it should provide more liquidity in the market in order to adjust interest rates. Industrial production on the other hand has a higher correlation with real economic production activity and hence it should be a better proxy. Chen, Roll and Ross (1986) use industrial production as one of the factors in their empirical Arbitrage Pricing Model. Likewise, the slope of the yield curve has been found to predict with high accuracy impending recessions (see Estrella and Hardouvelis, 1991; Campbell, 1995; Estrella and Mishkin, 1998; Hamilton and Kim, 2002, to name only a few studies). Therefore, this chapter is innovative also in the sense that it brings together financial and aggregate economic factors in deciphering the intertemporal risk premium.

Finally, from a methodological point of view, the bivariate EGARCH of Scruggs (1998) assumes that the correlation between the market returns and the second factor (long-term rate in this case) is constant over time. However, as Cappiello, Engle and Sheppard (2006) show for several international markets, the correlation between stock returns and bond returns is time-varying. In this chapter I will use the BEKK model of Engle and Kroner (1995). This model has the advantage that it ensures positive definite

variance-covariance matrices and it allows the covariance and the correlation coefficients to be time-varying.

The findings from this chapter are of interest to academics and practitioners alike. From the perspective of academic theory, the findings herein lend credible support to a positive intertemporal risk-return tradeoff in the context of the Merton (1973) ICAPM. These findings hold in international markets and suggest that perhaps conflicting extant findings are an artifact of omitting the second factor in the ICAPM which serves as a proxy for the investment opportunity set.

Another major finding from this empirical chapter is the observation that intertemporal risk is important and this can consistently be seen to play a significant role across most of the G-7 markets here in the sample. This finding sheds new light on existing studies. Namely, up until now, studies have not made it clear whether conflicting findings are the result of econometric (miss-)specifications or because of omission of the second factor which serves to proxy for the investment opportunity state. Whereas Scruggs (1998) argues in favor of the two-factor ICAPM, Scruggs and Glabadanidis (2003) report empirical evidence to the contrary. The findings in this empirical chapter, however, provide strong evidence in favor of the notion that intertemporal risk is an important ingredient in determining investors' risk premium in the stock market and may be a possibly strong reason for extant conflicting findings in the literature.

Furthermore, another major finding that has not been addressed before is that, consistent with the tests conducted in this chapter, is that the empirical evidence here supports the Merton (1973) theoretical view of the ICAPM without a constant term. This is conducted in this chapter via a likelihood ratio test to see whether restricting the

constant to zero is supported. The findings here lend support to the theoretical ICAPM of Merton (1973) and to the second assumption in his seminal paper regarding capital market structure which is the foundation for intertemporal asset pricing; namely, transactions costs do not exist and there are no taxes or other constraints (see Merton, 1973, p.868). This theoretical proposition has enabled motivation of the ICAPM, although Scruggs (1998) mentions perhaps it will be useful to include a constant term to account for these very market imperfections. Before this thesis chapter, the literature does not give a clear distinction as to whether the Merton (1973) theoretical two-factor model holds with or without constant. The findings here support the notion of the theoretical ICAPM and the empirical findings show that if we accept the assumptions that Merton (1973) establishes, the proposed state factors do a comparatively better job in explaining variations in investors' intertemporal risk premium relative to the model if we account for a constant term which attempts to capture such market inefficiencies.

From the perspective of practitioners, this chapter of the thesis, apart from investigating the intertemporal risk-return relation, sheds light on what kind of factors investors ought to consider when assessing economic conditions and when trying to explain variations in expected stock market returns. In particular, the empirical findings reported here show strongest evidence for suggesting that shifts in the yield curve describe states in the economy. This finding provides some basis for using the yield curve in order to track market and economic performance and predict future states of the economy. These empirical findings thus provide further support to studies which argue of the economic information content embodied in the yield curve (see Estrella and

Hardouvelis, 1991; Campbell, 1995; Estrella and Mishkin, 1998; Hamilton and Kim, 2002, to name only a few).

Finally, this chapter suggests that perhaps the long-term government bond yield may not be the only proxy for investment opportunities, given that it does not exhibit consistently reliable empirical significance in terms of explaining intertemporal variations in investors' risk premium. This provides support to the argument made in this chapter that the long-term bond yield is a financial variable that is, to a large extent, controlled by the actions of central banks (see Mishkin, 2005) and may not fully reflect investment opportunities. This may be a contributing reason why Scruggs and Glabadanidis (2003) do not find a positive risk-return relation when focusing on the U.S. market. However, the international evidence here corroborates the view of Guo and Whitelaw (2006, p.1435) that this does not "imply a rejection..." of the ICAPM, and contributes to literature by empirically showing the behavior of the intertemporal risk premium using proposed factors rooted in theory.

The remainder of this chapter is organized as follows: Section 3.2 provides a review of relevant literature. It discusses in-depth the importance and implications of Merton's (1973) ICAPM as well as empirical challenges associated with applying this model. The literature which applies a two-factor variant of the ICAPM is not quite as expansive as studies discussed in the second chapter which tend to examine the simple relation between the conditional first and second moments of returns on the market portfolio. Nonetheless, two-factor literature is very important within the context of the intertemporal risk-return tradeoff and it is important to understand what contributions it seeks to make over studies that apply a single-factor ICAPM variant. Namely, as is

discussed in greater detail, this two-factor literature argues of the importance of including a hedging factor in order to characterize shifts in the investment opportunity set and how the distribution of market returns changes through time. This factor was neglected in most studies discussed in the second chapter and may be the reason for their counterintuitive findings.

Section 3.3 discusses the methodology. It extends the work of Scruggs (1998) and Scruggs and Glabadanidis (2003) insofar as it uses the long-term government bond yield as a hedging factor to seven other industrialized countries. In addition, this chapter also uses industrial production as well as the slope of the yield curve, respectively, as potential hedging factors to account for changes in investment opportunities. These additional hedging instruments are also applied internationally to examine the behavior of the dynamic risk premium of other countries and to see if globalization has led them to behave in a similar manner. The multivariate BEKK-GARCH specification is applied in this section to describe the time-varying covariances between market returns and the instruments used to account for changes in the investment opportunity set. As is discussed in greater detail, it may be fallacious to assume that the covariance between the market portfolio and a specified hedging component is constant over the sampling period, as is assumed by Scruggs (1998).

Major empirical findings of this chapter are discussed in section 3.4 along with the nature of the data used to conduct this study. Finally, concluding remarks are offered in section 3.5.

## 3.2. Review of Literature

The second chapter discussed the possibility of variable misspecification as a reason for why studies cannot agree on the nature of the intertemporal risk-return relation. Namely, use of historical returns as unbiased estimates of the future required rate of return will yield a negative or insignificant tradeoff, as is consistent with the volatility feedback hypothesis. When E/P is used as a proxy for the required rate of return, there is international evidence of a positive intertemporal risk-return tradeoff both in the short- and long-run.

This third chapter introduces a strand of literature arguing that model misspecification may be the reason for the mixed results. Oftentimes, as cited in the second chapter, research tends to use some variant from the (G)ARCH-in-mean family of models to relate conditional mean returns on a market proxy (which serves as the regressand) with its conditional variance (which serves as the regressor) (see Pindyck, 1984; French, Schwert and Stambaugh, 1987; Baillie and DeGennaro, 1990; Nelson, 1991; Chan, Karolyi and Stulz, 1992; Glosten, Jaganathan and Runkle, 1993; Harrison and Zhang, 1999; Koulakiotis, Papasyriopoulos and Molyneux, 2006, to name only a few).

I now present literature in this chapter arguing that it may be necessary to include a second regressor that captures changes in the investment opportunity set. This second factor (or component) is theoretically motivated and selected from a universe of financial and macroeconomic variables. Usually referred to as a "state" or "instrumental" variable, it is also identified in the literature as a "hedging" component due to investors' desire to hedge against adverse changes in investment opportunities. This so-called hedging factor

is representative of shifts in the investment environment and is calculated as the conditional covariance between market returns and changes in some other factor (e.g. such as interest rates or possibly some other macroeconomic variable).

Inclusion of this hedging component is proposed in the intertemporal capital asset pricing model (ICAPM) of Merton (1973). The ICAPM, unlike the single-period Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965b) and Black (1972), is based on the premise that investment opportunities are stochastic and that the risk premium is time-varying. It further argues that investors are intertemporal utility maximizers and their investment decisions at time *t-1* depend on investment opportunities at time *t* (i.e. Current demand and investment decisions depend on possible future investment opportunities). An intertemporal utility maximizer therefore considers the uncertainties associated with future events and will select a portfolio based on a distribution of possible future returns and states of the economy. They also consider the relation between current returns and returns that may be available in the future. For example, suppose that the current return on a hypothetical asset is negatively correlated with the future state of the economy. By choosing to hold the asset, the investor would expect to earn a higher return if the economy experiences a recession in the near future.

Section 3.2 of this chapter will cover some of the underlying assumptions behind the two-factor ICAPM and what its critics have to say. It will explain the importance of including a hedging factor to motivate the ICAPM and what significance and economic interpretation this factor has. Finally, it will discuss relevant literature that deals with the two-factor ICAPM and what some of the major findings are. These findings are undoubtedly important since they set the scene for this chapter.

### 3.2.1. Introduction to the Two-Factor ICAPM

The two-factor ICAPM of Merton (1973) formulizes the notion that investment opportunities are time-varying and stochastic. It postulates that the conditional market risk premium, $E_{t-1}[r_{M,t}]$, is a linear function of its conditional market variance, $\sigma^2_{M,t}$, as well as its conditional covariance, $\sigma_{MF,t-1}$, with a state variable (factor) *F* that describes shifts in investment opportunities as in Equation (3.1):

$$E_{t-1}[r_{M,t}] = \left[\frac{-J_{WW,t}W_t}{J_{W,t}}\right]\sigma^2_{M,t} + \left[\frac{-J_{WF,t}}{J_{W,t}}\right]\sigma_{MF,t}, \qquad (3.1)$$

$$\text{where } \sigma_{MF,t} = \rho_{MF}\sigma_{M,t}\sigma_{F,t}$$

Intertemporal investors therefore demand compensation for carrying systematic (i.e., market) risk, $\sigma^2_{M,t}$, as well as an additional risk component (i.e. a hedging component), $\sigma_{MF,t}$, that reflects uncertain and potentially adverse changes in investment opportunities. Investors identify state variables that capture this latter type of risk and form portfolios that provide hedging protection against changes in these variables. $E_{t-1}[.]$ denotes an expected value that is conditional on information available at time *t*-1. Therefore the market risk premium is *conditional* on this past information, which is assumed to disseminate quickly and unrestrictedly to *all* investors.

Assuming markets are in equilibrium, and after aggregating *all* investors' demand curves, the ICAPM can now theoretically describe a representative risk-averse agent's utility of wealth function, *J*(W(t),F(t)).[11] W(t) and F(t) denote wealth and a state variable that describes shifts in investment opportunities, respectively. Since this an optimization

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[11] Merton (1969) presents a more involved discussion of how investors optimize their utility in a continuous-time economy where investment opportunities are stochastic. These very same principles are elaborated in Merton (1971, 1973), where he provides a formal mathematical and theoretical justification of his model.

problem to the representative investor's utility of wealth function, the subscripts $J$ denote partial derivates. The coefficient $[-J_{WW,t}W_t/J_{W,t}]$ represents *aggregate* relative risk aversion, since it describes the degree of risk-aversion that *all* investors exhibit. It is usually assumed to be an intertemporal constant and, consistent with theory, should have a positive sign (i.e. $J_{W,t} > 0$ and $J_{WW,t} < 0$). Some studies also justifiably refer to this as the price of "market risk" since it measures the degree to which conditional expected returns respond to changes in the conditional market variance, $\sigma^2_{M,t}$.

Being that there are two regressors, Merton's (1973) ICAPM in Eq. (3.1) suggests a positive *partial* relation between the market risk premium and the conditional market variance. The second chapter presented many studies which examine the intertemporal risk-return tradeoff in the context that the market risk premium is *simply* a function of its conditional market variance (see Nelson, 1991; Glosten, Jaganathan and Runkle, 1993). As mentioned, they mostly implement (G)ARCH-in-mean modeling techniques to simultaneously relate a representative market index's conditional mean with its conditional variance. Results are mixed due to the volatility feedback hypothesis that was discussed (see Campbell and Hentschel, 1992). However, many of these studies seem to omit the hedging component, $\sigma_{MF,t}$, from any empirical considerations. This factor, as Merton (1973) presented, is an important piece that describes how the distribution of returns changes through time (i.e. shifts in investment opportunities), which are assumed to be stochastic, and investors' desires to hedge this risk. Therefore, the conditional market premium is a function of both the conditional market variance *and* its conditional covariance with changes in investment opportunities. This contrasts sharply with the empirical approach of many studies (presented in the second chapter) that assume there is

a *simple* relation between conditional market risk premium and its conditional variance. It may also be the reason why some authors find a negative risk-return tradeoff while others find a positive one and still others find no statistical evidence of a relationship.

The coefficient in front of the hedging component is denoted as $[-J_{WF,t}/J_{W,t}]$ and can rightly be referred to as the price for bearing "intertemporal risk." In addition to bearing market risk, $\sigma^2_{M,t}$, investors face the risk of possibly adverse changes in the investment environment through time. As is discussed in further detail in this chapter, there is evidence to suggest that bearing intertemporal risk yields relatively higher premiums during recessionary periods. It is therefore an economically meaningful factor to consider in an investor's asset allocation decision-making, given their level of risk aversion. From an asset pricing perspective, it is also important because it provides insights into how the nature of the risk-return relation changes between economic recessions and expansions.

Whereas theory dictates that the sign of relative risk aversion is positive, the sign of the intertemporal risk coefficient is not readily apparent. Since a representative agent's utility increases relative to their wealth, W(t), it is implied that $J_{W,t}$ is positive. This is consistent with the notion of *non-satiation* in utility theory economics which states that individuals always prefer more wealth to less and are never satisfied (i.e. they can never have "too much" and any incremental increases in wealth will lead to a marginal increase in utility). Since therefore $J_{W,t}$ is positive, the sign of intertemporal risk is determined by the sign of $J_{WF,t}$. Alike investors' aggregate relative risk aversion, the coefficient $[-J_{WF,t}/J_{W,t}]$, regardless of its sign, is assumed to be an intertemporal constant.

If the marginal utility of wealth is independent of intertemporal risk (i.e. $J_{\text{WF},t} = 0$), the conditional expected market risk premium is solely a function of the conditional market variance. Therefore, there exists a *simple* relation between the conditional market risk premium (which can be denoted as $r_{\text{M},t}$ for short) and the conditional variance:

$$r_{\text{M},t} = \lambda_0 + \lambda_{\text{M}}\sigma^2_{\text{M},t} + \varepsilon_{\text{M},t}, \qquad (3.2)$$

The constant, $\lambda_0$, and the error term, $\varepsilon_{\text{M},t}$, are typically included in empirical surveys to account for market imperfections such as government interventions in the marketplace, transactions costs, and so forth. The coefficient of aggregate relative risk aversion is re-expressed as $\lambda_{\text{M}}$, and is equivalent to $[-J_{\text{WW},t}W_t/J_{\text{W},t}]$. As was previously discussed, the above relation in Eq. (3.2) is extensively investigated in existing literature (covered in the second chapter) by means of GARCH-in-mean modeling and has yielded mixed results up to now in the literature.

If, however, intertemporal risk plays a determining role (i.e. $J_{\text{WF},t} \neq 0$) in investors' decision-making, the conditional expected risk premium is then a function of its conditional market variance and its conditional covariance with the state variable *F*:

$$r_{\text{M},t} = \lambda_0 + \lambda_{\text{M}}\sigma^2_{\text{M},t} + \lambda_{\text{F}}\sigma_{\text{MF},t} + \varepsilon_{\text{M},t} \qquad (3.3)$$

If this is the case then models that omit the price for intertemporal risk (denoted as $\lambda_{\text{F}}$ for short), such as the conditional single-factor model in Equation 3.2, which were explored in the second chapter, are possibly misspecified and biased. Like in the conditional single-factor model, the constant, $\lambda_0$, and the error term, $\varepsilon_{\text{M},t}$, are included to account for market imperfections. As already mentioned, both aggregate relative risk aversion, $\lambda_{\text{M}}$, and the price for bearing intertemporal risk, $\lambda_{\text{F}}$, are assumed to be intertemporal constants.

Before proceeding any further, it is important to understand what is meant when I say a conditional single-factor model is potentially "biased." If intertemporal risk actually matters to investors (i.e. $J_{WF,t} \neq 0$), then it may be appropriate to use the conditional two-factor model in Equation (3.3). Let us suppose that this is the "true" model that describes the nature of the conditional risk premium demanded by investors on *aggregate*. If a researcher erroneously chooses to estimate the *simple* conditional risk-return relation, $\hat{\lambda}_M$, using the single-factor model in Equation (3.2) instead of the "true" relation, $\lambda_M$, using the two-factor model in Equation (3.3), then the direction and magnitude of the bias is driven by $J_{WF,t}$ and the covariance between market returns and the state variable *F*, as is indicated by Scruggs (1998):

$$\hat{\lambda}_M - \lambda_M = \lambda_F \left[ \frac{\text{cov}(\sigma^2_{M,t}, \sigma_{MF,t})}{\text{var}(\sigma^2_{M,t})} \right]$$

Let us now consider how the behavior of the risk premium is influenced by the sign of the price for intertemporal risk, $\lambda_F$, and what implications this has for investors. As already mentioned, since utility increases with wealth, $J_{W,t}$ is strictly positive. The sign of the price for intertemporal risk is therefore determined by the signs of $J_{WF,t}$ and $\sigma_{MF,t}$, respectively. For example, if $J_{WF,t}$ and $\sigma_{MF,t}$ are of the same sign (i.e. both positive or both negative), it therefore means that investors demand a lower risk premium on the market portfolio since the market portfolio has a higher payoff during periods when the marginal utility of wealth is higher. Conversely, if $J_{WF,t}$ and $\sigma_{MF,t}$ are of the opposite sign, then investors will demand a higher risk premium on the market portfolio since the market portfolio has a higher payoff when the marginal utility of wealth is lower.

If however we make the assumption that the investment opportunity set is constant and is state-independent (i.e. $J_{WF,t} = 0$), then the intertemporal utility maximization of the investor simplifies to a single-period utility function. Fama (1970) provides some justification for this. Namely, it can be shown that once we relax the assumption of a constantly-changing investment opportunity set and we assume that investor preferences are fixed, Merton's (1973) intertemporal model collapses to the classical single-period CAPM.

Observation of financial markets reveals that investors are forward-looking and are dynamically hedging their positions to respond to their stochastically changing investment environment (see Campbell and Hentschel, 1992). An investor's tastes and preferences therefore respond accordingly in order for them to maximize their lifetime consumption (i.e. at time $t+1$, $t+2$, $t+3,…,t+n$). Thus, the use of single-period utility maximization models and single-period asset pricing models, such as the CAPM, to study investors' dynamic consumption and decision-making behavior may be inappropriate.[12]

Since the investment opportunity set and investors' preferences are time-varying, it is natural to deduce that this is reflected in the price for bearing intertemporal risk, $\lambda_F$. As is discussed in greater detail, there is evidence to suggest that the premium demanded for bearing intertemporal risk fluctuates with the state of the economy (see Merton, 1973). In particular, during recessionary periods investors demand a relatively higher premium for bearing intertemporal risk than during periods of economic expansion. An important theoretical question to ask however is, what actually constitutes a hedging

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[12] Fama and Miller (1972) provide a more involved discussion of the restrictive properties that govern single-period asset pricing models. In particular, interested readers are directed to Chapter 8, which discusses the importance of multi-period models in solving investors' utility maximization problem.

factor? What underlying forces dictate which assets an investor will prefer over others to include in their hedging portfolio?

### 3.2.2. The ICAPM and Utility Theory

Before examining what the literature has to say about the two-factor ICAPM, we need to understand the fundamental message that the ICAPM is trying to convey. Investors are intertemporal utility maximizers and are therefore concerned with *all* possible future events that may impinge on their present and future consumption. Consider the following rather simple example: Suppose that over my lifetime I heavily rely on bread to feed myself and my family. Therefore, the utility over my lifetime is maximized through steady purchases and consumption of bread. However there is always the possibility that the price of bread will increase in the future, thereby reducing my future consumption. If there were future markets for bread for every date over the course of my life I could hedge against any potential upswings in the price of bread, which would impinge on my consumption. Such markets however do not exist. Instead, as a next best alternative, I can purchase wheat futures which are closely tied to the price of bread. I could even hold stocks of companies that produce the bread. Thus, should there be an unexpected rise in the price of bread (due to shocks in demand or supply), I can be partially protected. Another more common example is homeowners who rely on oil to heat their homes. Oftentimes, their heating agreements provide them with two options: Either the cost per unit of oil they consume within their contractual period can, to some degree, fluctuate with the price of oil on the open market, or, they can choose to "lock-in" the price of oil at a certain price. If they have reason to believe that the price of oil will rise considerably

in the near future, thereby impinging on their long-term consumption and wealth, they may choose the latter of the two options.

One can cite countless of such examples in everyday life where risk-averse individuals make decisions at time *t* to protect, or hedge, risks to their future consumption and wealth (at time *t*+1, *t*+2, *t*+3,…,*t*+*n*). This is the very essence behind Merton's (1973) model and allows us to describe investors' utility maximization behavior in a realistic multi-period framework instead of the unrealistic single-period framework proposed in the static CAPM.

In order to allow for investors to make decisions in a continuous-time economy to maximize their lifetime utility, Merton (1973) extends the classical assumption that capital markets operate void of transactions costs, taxes and other hindrances to free trade. Namely, Merton (1973) assumes that investors have the ability to constantly trade and revise their portfolios at any given time. This follows directly from the classical assumption that markets are perfectly free, thus enabling investors to constantly and unrestrictedly revise their portfolios at any time (should they choose to do so) without restrictions. This empowers investors to quickly respond to changes in their investment opportunity set and to maximize their lifetime utility of wealth. After all, an investor making a decision that is irrevocable (i.e. cannot be altered or changed) for many years will choose very differently than if they had the option (even at a cost) to revise their portfolio whenever they deemed necessary. The ICAPM is therefore dynamic in the strictest sense, whereby investors' preferences and their desire to hedge against unfavorable changes in investment opportunities follows a stochastic process.

Merton's (1973) generalization of continuous trading has sweeping implications for the structure of capital markets. If we assume that information disseminates freely and quickly to all market participants, the notion of continuous trading also ensures market efficiency. If *all* investors are informed and have the ability to quickly respond to changes in the marketplace, then no single (or group) of investors can consistently exploit inefficiencies to earn riskless rewards. In other words, there are no mispriced assets and, consequently, markets are in equilibrium. Deviations from this equilibrium are transitory and, should they occur, investors respond to quickly induce market equilibrium once again.

Since investors can freely trade at any given point in time a natural question to ask is, what dictates their choice of which assets make suitable candidates for their hedging portfolios? An investor with a long holding horizon holding the market portfolio is obviously sensitive to future news that may influence their consumption and, ultimately, their utility of wealth. He will be unhappy therefore if there is negative news that future returns will be lower. The risk premium he demands from holding the market portfolio may thus be expressed as a function of the sum of two important components: The variance of the portfolio's returns and the portfolio's covariance with news that are correlated with the investment opportunity set. Ceteris paribus, if an investor has reason to believe there will be a downturn in the market, they will naturally prefer a hedging portfolio that is negatively related to economic conditions.

In the context of Merton's (1973) ICAPM, an "unfavorable" shift in the investment opportunity set (i.e. negative news about future market conditions) occurs when (future) consumption declines for a given level of (future) wealth with respect to

changes in the state factor *F*.  More specifically, let us consider for a moment the implications of Merton's (1973) formula in Equation (3.3) and the role that each component plays on the dynamic risk premium, $r_{M,t}$.  For sake of argument, suppose an investor holds the market portfolio and to hedge their exposure to adverse changes in the investment environment holds a portfolio of gold, which denotes our state factor *F*.  If the returns on gold are counter-cyclical (i.e. offer higher returns during economic recessions and market downturns) and independent of those on other assets, then we can expect the conditional covariance between the market and gold,  $\sigma_{MF,t}$, to have a negative sign since they are oppositely related.  During periods of economic expansions, where market returns are generally high, intertemporal investors demand more of the market portfolio, ceteris paribus.  In periods of economic recession investors demand more gold and other assets that are positively related to gold in the hopes of realizing a higher risk premium (as a reward for bearing higher intertemporal risk).

Although the ICAPM provides an intuitively straightforward approach to modeling the dynamic risk premium, there appears to be a noticeable disconnect between its original inception in 1973 and when it began to receive rigorous empirical attention in the 1990s and onwards.  A possible explanation for this is the difficulty in theoretically motivating state variables to integrate into the ICAPM.  Cochrane (2001, p.172) argues that it is perhaps since, up to now, there was insufficient evidence to suggest that we can proxy for future returns on assets and, consequently, future states of the economy:  "The ICAPM remained on the theoretical shelf for 20 years mostly because it took that long to accumulate evidence that returns are, in fact, predictable."

### 3.2.3. The Identification of State Factors

There is a large body of empirical research that theorizes on the cross-sectional variations in expected stock returns. Apart from an asset's beta, they include additional factors that can better explain movements in expected returns. Prime examples of such research include the Fama and French (1993, 1995 and 1996) three-factor model whereby expected equilibrium excess returns on an underlying asset are a linear function of its beta, the returns on small-firm stocks less the returns on large-firm stocks (denoted as *SMB*) and the returns on high book-to-market stocks less the returns on low book-to-market stocks (denoted as *HML*).

The Arbitrage Pricing Theory (APT), developed by Ross (1976), is yet another such example whereby equilibrium expected returns on an asset $i$, $R_i$, are defined as a linear function of a set of $k$ factor loadings, $b_{ij}$, multiplied by their corresponding factor risk premia, $F$ (indexed by $j$) and whereby the regression error term, $\varepsilon_i$, represents the 'unexplained element' of $R_i$:

$$R_{i,t} = \alpha_i + \sum_{j=1}^{k} b_{ij,t} F_{j,t} + \varepsilon_{i,t} \, , \qquad (3.4)$$
$$\text{where } E(\varepsilon_i \varepsilon_j) = 0$$

The underlying premise behind the APT is that there exists two "news" components that, to some degree, determine the returns on the underlying asset, $R_i$: 'General news' that affects the aggregate market, and, 'specific news' that may affect a particular industry, asset class or, more specifically, a certain stock. Although general news may influence the overall direction of the economy, it also has, to some varying degree, an influence on *all* stocks. For example, a 1% unexpected rise in interest rates will have a greater impact

on firms that are more leveraged relative to firms with little or no leverage. Likewise, A 1% shock in the price of steel will have a greater impact on companies in the automotive industry than companies in the computer software industry.

The APT does not embody any of the assumptions about utility theory or that mean and variance are the only two elements that matter to investors. However, alike the CAPM and ICAPM, it does assume that investors carry homogeneous expectations about future outcomes and that they all perceive news in a similar fashion. To operationalize the APT, a researcher must first identify a set of systematic factors that impact the economy on aggregate. Such factors may include, for example, measures of economic activity (such as GDP, industrial production, etc.), short- and long-term interest rates, inflation, to name only a few. These economy-wide factors $F$ (each indexed by $j$) may have varying effects on different stocks, as is reflected in each 'beta' factor loading, $b_{ij}$, which take on different values for each $j$th stock.

In terms of which factors $F$ to choose from, a researcher need not select ones that can be theoretically motivated. Instead, a researcher can select literally any observable and measurable factor that can statistically characterize movements in the returns of the asset under scrutiny. The only assumption that must hold however, in addition to investor homogeneity, is that the covariance between each specified regressions' residuals should be (approximately) zero (i.e. $E(\varepsilon_i \varepsilon_j) = 0$). This is consistent with the idea that a holder's portfolio is fully diversified and that firm-specific (i.e. idiosyncratic) risks across securities are uncorrelated. A researcher typically stops adding factors $F_j$ if the next factor contributes relatively "little" additional explanation as to the movements of the returns in asset $i$.

I explicitly mention the APT here in order to make an important point. Since Merton's (1973) ICAPM does not specify the identity of the state factors which proxy for changes in investment opportunities, some researchers resort to using arbitrary factors, or even factors comprised of ad hoc portfolios, simply because they yield statistically significant test statistics and offer empirically pleasing results. Whereas this may be acceptable when implementing the APT, it is unacceptable when applying the ICAPM. Perhaps a reason why the ICAPM is misapplied is because it is oftentimes "confused" with the APT. Cochrane (2001, p. 183) expresses this concern: "The APT and ICAPM stories are often confused." The source for this confusion lies in the motivation for deriving empirically testable factors *F*.

In the APT, a researcher can select *any* arbitrary factor that is observable and measurable and can statistically characterize movements in the returns of the asset in question. On the other hand, the ICAPM requires theoretically motivated variables that can describe shifts in investment opportunities which impact investors' marginal utility of wealth function. Cochrane (2001, p.183) emphasizes the fundamental distinction in deriving factors for these two asset pricing models:

> "The biggest difference between APT and ICAPM for empirical work is in the inspiration for factors. The APT suggests that one start with a statistical analysis of the covariance matrix of returns and find portfolios that characterize common movement. The ICAPM suggests that one start by thinking about state variables that describe the conditional distribution of future asset returns. More generally, the idea of proxying for marginal utility growth suggests macroeconomic indicators, and indicators of shocks to nonasset income in particular."

Cochrane (2001) explains that, when putting the APT into practice, researchers may include in their regressions factors which increase the $R^2$ coefficient of their overall model. Such a practice however when implementing the ICAPM is inappropriate if the selected factors are theoretically incapable of describing changes in investment opportunities which influence investors' (future) consumption and utility of wealth. An important point to make here, as Cochrane (2001, p.172) notes, is that economic factors "need not forecast returns on any traded assets…" Instead, potential economic factors should affect the *average* investor and their (future) consumption decisions and utility of wealth.

The seeming open-endedness of the ICAPM, whereby researchers are free to select from a universe of factors, has drawn censure in the literature. Fama (1991) likens the ICAPM, and other multifactor models, as a "license" to fish for factors that, ex post, yield empirically desirable results. As Fama (1991) puts it, such models "leave one hungry for economic insights about how the factors relate to uncertainties about consumption and portfolio opportunities that are of concern to investors…" Of course, any such model comprised of ad hoc factors does not provide us with meaningful and objective information and only compromises the integrity of its arguments. Fama (1991, p.1594) makes this point clear:

> "Since multifactor models offer at best vague predictions about the variables that are important in returns and expected returns, there is the danger that measured relations between returns and economic factors are spurious, the result of special features of a particular sample (factor dredging)."

Instead, Fama (1991, p.1610) argues that inclusion of state factors must provide a "coherent story" of how the risk premium varies and interacts with changes in the real economy.

Perhaps a reason why it took so long for the Merton (1973) ICAPM to receive rigorous empirical attention is because of the difficulty associated with identifying relevant state factors. Identifying state factors that can be theoretically motivated has been the subject of much debate in the literature and is also a major criticism against the ICAPM. Namely, although Merton's (1973) model provides an empirically tractable method for modeling the dynamic risk premium, it does not directly address *which* factor(s) constitute hedgeable sources of risk. Bhattacharya and Constantinides (2005, p.9) point out that beyond Merton's (1973) two-factor formulization in Equation (3.3), his theory "does not provide an operational procedure for identifying state variables."

### 3.2.4. Some Possible Empirically Testable State Factors

In reality, there is an indefinite number of hedgeable sources of uncertainty that impact investors' utility maximization decision-making behavior. With an abundance of empirically observable data, how does a researcher know which factors can justifiably be used as proxies for changes in the investment opportunity set?

Observation lends support to the notion that asset prices are, to some varying degree, influenced by an array of unanticipated events and economic forces. Much of financial theory is devoted to the identification of these "systematic" phenomena and their role as a likely source of economic risk. As already mentioned, when attempting to identify state factors we must consider hedgeable sources of risk that are of concern to

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the *average* investor. Consistent with the ICAPM, these factors must be theoretically driven and may not consist of arbitrary factors that simply yield desirable results.

The seminal study by Chen, Roll and Ross (1986) is an important step in the right direction in identifying relevant state factors. As noted in their study, "A rather embarrassing gap exists between the theoretically exclusive importance of systematic 'state variables' and our complete ignorance of their identity" (p.384). Even though the prices of assets exhibit statistically significant comovement with one another, suggestive of the existence of common exogenous factors, research is still trying to uncover the identity of these factors. Chen, Roll and Ross (1986) begin by specifying a set of macroeconomic factors which, a priori, should affect (and proxy for changes in) firms' cash flows, $c$, and shifts in the discount factor, $k$, that investors use to appraise the price, $P$, of an underlying equity asset:

$$P = \frac{E(c)}{k}$$

where E(.) denotes an expectations operator.

It is reasonable to argue that systematic forces which influence returns also have a pervasive impact on firms' expected cash flows, $E(c)$, and investors' approximation of the appropriate discount factor, $k$. The discount factor used to discount expected cash flows may change over time and embodies general information such as investors' degree of risk aversion, returns on competing assets and the market portfolio and shifts in investors' consumption which, ultimately, impacts their marginal utility of wealth. The discount factor also encompasses firm-specific information such as future growth

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prospects for the issuing firm and the covariance of its returns with future economic 'news.'

Chen, Roll and Ross (1986) then begin their empirical investigation by examining whether a set of prespecified macroeconomic factors can systematically affect the returns of the *average* firm and, consequently, returns on the aggregate market portfolio. These factors are as follows, respectively: (a) the monthly growth rate in industrial production; (b) the change in expected inflation; (c) unexpected shifts in inflation; (d) the spread between low-grade (Baa and under) corporate bonds yields and long-term government bond yields (i.e. default premium); (e) the spread between long- and short-term government bond yields (i.e. maturity premium). If these factors have a statistically important impact on market returns (i.e. these risk exposures are "priced" in the marketplace) then investors may wish to hedge their exposure to shifts in these factors since they may lead to changes in their marginal utility of wealth.

Industrial production is the first factor considered in their study. It serves as a natural candidate for an economic state factor for its ability to identify (future) cyclical movements in macroeconomic conditions which impact investors' consumption and, ultimately, their utility of wealth function. More specifically, fluctuations in stock market levels are directly linked with shifts in industrial production, evidence suggesting that it may be a systematic source of risk which impacts investors' marginal utility of wealth and therefore merits attention.

A distinguished body of literature provides support for the relation between current stock market returns and future shifts in industrial activity (see Fama, 1981; James, Koreisha and Partch, 1985; Schwert, 1990; Fama, 1990, to name only a few).

Fama (1990) proposes that this result is attributable to three non-mutually exclusive explanations:[13]  Firstly, current prices of assets contain information about future real productive capacity and thus serve as a chief indicator to the direction of the overall economy.  Secondly, changes in the discount factor, $k$, may entail an immediate impact on assets' prices but may take relatively longer to influence real productivity.  Thirdly, it is possible that as prices of assets change (for whatever reason) investors' wealth also changes accordingly.  This subsequently affects their demand for (future) consumption and investment goods.  Therefore, from a supply-side perspective, industrial production levels take relatively longer to drop in order to compensate for dwindling demand.

Fama (1981) who found a positive relation between stock returns and future shifts in industrial production also documents a positive contemporaneous relation from his multivariate regression results.

This evidence lends support to industrial production as a significant risk factor that can possibly serve as an instrument to describe shifts in investment opportunities.  As Fama (1990) indicates through his three possible explanations, industrial production subsumes information regarding the general state of the economy and can predict future movements in economic activity which directly impacts investors' utility of wealth function.

A more recent study by Artis, Kontolemis and Osborn (1997) actually uses fluctuations in industrial production as a key variable to determine shifts in business cycle regimes for the United States and 11 other industrialized countries.

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[13] Fama (1990) does not formally discriminate between each of these explanations but instead proposes them as likely reasons for this relationship.

In the United States, studies typically reference the National Bureau of Economic Research (NBER) as an authoritative source for a chronology on the direction, duration and magnitude of shifts in business cycles (see Boldin, 1994).[14]  After constructing a chronology of business cycles based solely on industrial production, Artis, Kontolemis and Osborn (1997) find a striking resemblance to the chronology established by the NBER.  Since the NBER identifies business cycles using an exhaustive list of macroeconomic and other related factors (such as industrial activity, inflation, unemployment, interest rates, consumption, etc.), it suggests that industrial production also embodies a broad range of information content that represents hedgeable sources of risk to investors.  It can therefore justifiably be used as a state factor to proxy for shifts in the investment opportunity set.  Moreover, as this chapter does, industrial production data can be obtained and used as a hedging component to test for a risk-return tradeoff in international markets.

The findings from Artis, Kontolemis and Osborn (1997) not only support the position that industrial production subsumes a broad range of information content regarding the overall state of the economy, they also provides useful insights as to the nature and magnitude of business cycles.  Namely, economic ups and downs exhibit asymmetry; whereby industrial production declines more in absolute terms during recessions than it rises during periods of economic prosperity.  Preceding their study, this asymmetry is documented in other studies too; Neftci (1984) as well as Hamilton (1989) present evidence from the U.S. market and Acemoglu and Scott (1994) explore this asymmetry in the U.K. market, to name only a few authoritative examples.

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[14] The Business Cycle Dating Committee at the NBER defines a business cycle in the context of Burns and Mitchell (1946). Additional information about the NBER can be found at www.nber.org and, for a historical reference of business cycles, see www.nber.org/cycles.

Inflation (both expected and unexpected) serves as another empirically testable economic factor in the study by Chen, Roll and Ross (1986) to determine whether it can systematically influence stock market returns. Selecting it as a potential factor that explains shifts in economic conditions may be intuitively obvious; as inflation changes, so do investors' and firms' real purchasing power. Existing studies find a negative relation between contemporaneous changes in inflation and aggregate stock returns. This is contrary to the Fisherian notion of interest whereby the nominal expected return on an asset equals real interest and the real risk premium plus expected inflation. Geske and Roll (1983) however defend this seemingly counterintuitive relation on the basis that there exists a series of causal macroeconomic linkages.

More specifically, consider a negative (positive) shock in the aggregate stock market that persists for an indefinite time period. Such a shock may serve as a signal that corporate earnings will be lower (higher) and that unemployment may rise (decline). Since government revenues consist of personal taxes levied on individuals and investors as well as corporate taxes from firms, there is a possibility that its generated revenue will be lower (higher). Since government expenditures do not usually change in response to changes in its tax revenues, there is a rise (fall) in the Treasury deficit. The Treasury then increases (decreases) its borrowing activity from the public through its treasury notes and bonds. A portion of this Treasury debt is purchased by the Federal Reserve System, which eventually pays for it through monetization [i.e. an expansion (contraction) in the money supply]. An expansion (contraction) in the monetary base effectively leads to a proportional increase (decrease) in the rate of inflation. Given therefore this chain of

monetary and fiscal events, it is somewhat plausible that stock returns *cause* changes in inflation and that the two move in contra to one another.[15]

James, Koreisha and Partch (1985) employ a more refined econometric technique to improve on some of the limitations they identified in Chen, Roll and Ross (1986). Namely, they implement a vector autoregressive moving average (VARMA) model to simultaneously examine the causal relationships that tie together aggregate stock returns, real economic activity, changes in the monetary base, and inflation. Chen, Roll and Ross (1986), on the other hand, examine these relationships individually essentially implementing an "equation-by-equation" modeling procedure. Such a method may be inappropriate if the error terms across each of the equations correlate with one another. Another advantage that VARMA affords is that it imposes no structural or a priori precincts on the data or direction of the *causal* relationship(s).

Results from the VARMA estimation methodology substantiate the findings in Chen, Roll and Ross (1986) that there exists a link between aggregate stock returns, real productive activity, and inflation. More specifically, shocks in stock returns cause reductions in the productive capacity of real economic activity and "signal" higher unemployment and widening gaps in the Treasury deficit. This ultimately induces higher inflation through the Fed's monetization of Treasury debt and leads to increases in the money supply.

Chen, Roll and Ross (1986) explore whether each of the potential state factors discussed can adequately characterize stock market returns. Essentially extending the APT of Ross (1976), they empirically test the proposition of whether shocks (i.e. innovations) in each of the aforementioned factors impact stock market returns. Since

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[15] In this case, the term "cause" is used in an econometric context consistent with Granger (1969).

these factors are observed economic shocks, we can thus interpret each respective beta coefficient in an economically meaningful way. For example, we can determine whether movements in these sources of risk are "priced" in the marketplace; i.e. do these factors constitute pervasive sources of risk that impact investors' marginal utility of wealth?

They operationalize Equation (3.5) to see whether innovations in each of the aforementioned factors represent systematic sources of risk. Their model takes the form

$$R_{M,t} = \alpha + \beta_{MP}(MP_t) + \beta_{DEI}(DEI_t) + \beta_{UI}(UI_t)$$
$$+ \beta_{UPR}(UPR_t) + \beta_{UTS}(UTS_t) + \varepsilon_t$$

where the returns on the market portfolio, $R_{M,t}$, are a linear combination of the monthly changes in industrial production (MP), expected and unexpected shifts in inflation (DEI and UI, respectively), changes in the default risk premium (UPR), twists in the yield curve (UTS) and each of these factors' respective 'beta' factor loadings, $\beta_{MP}$, $\beta_{DEI}$, $\beta_{UI}$, $\beta_{UPR}$ and $\beta_{UTS}$. Each beta represents the market's sensitivity to shocks in each of the respective economic state variables. The constant as well as the idiosyncratic error term are denoted as $\alpha$ and $\varepsilon_t$, respectively.

From this model, they find that changes in IP, shifts in the default risk premium and in the yield curve and finally, somewhat more meekly, changes in expected and unanticipated inflation, significantly explain variations in stock market returns. These findings lend some support that these factors are systematic sources of risk and that the prices of assets are, to some degree, determined in accordance to these assets' exposures to these factors.

The signs and magnitudes of each of the coefficients are not surprising, given the literature that was discussed. For example, $\beta_{MP}$ is positive and statistically significant,

suggesting that, ceteris paribus, substantial declines in IP may signal periods of economic contractions and, as a result, diminished market returns. Since this coefficient is significant, it also emphasizes the importance for investors to hedge against shifts in real production. The signs of the coefficients for expected and unanticipated inflation, $\beta_{DEI}$ and $\beta_{UI}$, respectively, are also negative and statistically significant, as is consistent with existing literature. Chen, Roll and Ross (1986) argue that the reason for the negative sign is maybe because stock market assets are generally perceived by investors to afford more hedging protection against adverse changes in investment opportunities rather than other investment assets that are 'fixed' in a nominal sense. The sign of the risk premium, $\beta_{UPR}$, is positive since investors wish to protect themselves against increases in the risk premium caused by the general effects of uncertainty in the economy. Finally, the negative sign of $\beta_{UTS}$ can be interpreted as investors' desire to hold assets with returns that move contra to shifts in the yield curve. Such assets therefore carry a negative risk premium.

The yield curve is oftentimes used by macroeconomists and practitioners as a benchmark for other debt instruments and to evaluate the current state of the economy as well as predict future shifts in its movement (see Estrella and Hardouvelis, 1991; Campbell, 1995; Estrella and Mishkin, 1998; Hamilton and Kim, 2002, to name only a few). A 'normal' yield curve means that government bonds with a long-term maturity offer higher yields relative to short-term government bonds. This is to compensate investors for risks associated with the passage of time. When the spread between long- and short-term government bonds becomes thinner relative to its long-run average (i.e. the yield curve becomes 'flat'), it is likely that the economy may be heading towards a

recession. This probability increases in the case of an 'inverted' yield curve (i.e. when short-term government yields exceed long-term government yields). It makes sense, therefore, that investors prefer assets that do well when the yield curve flattens or becomes inverted.

Another interpretation for the negative sign of $\beta_{UTS}$ is that the long-term government bond yield also reflects the return on any capital investment. If the long-term rate falls, so does the return on capital. Investors naturally want to hedge against this possibility and therefore want to hold assets whose price appreciates during declines in the long-term government bond yield.

Overall, the results by Chen, Roll and Ross (1986) are consistent with the intertemporal asset pricing theory of Merton (1973) and that APT model of Ross (1976). Namely, their findings are consistent with rational expectations that assets prices move in accordance to their exposure to a set of state factors which depict underlying market and economic conditions.

As a side note, they also explore whether real consumption or the risk associated with exposure to innovations in oil prices are rewarded in the marketplace. A large body of asset pricing literature provides empirically tractable consumption-based theories which derive assets' betas according to investors' marginal utility of consumption (i.e. assets' covariance with aggregate real consumption) (see Breeden, 1979; Cox, Ingersoll and Ross, 1985).

Of course, it is worth mentioning that, although such consumption-based theories provide insights into the dynamics of assets' prices, they are not free from criticisms. For example, *instantaneous* consumption rates cannot be derived and, instead, researchers

obtain real consumption data at longer frequencies (such as quarterly or annually). Another perhaps more serious shortcoming is that consumption data contains significantly more measurement error when compared to asset pricing theories that instead utilize prices of the market portfolio which contain virtually no measurement error.

In their study, Chen, Roll and Ross (1986) find that the beta for aggregate consumption, both in the entire period and in subperiods, is statistically insignificant for pricing stock market returns.

As for oil prices, there is no a priori justification which supports its use as a state variable that will provide any incremental explanatory power for the variations in stock market returns beyond the main five factors that were just discussed. Instead, an intuitive justification for identifying oil price fluctuations as a systematic source of risk is because it exerts a significant impact on consumption, firms' real productive capacity, inflation, and the macroeconomic structure at large.

The relation between oil price fluctuations and shifts in macroeconomic conditions is a topical issue and of concern to investors, economists and policymakers. An extensive body of literature is devoted to examining this relation and whether fluctuations in oil prices drive business cycles. Hamilton (1983) presents evidence showing that substantial increases in the price of oil may be a contributing factor to recessions in the U.S. economy. In that regard, his study finds that languishing economic activity statistically coincides with rapid increases in the price of oil. Mork (1989) extends the work by Hamilton (1983) and, when investigating a longer data sample, concludes that oil prices and economic activity are asymmetrically related. Other more

recent studies find that positive shocks in oil prices have a large influence on macroeconomic factors which, to some degree, 'signal' that a recession is eminent. For example, LeBlanc and Chinn (2004) argue that rising oil prices coincide with high levels of inflation in the U.S., Japan and Europe.

Despite convincing evidence that oil price risk impacts economic conditions, Chen, Roll and Ross (1986) find that the beta for this risk is statistically insignificant, especially during the 1968 – 1977 subperiod, a time when the OPEC cartel imposed an oil embargo on the U.S. in October 1973.

All in all, although their study has not exhaustively explored all economic state factors that constitute fundamental sources of market risk, their findings have important implications for studies seeking to apply Merton's (1973) ICAPM to explore the risk-return tradeoff. Though there are numerous techniques for modeling volatility (i.e. estimating $\sigma^2_{M,t}$ in Equation (3.3), there is still the question of which factors, $F$, we can incorporate to estimate the hedging component, $\sigma_{MF,t}$. As Chen, Roll and Ross (1986) demonstrate, economic 'news' may be measured as innovations in the aforementioned state variables. Perhaps these variables can also be incorporated into Merton's (1973) intertemporal asset pricing framework and can take the role of hedging factors. This is something that, to my knowledge, has not been attempted in the literature thus far.

### 3.2.5. Criticisms against the Two-Factor ICAPM

Although the ICAPM is intuitively appealing, in practice, it is nearly impossible to specify all likely sources of risk. The study by Chen, Roll and Ross (1986) provides a comprehensive investigation of some factors that are likely candidates which can be

incorporated as hedging factors. As mentioned earlier, the fundamental differences between the APT and Merton's (1973) ICAPM are often confused because both models involve a multi-factor approach to explaining variations in expected market returns. However, whereas the APT gives the researcher the absolute freedom to select from a universe of observable factors, factors that enter into the ICAPM must theoretically justify *what* role they play in capturing shifts in investment opportunities that impact investors' utility of wealth function. As mentioned, there exist indefinite sources of risk that our beyond our means to estimate, quantify or explain. For example, I cite a body of literature in the second chapter which documents that bad weather appears to have an impact on stock returns (see Saunders, 1993; Hirshleifer and Shumway, 2003). Although this may appear as an unlikely, and rather farfetched, source of risk, it illustrates the point that no model is capable of capturing *all* sources of uncertainty.

As already mentioned, one of the most prevalent criticisms I found in the literature has to do with the fact that Merton's (1973) ICAPM does not provide a procedure for electing factors that represent hedgeable sources of risk. As Fama (1991, p. 1594) points out,

> "The multifactor asset-pricing models of Merton (1973) and Ross (1976)...involve multiple factors and the cross-section of expected returns is constrained by...factor loadings...The multifactor models are an empiricist's dream...that can accommodate...any set of factors that are correlated with returns."

The ICAPM should not be construed as an empiricist's dream but instead should be applied when one can theoretically justify why they selected the hedging factors they did and what role they play in describing shifts in the investment opportunity set.

Another common criticism worth mentioning has to do with the underlying assumption of investor homogeneity. Namely, it makes the assumption that, when markets are in equilibrium, all heterogeneous investors can be simplified to *one* investor (the "representative" agent) with preferences that are equivalent to the sum of the heterogeneous investors. This assumption also forms a pillar for which makes application of the classical CAPM possible. Namely, if one can stomach such an assumption, they can proceed to deduce an asset's expected returns solely on the basis of its underlying beta.

Now, however, we see the same assumption behind Merton's (1973) ICAPM. This criticism is warranted since observation of financial markets and market participants reveals diversity in the investment world. After all, different market participants (institutional investors, hedge funds, small investors, households, etc.) implement different strategies within their unique levels of risk aversion to satisfy their unique goals and objectives. Furthermore, markets are *not* in a steady state of equilibrium and, even if they were, such an ideal state may merely be transitory.

As was mentioned in the second chapter however, it oftentimes necessary to make a set of assumptions which govern the seemingly chaotic intricacies and dynamics that drive financial markets. This enables us to establish relationships and to better understand the effects different factors have, ceteris paribus, on others. For example, the study by Chen, Roll and Ross (1986) is very precise in the factors it wishes to investigate

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and their impact on stock market returns; the Fama and French three-factor model is yet another example which posits that an asset's returns are a function of a particular set of factors (see Fama and French, 1993; 1995 and 1996). This model, has drawn criticisms however that it merely "hunts" for factors which, ex post, yield favorably significant coefficient parameters; Black (1993, p.10) expressed a strong criticism towards the Fama and French three-factor model expressing that "...the Fama and French results are attributable to data mining"

In reality, there is no model that can perfectly describe returns of assets, or that can answer any of our questions for that matter, with absolute certainty. This is why it is necessary to establish a set of assumptions that will allow us come to grips with the financial world. Merton (1973, p. 868) willingly expresses this:

"...Such a model cannot be constructed without costs. The assumptions, principally homogeneous expectations, which it holds in common with the classical model, make the new model subject to some of the same criticisms."

It is important to acknowledge however that this assumption may not pose serious theoretical objections against, or necessarily disrepute, the ICAPM or any estimates associated with its use. Constantinides (1980) illustrates that the simplification of investor homogeneity can be attained in a simple economy with heterogeneous investors, so long as prices are established as if buyers and sellers are homogeneous. Constantinides (1980) describes that an aggregation property holds when equilibrium prices are ascertained

when all market participants hold homogeneous beliefs, expectations, and have similar preferences.

Despite some of its shortcomings, the ICAPM is a significant theoretical improvement over the classical single-period CAPM. It is now widely accepted in the literature as a paradigm for how to model the dynamic risk premium in an investment environment where the investment opportunity set is stochastically evolving throughout time.

### 3.2.6. Empirical Literature on the Two-Factor ICAPM

Scruggs (1998, p.576) describes the existing inconclusive state of the risk-return tradeoff literature as "unsatisfactory" and proposes using long-term government bond returns as a state factor to describe the dynamics of the investment opportunity set and how the distribution of the market risk premium changes through time. Long-term government bonds make for a potentially suitable hedging factor since they are used as an instrument to hedge against risks in the market and changes in interest rates. Merton (1973, p. 879) proposed considering the implications behind changes in interest rates:

> "The interest rate has always been an important variable in portfolio theory, general capital theory, and to practitioners...while it is surely not the sole determinant of yields on other assets, it is an important factor. Hence, one should interpret the effects of a changing interest rate in the forthcoming analysis in the way economists have generally done in the past: namely, as a single (instrumental) variable representation of shifts in the investment opportunity set."

If the behavior of interest rates accurately reflects shifts in economic conditions then long-term government bond returns can justifiably be used as a hedging factor. Scruggs' (1998) main objective is to see whether a conditional two-factor model can better explain variations in the market risk premium. Since long-term government bond returns may provide hedging protection against adverse changes in interest rates. In particular, long-term government bond returns are negatively, albeit not perfectly, related to changes in interest rates and other market conditions.

Suggesting that long-term interest rates embody a broad range of information content regarding market conditions which represent hedgeable sources of risk is also motivated from the findings of other researchers. For example, Sweeny and Warga (1986) investigate whether unanticipated shifts in interest rates are priced in the market. Employing a two-factor APT model [as in Equation (3.4)], they test whether shifts in the long-term government bond yield can statistically characterize movements in stock market returns. They test this proposition across stocks in several industries to see whether specific industries are particularly sensitive to fluctuations in the long-term government bond yield. Findings from their study indicate that movements in the long-term government bond yield tend to exert a negative influence on stock portfolio returns regardless of industry; evidence that it represents a likely source of systematic risk in the market and merits investors' attention.

The negative relation between bond yields and stock returns documented by Sweeny and Warga (1986) also corroborate the findings of Chen, Roll and Ross (1986) mentioned earlier. The explanation given by them is that the long-term government bond yield is a reflection of the return on any capital investment. Thus, if the long-term

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government bond yield falls, so does the return on capital. Investors naturally want to hedge against this possibility and will therefore desire assets with returns that move opposite to shifts in the long-term government bond yield.

Sweeny and Warga (1986) afford an alternative explanation for this negative sign based on the present value of firms' dividend payouts. Namely, if the real interest rate increases, so does the discount rate by which future dividend cash flows are discounted. Ceteris paribus, discounting future dividend cash streams at a higher rate tends to decrease the overall investment attractiveness of the firm.

Interestingly, the negative relation between the long-term government bond yield and stock returns is most pronounced for firms within the utilities industry. This oddity may lend support to their dividend argument since utility companies tend to pay higher dividends relative to firms in other industries. Therefore, investors pay a (relatively higher) premium to invest in such companies in the hopes of reaping higher dividends. When the long-term government yield rises, utilities' dividend future cash flows will be most affected (relative to other firms) and this will exert (relatively more) downward pressure on their stock price.

Scruggs (1998) is also motivated to use the long-term government bond yield as a second factor since there was a preceding study by Turtle, Buse and Korkie (1994) that used it as a hedging factor within the context of Merton's (1973) ICAPM. In that study, they conclude that the long-term government bond yield, within a GARCH-in-mean framework to capture the first two moments of market returns, serves as a good proxy for shifts in the investment opportunity set and that "previous rejections of the conditional CAPM using only stock market data may be due to omitted hedge terms…" (p. 15).

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Scruggs (1998) proceeds to model the *partial* relation between the market risk premium and conditional market volatility [i.e. Equation 3.3], postulating that previous research which estimates the *simple* relation [i.e. Equation 3.2] suffers from an omitted variable bias and is the reason why many researchers do not find a positive and statistically significant relation between the first two moments of stock market returns. To accomplish this, Scruggs (1998) employs a bivariate EGARCH-in-mean system to estimate the relation between the first two moments of market returns. As is discussed later on in greater depth, and in the proceeding section of this chapter, the methodology by Scruggs (1998) assumes a constant correlation parameter between movements in the long-term government bond yield and changes in the market portfolio. As is discussed later on, making such an assumption may be fallacious and, accordingly, is relaxed to allow a time-varying interaction between the market portfolio and the specified hedge portfolios I introduce later on.

The bivariate EGARCH-in-mean methodology of Scruggs (1998) takes the form

$$r_{M,t} = \lambda_0 + \lambda_M \sigma_{M,t}^2 + \lambda_F \sigma_{MF,t} + \varepsilon_{M,t}$$
$$r_{F,t} = \mu_F + \varepsilon_{F,t}$$
$$\ln(\sigma_{M,t}^2) = \omega_{M,t} + \alpha_{M,t}\phi(\zeta_{M,t-1}) + \beta_{M,t}\ln(\sigma_{M,t-1}^2) + \gamma_{M,t}r_{F,t}$$
$$\ln(\sigma_{F,t}^2) = \omega_{F,t} + \alpha_{F,t}\phi(\zeta_{F,t-1}) + \beta_{F,t}\ln(\sigma_{F,t-1}^2) + \gamma_{F,t}r_{F,t}$$
$$\sigma_{MF,t} = \rho_{MF,t}\sigma_{M,t}\sigma_{F,t}$$
$$\phi(\zeta_{M,t-1}) = |\zeta_{M,t-1}| - \varepsilon_{t-1}[|\zeta_{M,t-1}|] + \delta_{M,t}\zeta_{M,t-1}$$
$$\phi(\zeta_{F,t-1}) = |\zeta_{F,t-1}| - \varepsilon_{t-1}[|\zeta_{F,t-1}|] + \delta_{F,t}\zeta_{F,t-1} \qquad (3.5)$$

This model, alike other traditional GARCH specifications, allows researchers to explore asset pricing relations within a framework that allows a time-varying interaction between the first two moments of market returns. It explicitly models the conditional variance as a deterministic function of past squared variances and past innovations in the disturbance

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term. As Turtle, Buse and Korkie (1994) indicate, GARCH-type models are intended to "fit" volatility rather than strictly describe it in an economic sense (p. 16).

Given the structure of the EGARCH specification, introduced by Nelson (1991), negative estimates of the conditional market variance, $\sigma_{M,t}^2$, are precluded. This is a desirable feature and an improvement over other traditional GARCH-type models since researchers need not manually impose any non-negativity constraints on the parameters. The EGARCH-in-mean system of equations also allows $\sigma_{M,t}^2$ to respond asymmetrically according to the signs and magnitudes of innovations and allows researchers to relate the conditional mean and variance of an asset's returns.

The construct of Scruggs' (1998) EGARCH specification, as is expressed in Equation (3.5), allows the conditional variance to be estimated as a deterministic function of past squared variances and innovations in the disturbance term. Although not the main purpose of his paper, he also includes the nominal one-month Treasury bill yield, $r_{F,t}$, in the conditioning information set to estimate the conditional variances of the market portfolio and the long-term government bond yield, $\sigma_{M,t}^2$ and $\sigma_{F,t}^2$, respectively, and see what influences it has on these parameters.

The conditional covariance between the market portfolio and the long-term government bond yield is denoted as $\sigma_{MF,t}$. This is equivalent to the product of the correlation between the market portfolio and the long-term government bond yield, $\rho_{MF,t}$, and the respective conditional variances of the market portfolio and the long-term government bond yield, $\sigma_{M,t}$ and $\sigma_{F,t}$ respectively. An important point to make here is that Scruggs (1998) assumes that the conditional correlation between the market and long-term government bond yield is constant (i.e. time-invariant). Recent research

however argues that the correlation between market returns and bond returns is not 'static' but dynamic and time-varying (see Cappiello, Engle and Sheppard, 2006). One of the contributions of this chapter is to relax this assumption and explore the intertemporal risk-return tradeoff on an international level utilizing alternative factors as the hedging component. Allowing the covariance parameter between the state factor and the market portfolio to be time-varying is more intuitively realistic since the interaction between the investment opportunity set and the market portfolio undoubtedly changes through time (especially during changes in the business cycle).

In Equation (3.5), the parameter $\zeta_{M,t-1}$ represents the conditional standardized innovation in the returns of the market portfolio (i.e. $\varepsilon_{M,t-1}/\sigma_{M,t-1}$). $\phi(\zeta_{M,t-1})$ is a characterization of the 'news response function' in the context of Engle and Ng (1993). Since the EGARCH model is asymmetric in nature, the news response function allows $\sigma_{M,t}^2$ to respond in accordance with the direction and magnitude of the lagged innovation. If the parameter $\delta_{M,t} = 0$, the news response function, $\phi(\zeta_{M,t-1})$, is determined solely by the scale of the market return innovation, $\zeta_{M,t-1}$. The parameter $\delta_M$ describes the reaction of the conditional market variance to the direction of the lagged innovation in market returns. If, for example, $0 < \delta_M < 1$ or conversely, $(-1 < \delta_M < 0)$, then conditional market volatility tends to rise more with respect to positive (negative) return innovations relative to negative (positive) return innovations of equal magnitude. In the case where $\delta_M = 1$ ($\delta_M = -1$), the news response function, $\phi(\zeta_{M,t-1})$, slopes upwards (downwards) if $\delta_M > 1$ ($\delta_M < -1$).

Intuitively, the news response function for the state factor $F$, which is the long-term government bond yield, is denoted as $\phi(\zeta_{F,t-1})$. The constituent parameters that

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determine this function can be interpreted in a similar fashion with the parameters that form the news response function for the market portfolio.

Implementing the model in Equation (3.5), and assuming that the correlation between shifts in the long-term government bond yield the market portfolio is constant, Scruggs (1998) finds that the partial relation between $r_{M,t}$ and $\sigma_{M,t}^2$ is positive and statistically significant. Therefore, investors' degree of relative risk aversion, $\lambda_M$, is positive and means that investors demand a higher risk premium to take on an additional unit of systematic risk. This conclusion is now coherent with the basic tenet of portfolio theory which advocates a positive relation between risk and return and also provides support to Scruggs' (1998) claim that previous studies suffer from an omitted variables bias, and this is why they find a negative or insignificant risk-return relation.

Furthermore, his study finds that the partial relation between $r_{M,t}$ and $\sigma_{MF,t}$ is negative and statistically significant. This result is consistent with the findings of Chen, Roll and Ross (1986) who find that the beta which captures interest rate risk is negatively related to movements in stock market returns. This can be interpreted as investors' desire to hold assets with returns that move opposite to shifts in the long-term government bond yield. Furthermore, the long-term government bond yield also reflects the return on capital investment and, if it declines, so does the return on capital. Investors seeking to hedge against this possibility will hold assets whose price appreciates during downturns in the long-term government bond yield. Scruggs' (1998) results substantiate this proposition. Namely, an investor demands a lower (higher) premium on the market portfolio when $\sigma_{MF,t}$ is positive (negative).

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Finally, the study by Scruggs (1998) is an important piece in understanding the intertemporal risk-return puzzle. He concludes that estimates of the *simple* relation between $\sigma_{M,t}^2$ and $r_{M,t}$ [i.e. as in Equation (3.2)], are biased and yield estimates of investors' aggregate risk aversion which is statistically negligent. Therefore we must not overlook the importance of identifying state factors that accurately depict economic conditions and shifts in the investment opportunity set which are of hedgeable concern to market participants. By including this so-called state factor into our model (i.e. implementing a two-factor approach as is depicted in Equation (3.3) and advocated by Scruggs (1998), we ensure that our model is correctly specified and can estimate a true and unbiased relationship between market risk and the dynamic market risk premium.

Scruggs and Glabadanidis (2003) address the potential shortcoming in Scruggs' (1998) study of a constant correlation restriction imposed on the covariance matrix between returns on the market portfolio and the long-term government bond yield. Comparable to Scruggs (1998), they employ a two-factor variant of Merton's (1973) ICAPM whereby the long-term government bond yield serves as a state variable that proxies for systematic sources of risk and changes in investment opportunities. However, their model allows the correlation parameter to be time-varying instead of constant by implementing the Asymmetric Dynamic Covariance (ADC) model proposed by Kroner and Ng (1998) in order to estimate the conditional moments of market and government bond returns and to explore the risk-return tradeoff.

The ADC specification is advantageous given its flexibility and ability to describe important characteristics in data such as volatility clustering and persistence, and the

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asymmetric influence past innovations have on current volatility.[16] It also allows for time-varying correlation between state factor(s) and the market portfolio.

Scruggs and Glabadanidis (2003) examine the puzzling relation between the market risk premium and its conditional second moments. They utilize the ADC framework whereby, similar to Scruggs (1998), the long-term government bond yield serves as a hedge portfolio. Findings from their study show that their conditional two-factor model is unsuccessful in explaining variations in the dynamic market risk premium. Namely, the estimate for investors' aggregate degree of relative risk aversion is statistically marginal. This finding contrasts sharply with the findings of Scruggs (1998), who argues that the reason why studies cannot find a positive and statistically significant risk-return tradeoff is because they omit the hedging component from their models. Now, however, Scruggs and Glabadanidis (2003) report counterintuitive results when they allow the correlation parameter between the market portfolio and the long-term government bond hedging portfolio to be time-varying.

They argue that perhaps the risk-return tradeoff reported in Scruggs (1998) is an artifact of the restrictive constant correlation assumption imposed in his model. Scruggs and Glabadanidis (2003) provide evidence that the correlation parameter is clearly time-varying and, therefore, making the assumption that it is constant is fallacious and unrealistic. This chapter seeks to contribute to existing research by investigating the intertemporal risk-return tradeoff using a BEKK framework whereby the correlation parameter between the market portfolio and the respective hedging factors varies with time.

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[16] The notion of volatility clustering is illustrated in the literature review section of the second chapter of this thesis.

Scruggs and Glabadanidis (2003) conclude their paper by suggesting that future research needs to perhaps investigate whether other factors or modeling techniques can better explain the behavior of the dynamic risk premium: "It is left for further research to determine whether an alternative set of risk factors or an alternate empirical specification might perform better" (p. 314). The aim of this chapter is to address this very matter. Perhaps the long-term government bond yield is not purely representative of shifts in economic conditions since it is correlated with the decisions of the central banks and government. Alternative factors within a BEKK framework are discussed in greater depth in the proceeding section of this chapter.

Guo and Whitelaw (2006) approach the risk-return puzzle from a different angle in relation to the studies by Scruggs (1998) and Scruggs and Glabadanidis (2003), which both use the long-term government bond yield as a hedging portfolio. Instead, Guo and Whitelaw (2006) establish an empirical framework whereby monthly implied volatility on the S&P100 options index serves as an instrumental variable for the conditional market variance. This is an innovation relative to exiting studies and is justified on the basis that implied volatility subsumes the information content of past volatility and is a forward-looking measure of future volatility (see Christensen and Prabhala, 1998).

Of course, it is worth noting that using implied volatility may not generally provide researchers with a better estimate of volatility beyond what is produced by conventional models (such as the GARCH framework). For example, literature on this subject has drawn mixed conclusions. Jorion (1995) documents that implied volatility predicts future volatility for foreign currency futures. Day and Lewis (1992) and Canina

and Figlewski (1993) find that implied volatility on S&P100 index options is not a reliable predictor of future volatility.

These above findings notwithstanding, Guo and Whitelaw (2006) find, using implied volatility, that the coefficient of relative risk aversion is positive and statistically significant. Furthermore, shifts in the dynamic market risk premium appear to be driven primarily by shifts in the investment opportunity set and not changes in volatility. Therefore, they reach a conclusion similar to Scruggs (1998). Namely, existing studies which document counterintuitive and insignificant results suffer from a "classical omitted variables problem" (p. 1436).

One obvious drawback to using implied volatility is the fact that it only goes back until November 1983. To counter this problem and to check the robustness of their results over a larger sample, they estimate volatility using the consumption-wealth ratio (see Lettau and Ludvigson, 2001) and the stochastically detrended risk-free rate.[17] Even when using this approach they obtain qualitatively similar results. Although the standard error for their estimate is higher, they still find relative risk aversion to be significantly positive and that the risk premium is driven by changes in the investment opportunity set. Therefore, its omission may be responsible for the conflicting findings documented in the literature and can result in biased estimates of the coefficient of relative risk aversion.

In terms of defining the hedge component, Guo and Whitelaw (2006) employ an empirical specification to describe shocks to expected returns and to the hedge component. This methodology is based on a long-linearization model by Campbell and

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[17] Details on the importance and uses of the consumption-wealth ratio, as well as actual data, are available at Professor M. Lettau's website, http://faculty.haas.berkeley.edu/lettau/.

Shiller (1988) and models the risk and hedge component using the risk-free rate and cash flow forecasts.[18]

When discussing previous studies and the reason why Scruggs (1998) and Scruggs and Glabadanidis (2003) document conflicting results, they argue that this result "Does not imply a rejection of… (Merton's ICAPM); rather, it challenges the assumption that bond returns are perfectly correlated with investment opportunities" (p. 1435). This conclusion is similar to the one discussed from Scruggs and Glabadanidis (2003) in the sense that these authors question whether the long-term government bond yield is a perfect proxy for investment opportunities. Perhaps an alternative set of factors should be explored when testing Merton's (1973) ICAPM; one of the principal suggestions of existing authors and the contribution of this chapter.

Gerard and Wu (2006) examine the importance of the hedging component within the context of investors' asset allocation strategy and whether omission of this component is responsible for the weak risk-return relation described by many authors. Consistent with Turtle, Buse and Korkie (1994), Scruggs (1998) and Scruggs and Glabadanidis (2003), they too employ the long-term government bond yield as a hedge factor that characterizes how the distribution of returns changes through time as investment prospects and economic conditions change. The study by Gerard and Wu (2006) is innovative in the sense that it tests the proposition that the long-term government bond yield represents a significant priced risk factor on four broad asset classes: Large stocks, small stocks, long-term treasuries and corporate bonds, respectively. They further examine the time-varying nature of the market risk component, $\sigma_{M,t}^{2}$, and the

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[18] Campbell, Lo and Mackinlay (1997, Chapter 7) provide a thorough discussion of this methodology.

intertemporal risk component, $\sigma_{MF,t}$, for these broad asset portfolios and whether their respective premia fluctuate with shifts in the business cycle. The benefits associated with diversification are equally addressed and whether such benefits are more pronounced during recessionary periods relative to periods of economic expansion.

They propose a unified framework to explore these questions, adopted from Glen and Jorion (1993), in which they construct optimal asset allocation portfolios for different classes of investors. Their objective is to model the respective prices for bearing market and intertemporal risk, as well as to allow the covariance between the long-term government bond yield and each of the broad asset portfolios mentioned to be time-varying. This framework thus provides useful insights as to which portfolios are most or least sensitive to changes in investment opportunities. This approach is also instrumental in identifying whether shifts in the business cycle play a significant role in estimating the premia for the market and intertemporal risk components.

From their analysis, Gerard and Wu (2006) find that exposure to market and intertemporal risk is significantly priced. However, market risk is the dominant form of risk for equities while exposure to intertemporal risk accounts for the majority of the risk premium for assets comprised of fixed-income instruments. Therefore, this evidence suggests that stocks (especially from small firms) can serve as hedges against shifts in investment opportunities: "Our findings point to the merit of including small stocks in long-term strategic asset allocations for investors such as pension funds and insurance companies" (p. 2205).

As mentioned previously, Artis, Kontolemis and Osborn (1997) find that economic conditions respond asymmetrically to shifts in business cycle regimes. For

example, they find that industrial production in the United States declines substantially more during economic downturns than it rises during expansionary periods. Therefore one can intuitively deduce that intertemporal risk also varies according to general market conditions and, especially, to changes in the business cycle. More specifically, we would expect investors to demand a higher premium for bearing intertemporal risk during market downturns.

Gerard and Wu (2006) test this proposition and find that the effects of business cycle shifts on the market and intertemporal risk premia are, in fact, asymmetric in nature. Namely, the price for bearing intertemporal risk during periods of economic contraction is much higher relative to periods of economic expansion. Therefore, investors demand a relatively higher return to carry intertemporal risk during market downturns proportionate to periods when the market is doing well. Likewise, and not surprisingly, the price for bearing systematic risk is also much higher during market downturns.

These results complement the findings of Artis, Kontolemis and Osborn (1997) and highlight the economic significance of considering intertemporal risk when constructing a portfolio, especially during down markets. Their study concludes that, during economic recessions, the benefits of intertemporal hedging are more pronounced and that investors are even willing to pay a premium for this hedging. Gerard and Wu (2006) point out that their results are in agreement with a study by Ang and Bekaert (2004), who find that investors switch to more liquid investments during periods of adverse economic conditions. This finding is also evocative of the recognized market phenomena known as "flight to liquidity;" whereby investors, in the face of augmented

market volatility and uncertainty, sell their positions in risky and illiquid assets and invest in relatively "safer" and more liquid instruments (such as short-term treasuries).

Faff and Chan (1998) apply a two-factor variant of Merton's ICAPM to the Australian and World market indices, respectively. Unlike some of the other studies cited which use the long-term government bond yield as a hedging factor, they explore whether the price of gold bullion can capture intertemporal risk and if, along with the price for market risk, their model can better characterize movements in the dynamic risk premium. They explicitly investigate the possibility of price movements in gold as a potential hedging factor in the Australian market and cite three reasons for this: (a) Australia is a leader among nations in the production of gold; (b) a large portion of the mining companies in Australia are gold mining companies; and (c) Australia's mining sector is a huge source of wealth for its economy.[19]

Their decision to use movements in gold as a hedging factor is also motivated by a study by Rubio (1989), which explores the empirical implications of the ICAPM when using gold and the long-term government bond yield, respectively, as state factors within the Spanish stock exchange. Findings from Rubio's (1989) study give a statistically unambiguous rejection of Merton's (1973) ICAPM, regardless of whether the long-term government bond yield or gold serves as a hedging factor. This result calls into question whether gold and the long-term government bond yield can serve as adequate proxies for the hedging component. As Rubio (1989) points out, with regards to the long-term risk-free rate, the Spanish economic authorities imposed tight regulations on the issuance of public debt and maintained absolute control over the level of its interest rates. In addition, publicly issued securities came with a predefined set of conditions which had to

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[19] For more information, see the Australian Bureau of Labor Statistics at http://www.abs.gov.au.

be met in order to be qualified for investment by banks and other financial institutions. This tight regulation depressed the trading volume of these securities and essentially immobilized the exchange of bonds in the secondary market. This was not surprising considering that the market for government issued bonds represented only a small percentage of the value of the total market.

Although in the United States market such tight regulation does not exist as it prevailed for some time in Spain, the long-term government bond yield is still correlated to the decisions and actions of the Federal Reserve Bank. Hence, implementation of this factor as a hedging component may not necessarily reflect all true intertemporal risk which impacts the consumption and marginal utility of investors on aggregate. This point forms the basis for the argument in this chapter that perhaps we should seek alternative proxies, such as industrial production and twists in the yield curve, which may serve as hedging factors.

Keeping this in mind, it is not surprising that Rubio's (1989) findings reject the ICAPM when the long-term government bond yield is used as a hedging factor. As far as gold is concerned, when used as a hedging factor within the framework of Merton's (1973) ICAPM, Rubio (1989) finds that it is no better in characterizing movements in the dynamic risk premium: "It seems, at least when gold is used as the hedging asset, that the empirically implemented ICAPM does not provide a more reasonable description of security returns than the CAPM" (p. 734). Rubio (1989) expresses in his paper that perhaps alternative hedging factors merit consideration and that more research in this area is warranted: "Unfortunately, the failure of the model might be due to the practical

impossibility of finding an adequate hedging asset. More research in this direction is largely justified" (p. 737).

Faff and Chan (1998) seek to expand on this topic by applying gold as a hedging factor to the Australian market for the reasons mentioned earlier. If gold is such an important element in Australia's economy, intuitively, it may therefore serve as an appropriate hedging factor which can proxy for changes in intertemporal risk. Faff and Chan (1998) explore this possibility and provide evidence from an earlier paper of theirs (see Chan and Faff, 1998) which tests whether price movements in gold have a pervasive influence on various industry sector returns in the Australian market. Similar to applying an extended single-period CAPM using ordinary least squares (OLS) estimation (i.e. a two-factor CAPM), their model takes the form

$$R_{i,t} = \alpha_i + \beta_i R_{M,t} + \gamma_i GPR_t + \varepsilon_{i,t}$$

where $R_{i,t}$ represents the return on the *i*th industry portfolio at time *t*. The return on the market index and its corresponding market beta are denoted as $R_{M,t}$ and $\beta_i$, respectively. The return series for the price of gold is denoted as $GPR_t$ and its corresponding factor loading is represented by $\gamma_i$. The disturbance term is indicated by $\varepsilon_i$.

When applying this model across different industry sectors, estimates for their asset pricing parameters indicate prevalent sensitivity to price movements in gold over and above the return on the market index.

Further evidence on the usefulness of gold as an effective hedging asset in investors' portfolios has been discussed extensively in literature aimed to practitioners

and investors.[20] These studies all point to the merit of including gold in investment portfolios which, in some cases, can reduce the variance of the overall portfolio.

Other academic studies provide evidence that gold is tied to a broad range of macroeconomic, and even political, factors; all of which directly impact investors' consumption and ultimately their marginal utility of wealth. Spieler (1967) presents views on how gold can act as a hedge against political unsteadiness. Koutsoyiannis (1983) presents evidence from the U.S. market on the interlinkages gold has with a comprehensive set of factors; namely, among others, the strength of the U.S. dollar, changes in the interest rate, movements in the expected rate of inflation, the prices of other equities and financial instruments, and the world price for oil. Consistent with a priori expectations, the demand for gold (and consequently its price) is inversely related to the strength of the U.S. dollar, the rate of interest (which can be rightly construed as the opportunity cost of holding gold instead of investing money in possibly other income-earning assets), and the prices of equities and other financial instruments. Movements in the price for crude oil are positively related to the demand and price for gold insofar as the official decisions of the OPEC cartel are coherent with real market supply and demand conditions. Thus, gold exhibits no statistical relation to the official price in Saudi Arabia of crude oil established by the OPEC cartel; an indication that gold reflects real fundamentals in the marketplace and not arbitrary forces.

Of course, a caveat when measuring the movements of any economic factor against another is that no empirical model can wholly give us a pure representation and oftentimes there are a multitude of other factors that have not been accounted for. Capie

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[20] See for example Shishko (1977), Carter, Affleck-Graves and Money (1982), Sherman (1982), Landa and Irwin (1987), Jaffe (1989), and Adrangi, Chatrath and Raffiee (2003), to name only a few.

and Wood (2005) make this point and although find some support that gold can hedge against inflation, they remark that this relationship holds "*faute de mieux*" (p. 352).

Nonetheless, given the evidence from their earlier paper; i.e. Chan and Faff (1998), and literature discussing gold as a unique asset class which can guard investors' portfolios from adverse shifts in economic conditions, Faff and Chan (1998) proceed to test empirically Merton's (1973) ICAPM. They focus on the Australian market for the reasons outlined earlier and, unlike some of the other studies mentioned which utilize some form of the bivariate GARCH framework, instead use the GMM estimation procedure.

Others explore whether other factors, apart from the macroeconomic factors proposed by Chen, Roll and Ross (1986) can possibly serve as proxies for the investment opportunity set, though not exactly within the context of the risk-return tradeoff. For example, Breenan and Xia (2006) explore a variant of Merton's (1973) ICAPM whereby stochastic shifts in investment opportunities are characterized by movements in the interest rate and the Sharpe ratio; i.e. the slope of the capital market line (CML). Their study is motivated by an earlier model they developed (see Breeden, Wang and Xia, 2004) in which variations in the opportunity set are contingent only on the dynamics of the interest rate and the Sharpe ratio and, as they report, this model compares favorably to the three-factor model proposed by Fama and French (1993, 1995 and 1996).

They defend using the Sharpe ratio on theoretical grounds. Namely, the slope of the CML is dependent on the volatility and risk premium of the market portfolio. As already mentioned, one of the major criticisms against the classical single-period CAPM is the fact that it ignores changes in the investment opportunity set and does not capture

the time-varying properties of risk and the risk premium on the market portfolio. However, strong evidence suggests that these parameters are time-varying across different time periods and business cycles. For example, Fama and French (1989), Keim and Stambaugh (1986), Kandel and Stambaugh (1989) and Whitelaw (1994), to name only a few, use various macroeconomic factors in an attempt to predict returns on the market portfolio. The general consensus is that these macroeconomic factors vary in terms of explanatory power across sample periods and shifts in business cycle regimes; evidence which supports the notion that the conditional first and second moments of market returns are time-varying. Therefore, given this stylized fact in the literature, we would also expect to see time variation in the market Sharpe ratio; something which has in fact been documented by authors (see Perez-Quiros and Timmermann, 2000). Nielsen and Vassalou (2001) provide a formal discussion demonstrating that investors wish to hedge against any shifts in the intercept (i.e. the interest rate) and slope (i.e. Sharpe ratio) of the CML.

In light of these previous findings, Breenan and Xia (2006) proceed to test the relationship between security betas and the respective risk qualities of their cash flows. Consistent with other empirical findings (see for example Cornell, 1999) and with a priori expectations, security betas rise when the cash flow maturity is higher. Expected returns on securities appear to be more difficult to decipher than betas on these securities. Even so, their evidence suggests that expected returns are a function of the 'riskiness' behind a firm's cash flows as well as shifts in their two state factors; namely, the Sharpe ratio and the interest rate. They conclude that state factors are "likely to be an important determinant of the level of stock prices…" (p. 28).

Given the vital importance of considering state factors as a proxy for shift in the investment opportunity set, this chapter proceeds to test a two-factor version of the Merton (1973) ICAPM in Equation (3.3) across the G-7 stock markets to see whether it is possible to detect a positive intertemporal risk-return tradeoff. If so, it is quite possible that existing studies which predominantly use some GARCH-in-mean methodology are omitting the importance of intertemporal risk in agents' utility maximization investment decision-making.

## 3.3. Methodology

The empirical version of the dynamic two-factor model, based on Merton's (1973) ICAPM can be described by equations (3.6a) and (3.6b):

$$r_{m,t} = \lambda_{m,0} + \lambda_{m,m} \sigma^2_{m,t} + \lambda_{m,h,t} \sigma_{mh,t} + \varepsilon_{m,t} \qquad (3.6a)$$
$$r_{h,t} = \lambda_{h,0} + \lambda_{h,m} \sigma_{mh,t} + \lambda_{hh} \sigma^2_{h,t} + \varepsilon_{h,t} \qquad (3.6b)$$

where, $r_{m,t}$ is the excess return on the market portfolio, $r_{h,t}$ is the excess return on the hedging factor, $\sigma^2_{m,t}$ is the conditional variance of the market, $\sigma^2_{h,t}$ the conditional variance for the hedging factor, $\varepsilon_{m,t}$ and $\varepsilon_{h,t}$ are the error terms and $\lambda_{m,0}$, $\lambda_{m,m}$, $\lambda_{m,h,t}$, $\lambda_{h,0}$, $\lambda_{h,m}$, $\lambda_{h,h,t}$ are parameters to be estimated. As can be seen from Equations (3.6a) and (3.6b) the conditional means of $r_{m,t}$ and $r_{h,t}$ are functions of their corresponding conditional variances and the conditional covariance. Using matrix notation, the variance-covariance equation of the joint distribution of the error terms can be written as:

$$H_t = C'C + A'E_{t-1}E'_{t-1}A + D'U_{t-1}U'_{t-1}D + B'H_{t-1}B \qquad (3.7)$$

where, $H_t$ is the (2x2) variance covariance matrix; $E_t$ is the (1x2) vector of error terms; $U_t$ is the (1x2) vector of negative errors i.e., $U_t = min(0, E_t)$; A, B, and D are symmetric (2x2) matrix of slope coefficients; and C is the (1x2) vector of constants.

Expanding Equation (3.7) and imposing the restriction that the off diagonal elements of A, B, and D are zero we obtain the following scalar expressions for the variances and the covariance:[21]

$$\sigma^2_{m,t} = c^2_m + a^2_m \varepsilon^2_{m,t-1} + d^2_m u^2_{m,t-1} + b^2_m \sigma^2_{m,t-1} \tag{3.8a}$$
$$\sigma^2_{h,t} = c^2_h + a^2_h \varepsilon^2_{h,t-1} + d^2_h u^2_{h,t-1} + b^2_h \sigma^2_{h,t-1} \tag{3.8b}$$
$$\sigma_{mh,t} = c_m c_h + a_m a_h \varepsilon_{m,t-1} \varepsilon_{h,t-1} + d_m d_h u_{m,t-1} u_{h,t-1} + b_m b_h \sigma_{mh,t-1} \tag{3.8c}$$

The structure of $H_t$ described by Equations (3.8a), (3.8b) and (3.8c) is referred to as the BEKK model and it has two advantages over competing multivariate GARCH models. Firstly, it ensures that the variance-covariance matrix is positive semi-definite and secondly it allows the covariance and the correlation coefficient to be time varying (see Engle and Kroner, 1995). The conditional variances in Equations (3.8a) and (3.8b) are functions of past squared residuals and past conditional variances very much like in the standard GARCH models. The parameters are squared to ensure non-negativity. Likewise, the covariance is a function of the product of past errors and past covariances. The model allows for both variances and the covariance to respond asymmetrically to past residuals. This asymmetry is introduced via the terms $u_{m,t} = min(0, \varepsilon_{m,t})$ and $u_{h,t} = min(0, \varepsilon_{h,t})$. For example, when $\varepsilon_{m,t} = +1\%$ the conditional variance will increase by $a^2_m$ and when $\varepsilon_{m,t} = -1\%$ the conditional variance will increase by $a^2_m + d^2_m$ so that $d^2_m$ measures the incremental impact of the negative errors. A measure of volatility asymmetry can be based on the ratio $(a^2_m + d^2_m)/ a^2_m$. In the covariance function

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[21] Setting the off-diagonal parameters equal to zero is very common and it is done to make the model easier to estimate and interpret.

asymmetry is captured by $d_m d_h$.  The time-varying correlation coefficient is equal to

$\sigma_{mh,t} / \sigma_{m,t} \; \sigma_{h,t}$.

In order to estimate the parameters of the model some assumption needs to be made about the joint distribution of the error terms.  Assuming conditional normality, we can estimate the parameters by maximizing the sample log-likelihood function which can be written as:

$$L(\Theta)= -T \, log(2\pi) - (1/2)\Sigma_t(log \, /H_t/ + E_t H_t^{-1} E'_t) \text{ for t=1,...T} \qquad (3.9)$$

where, T is the number of observations, $E_t=[ \; \varepsilon_{m,t} \; , \; \varepsilon_{h,t}]$ is the vector of errors and $H_t$ is the variance-covariance matrix described by Equations (3.7) through (3.8c). The maximization of Equation (3.9) is based on the Berndt, Hall, Hall and Hausman (1974) algorithm.  The code is written in RATS version 7.


## 3.4. Data and Major Empirical Findings

This study applies the dynamic two factor model to the markets of the G-7 (Canada, France, Germany, Italy, Japan, UK and USA). It is important to examine the intertemporal risk-return tradeoff in international markets because this carries implications about how investors' risk premium varies with changes in market volatility and intertemporal risk of various respective countries.

The data used are monthly and they consist of the following variables for each country: The stock price index, the dividend yield, the 10-year yield to maturity on government bonds, the short term-rate on Treasury bills and the industrial production index. The sample periods and the number of observations are reported in Table 3.1 and are dictated by the availability of all data necessary to complete this study at the time of

data collection. It is important that the data came from a single source and I avoided splicing together data from different sources such as, for example, adjoining data from DataStream with data from the International Monetary Fund (IMF), the National Bureau of Economic Research (NBER), or other research divisions within various Central Banks.

**Table 3.1:   Markets and Sample Sizes**

| COUNTRY | EXCHANGE | SAMPLE PERIOD | NUMBER OF OBSERVATIONS |
|---|---|---|---|
| Canada | Toronto | January 1980 – May 2008 | 341 |
| France | Paris | January 1989– May 2008 | 234 |
| Germany | Frankfurt | January 1975 – May 2008 | 401 |
| Italy | Milan | January 1980 – May 2008 | 341 |
| Japan | Tokyo | January 1973 – May 2008 | 425 |
| UK | London | January 1967 – May 2008 | 498 |
| USA | New York | January 1968 – May 2008 | 485 |

Note:  For each market, the data set consists of monthly observation on the stock price index and its corresponding dividend yield, the industrial production index, the yield on the 10-year government bond and the yield on the 3-month Treasury bill.

The stock price index and the dividend yield are used to calculate monthly excess returns on the stock market portfolio.  The 10-year yield to maturity is used to calculate the one-month holding period excess return on the long-term bond. The calculation is based on the duration, assuming yields to maturity correspond to par value bonds. The slope of the yield curve is calculated as the difference between long-term and short-term yields to maturity.

Preliminary statistics for the market excess return, the long-term rate excess return, percent changes in industrial production and changes in the slope of the yield curve are reported in Table 3.2.

**Table 3.2: Descriptive Statistics**

| | Canada | France | Germany | Italy | Japan | UK | USA |
|---|---|---|---|---|---|---|---|
| **Market Excess Returns** | | | | | | | |
| Mean | 0.7977 | 0.5220 | 0.7849 | 0.9682 | 0.2872 | 0.9759 | 0.7264 |
| Standard Deviation | 4.6206 | 5.6549 | 5.9144 | 6.9904 | 5.1724 | 5.6222 | 4.4983 |
| Skewness | -1.2083 | -0.5454 | -0.8473 | 0.3157 | -0.4537 | 0.0513 | -0.7140 |
| Kurtosis | 5.0432 | 0.4772 | 3.0797 | 1.4985 | 1.9454 | 8.4582 | 2.7063 |
| Minimum | -25.3622 | -18.9168 | -29.1330 | -22.9901 | -22.7172 | -30.7932 | -24.2862 |
| Maximum | 13.7084 | 12.8619 | 19.6155 | 28.6602 | 16.7493 | 42.7850 | 15.3846 |
| **Long Bond Excess Returns** | | | | | | | |
| Mean | 0.8418 | 0.6223 | 0.6301 | 1.0038 | 0.50030 | 0.7809 | 0.6481 |
| Standard Deviation | 2.2121 | 1.5525 | 1.4443 | 2.0213 | 2.0179 | 1.8956 | 2.0171 |
| Skewness | 0.3414 | 0.2437 | -0.2627 | 0.6272 | 0.0621 | 0.7404 | 0.3832 |
| Kurtosis | 3.3312 | 0.2354 | 0.7106 | 2.9255 | 4.2992 | 2.0542 | 2.5335 |
| Minimum | -7.8612 | -3.2885 | -5.2204 | -4.9533 | -9.2922 | -5.3024 | -7.8500 |
| Maximum | 12.3358 | 5.2112 | 5.6695 | 11.2142 | 9.7178 | 9.5779 | 9.7851 |
| **% Change in Industrial Production** | | | | | | | |
| Mean | 0.1276 | 0.0076 | 0.9867 | 0.00198 | 0.0841 | 0.0637 | 0.1733 |
| Standard Deviation | 5.8888 | 1.1987 | 1.7247 | 32.6098 | 1.6744 | 1.3988 | 0.7576 |
| Skewness | -0.7366 | -0.4506 | -0.0295 | -0.0705 | -1.4901 | -0.1295 | -1.0570 |
| Kurtosis | 0.1277 | 2.0115 | 6.3930 | 2.8084 | 8.5569 | 10.6126 | 4.4613 |
| Minimum | -15.9697 | -5.4250 | -9.4310 | -9.7082 | -10.6272 | -8.1973 | -4.0380 |
| Maximum | 10.7418 | 3.3052 | 11.2711 | 9.6522 | 5.7787 | 9.4243 | 2.3643 |

**Table 3.2 {Continued}**

**Changes in the Slope of the Yield Curve**

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Mean | 0.0151 | 0.0133 | 0.0008 | 0.0114 | -0.0012 | 0.0092 | 0.0056 |
| Standard Deviation | 0.5514 | 0.3929 | 0.3530 | 0.5646 | 0.3973 | 0.5532 | 0.4066 |
| Skewness | -0.9895 | 0.0225 | -2.0099 | 0.5377 | 0.0437 | -0.8791 | 0.6714 |
| Kurtosis | 12.7435 | 6.0008 | 23.4449 | 6.0925 | 3.2773 | 5.8169 | 12.8650 |
| Minimum | -4.1400 | -1.8600 | -3.4700 | -2.0180 | -1.6500 | -3.6700 | -2.1900 |
| Maximum | 2.8100 | 2.0100 | 1.4762 | 3.5480 | 1.8861 | 1.8300 | 3.3300 |

Note: The sample period of these statistics are found in Table 3.1. The following indices are used: Toronto 300 Composite (Canada), CAC industrial price index (France), DAX price index (Germany), Milano price index (Italy), Nikkei 225 (Japan), FT All Share Index (UK) and the S&P 500 (USA).

The sample means for the market and the long term rate excess returns are mostly significant with minor exceptions, whereas the means of percent changes in industrial production and changes in the slope of the yield curve are insignificant. Measures of skewness and kurtosis are almost always significant implying that the sample distributions are not normal. A good part of the non-normality is due to conditional heteroskedasticity (i.e., ARCH effects) which is present in most economic and especially financial time series and was discussed in further detail in the second chapter of this thesis.

Table 3.3 reports pairwise correlations along with the corresponding t-statistics for the three hedging instruments used in this study. As can be seen, the correlations between changes in the long-bond rate and changes in industrial production are very low and statistically no different than zero. The same is true for the correlations between industrial production and changes in the yield curve. On the other hand, the correlations between the changes in the long term rate and changes in the yield curve are negative and in most cases statistically significant, even though the numerical values are very low. It

should be pointed out though that these correlations are not very informative as far as their independent explanatory power in the dynamic two-factor ICAPM. The reason is that the model uses as explanatory variables the variances and the covariances rather than the variables themselves.

**Table 3.3:    Pairwise Factor Correlations**

|  | Canada | France | Germany | Italy | Japan | UK | USA |
|---|---|---|---|---|---|---|---|
| $\rho_{B,IP}$ | 0.0605 | -0.0549 | -0.0315 | 0.0120 | -0.0709 | -0.0321 | -0.0545 |
|  | (1.084) | (-0.902) | (-0.742) | (0.228) | (-1.081) | (-0.725) | (-0.579) |
| $\rho_{B,YC}$ | -0.2745 | -0.3749 | -0.1438 | -0.2134 | -0.6009 | -0.1351 | -0.1340 |
|  | (-3.648)** | (-4.606)** | (-1.830)* | (-3.255)** | (-7.139)** | (-2.621)** | (-1.597) |
| $\rho_{IP,YC}$ | -0.0718 | -0.0367 | -0.0776 | 0.0298 | 0.0331 | -0.0169 | -0.0782 |
|  | (-1.555) | (-0.227) | (-1.408) | (0.662) | (0.861) | (-0.379) | (-1.255) |

Note:   (**) and (*) denote significance at the 5% and 10% significance level, respectively.
$\rho_{B,IP}$ is the correlation coefficient between the holding period return on the long bond and percent changes in industrial production;
$\rho_{B,YC}$ is the correlation coefficient between the holding period return on the long bond and changes in the slope of the yield curve;
$\rho_{IP,YC}$ is the correlation coefficient between percent changes in industrial production and changes in the slope of the yield curve.
Under the null hypothesis that the true correlation is zero, the t-statistic is calculated as  $t = [\rho(T-2)^{1/2}] / [(1-\rho^2)^{1/2}]$ where $\rho$ is the estimated correlation coefficient.

Tables 3.4 through 3.7 report results from univariate asymmetric GARCH models (see Glosten, Jagannathan and Runkle, 1993) for the market excess returns and the three variables used as hedging instruments; namely, the long bond excess returns, percent changes in industrial production and changes in the slope of the yield curve.

**Table 3.4: Asymmetric GARCH-M for Excess Market Returns ($r_{m,t}$)**

$$r_{m,t} = \lambda_0 + \lambda_1 \sigma^2_{m,t} + \varepsilon_{m,t} \text{ and } \sigma^2_{m,t} = c^2 + a^2 \varepsilon^2_{m,t-1} + d^2 u^2_{m,t-1} + b^2 \sigma^2_{m,t-1}$$

|  | Canada | France | Germany | Italy | Japan | UK | USA |
|---|---|---|---|---|---|---|---|
| $\lambda_0$ | 1.2641 | 1.0082 | 0.7407 | 1.0584 | 1.0691 | 0.7155 | 0.7321 |
|  | (1.755)* | (1.088) | (1.457) | (1.420) | (2.451)** | (2.195)* | (1.167) |
| $\lambda_1$ | -0.0131 | -0.0058 | 0.0063 | 0.0008 | 0.0243 | 0.0162 | 0.0065 |
|  | (-0.290) | (-0.174) | (0.367) | (0.046) | (1.220) | (1.502) | (0.188) |
| $c^2$ | 11.9994 | 8.9349 | 1.3721 | 5.0446 | 0.4801 | 1.3964 | 7.8077 |
|  | (5.199)* | (2.099)** | (2.145)** | (1.820)* | (2.159)** | (2.036)** | (3.682)** |
| $a^2$ | 0.0695 | 0.0536 | 0.1838 | 0.2120 | 0.0615 | 0.1696 | 0.0730 |
|  | (1.512) | (0.633) | (2.727)* | (2.973)* | (2.549)* | (3.590)* | (1.506) |
| $d^2$ | 0.6723 | 0.2988 | 0.0748 | 0.0701 | 0.0422 | 0.0110 | 0.2835 |
|  | (5.303)* | (1.739)* | (1.337) | (1.098) | (1.422) | (0.228) | (2.620)** |
| $b^2$ | 0.1503 | 0.4837 | 0.8277 | 0.7216 | 0.9002 | 0.7974 | 0.4981 |
|  | (1.295) | (2.263)** | (18.469)* | (6.890)** | (41.479)** | (18.263)** | (3.210)** |

Note:  (**) and (*) denote significance at the 5% and 10% significance level, respectively.

**Table 3.5: Asymmetric GARCH-M for Excess Long-Term Bond Returns ($r_{h,t}$)**

$$r_{h,t} = \lambda_0 + \lambda_1\, \sigma^2_{h,t} + \varepsilon_{m,t} \ \text{ and } \ \sigma^2_{h,t} = c^2 + a^2 \varepsilon^2_{m,t-1} + d^2\, u^2_{h,t-1} + b^2 \sigma^2_{h,t-1}$$

|  | Canada | France | Germany | Italy | Japan | UK | USA |
|---|---|---|---|---|---|---|---|
| $\lambda_0$ | 0.3621 | 1.7233 | 0.5623 | 0.6802 | 0.3207 | 0.3046 | 0.1967 |
|  | (2.210)** | (2.445)** | (0.585) | (4.989)** | (2.773)** | (1.907)* | (1.072) |
| $\lambda_1$ | 0.1139 | -0.4302 | 0.2767 | 0.0218 | 0.0426 | 0.1301 | 0.1172 |
|  | (2.501)** | (-1.430) | (4.987)** | (0.600) | (1.148) | (2.417)** | (2.196)** |
| $c^2$ | 0.0265 | 0.5044 | 1.9158 | 0.7577 | 0.4488 | 0.0055 | 0.1884 |
|  | (0.817) | (1.167) | (9.019)** | (3.429)** | (4.366)** | (0.366) | (2.937)** |
| $a^2$ | 0.0271 | 0.0187 | 0.0378 | 0.6311 | 0.5286 | 0.0422 | 0.1093 |
|  | (1.170) | (0.376) | (5.575)** | (4.143)** | (4.887)** | (2.773)** | (3.001)** |
| $d^2$ | 0.0432 | 0.1161 | 0.1150 | 0.1175 | 0.2146 | 0.0070 | 0.0047 |
|  | (1.325) | (1.013) | (9.610)** | (0.679) | (1.769)* | (0.356) | (0.137) |
| $b^2$ | 0.9394 | 0.7251 | 0.08623 | 0.3701 | 0.5353 | 0.9537 | 0.8448 |
|  | (52.829)** | (3.751)** | (0.974) | (4.247)** | (7.817)** | (99.295)** | (25.508)** |

*Note:* (**) and (*) denote significance at the 5% and 10% significance level, respectively.

**Table 3.6: Asymmetric GARCH-M for Percent Changes in Industrial Production ($r_{h,,t}$)**

$$r_{h,t} = \lambda_0 + \lambda_1 \sigma^2_{h,t} + \varepsilon_{m,t} \text{ and } \sigma^2_{h,t} = c^2 + a^2 \varepsilon^2_{m,t-1} + d^2 u^2_{h,t-1} + b^2 \sigma^2_{h,t-1}$$

| | Canada | France | Germany | Italy | Japan | UK | USA |
|---|---|---|---|---|---|---|---|
| $\lambda_0$ | -2801 | -6.4870 | 0.1944 | -4.0292 | -2.9584 | 0.0200 | 0.7719 |
| | (-0.685) | (-1.028) | (3.056)** | (-2.374)** | (-2.066)** | (0.344) | (11.900)** |
| $\lambda_1$ | 8.1088 | 6.6040 | 23.7310 | 1.5040 | 1.8278 | 0.0451 | -1.3188 |
| | (0.115) | (1.048) | (0.087) | (0.165) | (2.140)** | (1.197) | (-7.181)** |
| $c^2$ | 15.7849 | 1.3533 | 3.1394 | 16.768 | 2.4346 | 0.7190 | 0.0695 |
| | (3.562)** | (9.200)** | (6.012)** | (2.946)** | (7.503)** | (6.995)** | (3.201)** |
| $a^2$ | 0.3290 | 0.0328 | 0.0718 | 0.2482 | 0.0536 | 0.5083 | 0.0681 |
| | (5.381)** | (1.006) | (5.741)** | (6.008)** | (1.847)* | (4.496)** | (5.346)** |
| $d^2$ | 0.4346 | 0.0859 | 0.3890 | 0.4736 | 0.1070 | 0.3724 | 0.2611 |
| | (2.593)** | (1.012) | (6.635)** | (4.763)** | (2.041)** | (2.181)** | (4.997)** |
| $b^2$ | 0.5538 | 0.3718 | 0.0250 | 0.0329 | 0.8526 | 0.0632 | 0.7790 |
| | (4.242)** | (3.417)** | (0.162) | (0.169) | (11.294)** | (1.202) | (12.050)** |

*Note:* (**) and (*) denote significance at the 5% and 10% significance level, respectively.

**Table 3.7: Asymmetric GARCH-M for Changes in the Yield Curve ($r_{h,,t}$)**

$$r_{h,t} = \lambda_0 + \lambda_1\, \sigma^2_{h,t} + \varepsilon_{m,t} \text{ and } \sigma^2_{h,t} = c^2 + a^2 \varepsilon^2_{m,t-1} + d^2\, u^2_{h,t-1} + b^2 \sigma^2_{h,t-1}$$

|  | Canada | France | Germany | Italy | Japan | UK | USA |
|---|---|---|---|---|---|---|---|
| $\lambda_0$ | -0.0678 | -0.0278 | -0.0205 | -0.0266 | -0.0097 | 0.0050 | -0.0181 |
|  | (-2.713)** | (-1.763)* | (-1.154) | (-1.750)* | (-0.847) | (0.239) | (-1.018) |
| $\lambda_1$ | 0.2552 | 0.1720 | 0.1706 | 0.0849 | 0.0537 | -0.0491 | 0.0478 |
|  | (2.432)** | (0.892) | (0.714) | (0.772) | (0.404) | (-0.479) | (0.308) |
| $c^2$ | 0.0090 | 0.0003 | 0.0006 | 0.0006 | 0.0008 | 0.0001 | 0.0107 |
|  | (3.057)** | (0.296) | (1.274) | (0.540) | (2.084)** | (0.448) | (3.446)** |
| $a^2$ | 0.3255 | 0.2059 | 0.0763 | 0.2119 | 0.0413 | 0.0721 | 0.3185 |
|  | (3.942)** | (2.635)** | (3.660)** | (2.819)** | (2.201)** | (5.184)** | (4.832)** |
| $d^2$ | 0.1231 | 0.0490 | 0.0535 | 0.0569 | 0.1810 | 0.0470 | 0.0400 |
|  | (1.580) | (0.473) | (1.577) | (0.569) | (3.662)** | (2.843)** | (0.462) |
| $b^2$ | 0.7405 | 0.7909 | 0.9032 | 0.7892 | 0.8712 | 0.9539 | 0.6333 |
|  | (16.420)** | (16.804)** | (48.811)** | (21.088)** | (47.776)** | (132.487)** | (11.154) |

*Note:* (**) and (*) denote significance at the 5% and 10% significance level

We can think of these models as restricted bivariate GARCH models where the covariances are set equal to zero. Table 3.4 reports the results for the market excess returns. As can be seen the market premium linked to the market risk (variance) is insignificant for all seven countries. Of course, this is a recurrent theme by most studies mentioned in the second chapter of this thesis. One of the explanations for this finding is based on the argument that the univariate model is misspecified because it ignores the role of the hedging factor (see Merton, 1973; Scruggs, 1998).

Regarding the dynamics of the conditional variance, the results show that the variance at time $t$ is a function of the innovation or, error term, and the conditional variance at time $t$-$1$. There is evidence of asymmetry (measured by coefficient $d$) in the conditional variance in the case of Canada, France and the USA. The implication of this is that the variance rises more when innovations are negative (market declines) than it does when innovations are positive (market advances). For the remaining markets there is no evidence of asymmetry. Also, with the exception of Canada, the degree of persistence measured by coefficient $b$ is high.

Table 3.5 reports the results for the excess returns on the long bond. It is interesting to observe that in four out of the seven cases, the risk premium linked to the conditional variance is positive and statistically significant. Specifically, in the cases of Canada, Germany, the UK and the USA the excess return on the long bond is a positive function of the level of the conditional variance. The relevant coefficient $\lambda_1$ is positive and statistically significant at the 5% level of significance at least. This contrasts sharply with the total lack of such a relationship in the case of excess stock market returns. The dynamics of the conditional variances are similar to those for excess stock returns, i.e.,

the variance at time $t$ is a function of innovations and variances at time $t-1$. There is little evidence asymmetries in the variance given that the asymmetry parameter $d$ is insignificant with the exception of Germany (at 5%) and Japan at (10%).

The results for industrial production are reported on Table 3.6. It is remarkable that in most cases (with the exception of France) the volatility of industrial production is asymmetric. The asymmetry parameter $d$ is statistically significant at the 5% level at least. This in turn implies that negative innovations to industrial production are associated with higher volatility than positive innovations. Moreover, in the case of the USA the higher volatility leads to reduced industrial production as can be seen from coefficient $\lambda_1$. The opposite is true for Japan, whereas for the rest of the countries $\lambda_1$ is insignificant. Similarly, for yield curve slope changes, Table 3.7 shows that volatility is a function of past innovations and past volatilities. Asymmetry is significant only for Japan and the UK and the risk premium parameter $\lambda_1$ is significant only for Canada.

These preliminary results shed some light into the time-series properties of the excess market returns as well as the three variables that are being used as candidates for hedging instruments namely, excess returns on long-term bonds, changes in industrial production and changes in the yield curve. They do not take into account however the potential impact of the hedging factor. For that we turn to the dynamic two-factor ICAPM described by equations (3.6a) and (3.6b).

The results of the bivariate dynamic model are reported in Tables 3.8, 3.9, and 3.10, for each respective hedging factor. The focus now is on the behavior of the conditional risk premium and to see whether there is a positive intertemporal risk-return tradeoff.

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**Table 3.8: Bivariate BEKK Model with the Long Term Excess Return as Hedging Factor**

$$r_{m,t} = \lambda_{m,0} + \lambda_{m,m}\,\sigma^2_{m,t} + \lambda_{m,h}\,\sigma_{m,f,t} + \varepsilon_{m,t}$$

$$r_{h,t} = \lambda_{h,0} + \lambda_{h,m}\,\sigma_{m,f,t} + \lambda_{h,h}\,\sigma^2_{h,t} + \varepsilon_{h,t}$$

$$H_t = C'C + A'\,E_{t-1}E'_{t-1}\,A + D'\,U_{t-1}U'_{t-1}\,D + B'\,H_{t-1}B$$

| | Canada | France | Germany | Italy | Japan | UK | USA |
|---|---|---|---|---|---|---|---|
| $\lambda_{m,0}$ | 0.9656 | -1.9728 | 1.1429 | 0.3518 | 0.6487 | 0.3842 | 0.2294 |
| | (2.570)** | (-1.159) | (2.054)** | (0.469) | (1.406) | (1.091) | (0.459) |
| $\lambda_{mm}$ | -0.0094 | 0.0069 | -0.0061 | 0.0086 | -0.0051 | 0.0077 | 0.0090 |
| | (-1.163) | (0.391) | (-0.501) | (0.724) | (-0.331) | (1.218) | (0.453) |
| $\lambda_{mh}$ | 0.0745 | 2.0637 | -0.1620 | 0.1978 | -0.0867 | 0.1240 | 0.2787 |
| | (0.663) | (1.531) | (-0.307) | (1.238) | (-0.640) | (2.275)** | (1.858)* |
| $\lambda_{h,0}$ | 0.3193 | 1.7602 | 1.2113 | 0.9099 | 0.4740 | 0.2529 | 0.2675 |
| | (1.292) | (3.277)** | (6.493)** | (5.546)** | (3.647)** | (1.564) | (1.486) |
| $\lambda_{hm}$ | 0.0271 | -0.3775 | -0.1445 | 0.0224 | 0.0209 | 0.0642 | 0.1736 |
| | (0.489) | (-0.935) | (-1.121) | (0.472) | (0.377) | (3.558)** | (2.417)** |
| $\lambda_{hh}$ | 0.1031 | -0.2586 | -0.2539 | 0.0143 | 0.0035 | 0.0861 | 0.0343 |
| | (3.098)** | (-1.759)* | (-3.385)** | (0.848) | (0.228) | (2.475)** | (0.831) |
| **Model with Zero Constants** | | | | | | | |
| $\lambda_{mm}$ | -0.0031 | 0.0020 | 0.0123 | 0.0130 | 0.0119 | 0.0112 | 0.0164 |
| | (-0.396) | (0.115) | (1.479) | (1.725)* | (1.264) | (2.046)** | (1.381) |
| $\lambda_{mh}$ | 0.2604 | 0.6187 | 0.2545 | 0.2266 | -0.0637 | 0.1460 | 0.3156 |
| | (3.005)** | (1.205) | (0.520) | (1.539) | (-0.473) | (2.882)** | (2.495)** |
| $\lambda_{hm}$ | 0.0727 | 0.5675 | 0.2002 | 0.1575 | 0.0889 | 0.0721 | 0.2035 |
| | (1.699)* | (1.968)** | (1.623) | (3.712)** | (1.674)* | (4.163)** | (2.947)** |
| $\lambda_{hh}$ | 0.1328 | -0.0389 | 0.1701 | 0.0625 | 0.0286 | 0.1282 | 0.0754 |
| | (5.514)** | (-0.291) | (4.385)** | (4.149)** | (2.054)** | (5.793)** | (2.451)** |
| LM | 5.5665 | 5.4754 | 8.3428 | 3.2626 | 5.7856 | 3.6276 | 3.4299 |

Note: (**) and (*) denote significance at the 5% and 10% significance level.
The variance covariance matrix is estimated using the BEKK model. LM is the likelihood ratio test for the hypothesis that the constants are zero. It is distributed as a $\chi^2$ with 2 degrees of freedom. The 5% critical value is 5.99.

**Table 3.9: Bivariate BEKK Model with Industrial Production as Hedging Factor**

$$r_{m,t} = \lambda_{m,0} + \lambda_{m,m}\, \sigma^2_{m,t} + \lambda_{m,h}\, \sigma_{m,f,t} + \varepsilon_{m,t}$$

$$r_{h,t} = \lambda_{h,0} + \lambda_{h,m}\, \sigma_{m,f,t} + \lambda_{h,h}\, \sigma^2_{h,t} + \varepsilon_{h,t}$$

$$H_t = C'C + A'\, E_{t-1}E'_{t-1}\, A + D'\, U_{t-1}U'_{t-1}\, D + B'\, H_{t-1}B$$

|  | Canada | France | Germany | Italy | Japan | UK | USA |
|---|---|---|---|---|---|---|---|
| $\lambda_{m,0}$ | 1.4878 | 0.3417 | 0.8827 | 1.6958 | 0.6308 | 0.6871 | 0.6821 |
|  | (3.795)** | (0.515) | (1.625) | (1.211) | (1.369) | (2.090)** | (1.604) |
| $\lambda_{mm}$ | -0.0132 | 0.0100 | -0.0074 | 0.0092 | -0.0068 | 0.0112 | 0.0017 |
|  | (-1.521) | (0.566) | (-0.605) | (0.766) | (-0.457) | (1.794)* | (0.087) |
| $\lambda_{mh}$ | 0.0970 | -1.3473 | 0.8518 | 0.0509 | -0.3036 | -0.1190 | -0.7201 |
|  | (1.354) | (-0.720) | (1.087) | (0.811) | (-0.371) | (-0.811) | (-0.958) |
| $\lambda_{h,0}$ | -5.5904 | -0.4023 | -0.1145 | -0.4295 | -0.1870 | -0.0852 | 0.3503 |
|  | (-5.079)** | (-1.640) | (-0.481) | (-0.706) | (-1.174) | (-1.297) | (8.779)** |
| $\lambda_{hm}$ | 0.0596 | 0.0871 | -0.1082 | -0.3813 | -0.3320 | 0.1120 | 0.0443 |
|  | (0.686) | (0.235) | (-0.483) | (-1.556) | (-1.503) | (3.183)** | (0.382) |
| $\lambda_{hh}$ | 0.1729 | 0.3934 | 0.1010 | 0.0421 | 0.2025 | 0.0739 | -0.2538 |
|  | (5.677)** | (1.984)** | (1.442) | (13.145)** | (2.690)** | (6.334)** | (-7.258)** |
| | **Model with Zero Constants** | | | | | | |
| $\lambda_{mm}$ | 0.0089 | 0.0174 | 0.0075 | 0.0145 | 0.0101 | 0.0196 | 0.0291 |
|  | (1.359) | (1.758)* | (0.923) | (1.298) | (1.207) | (4.095)** | (2.758)** |
| $\lambda_{mh}$ | -0.0884 | -1.5392 | 1.2714 | -0.0152 | -0.1871 | -0.1113 | -0.8532 |
|  | (-1.652)* | (-0.841) | (1.714)* | (-0.487) | (-0.229) | (-0.756) | (-1.140) |
| $\lambda_{hm}$ | 0.1319 | 0.1311 | -0.1399 | 1.1185 | -0.3978 | 0.1095 | -0.3846 |
|  | (1.485) | (0.353) | (-0.653) | (8.515)** | (-1.860)* | (3.116)** | (-3.400)** |
| $\lambda_{hh}$ | 0.0281 | 0.0836 | 0.0706 | 0.0295 | 0.1229 | 0.0679 | -0.1041 |
|  | (2.53)** | (1.385) | (2.326)** | (10.353)** | (3.744)** | (6.335)** | (-3.166)** |
| LM | 8.5387 | 2.2613 | 3.7104 | 3.8447 | 2.3070 | 4.7288 | 5.7699 |

Note: (**) and (*) denote significance at the 5% and 10% significance level.
The variance covariance matrix is estimated using the BEKK model. LM is the likelihood ratio test for the hypothesis that the constants are zero. It is distributed as a $\chi^2$ with 2 degrees of freedom. The 5% critical value is 5.99.

**Table 3.10: Bivariate BEKK Model with Yield Curve as Hedging Factor**

$$r_{m,t} = \lambda_{m,0} + \lambda_{m,m}\, \sigma^2_{m,t} + \lambda_{m,h}\, \sigma_{m,f,t} + \varepsilon_{m,t}$$

$$r_{h,t} = \lambda_{h,0} + \lambda_{h,m}\, \sigma_{m,f,t} + \lambda_{h,h}\, \sigma^2_{h,t} + \varepsilon_{h,t}$$

$$H_t = C'C + A'\, E_{t-1}E'_{t-1}\, A + D'\, U_{t-1}U'_{t-1}\, D + B'\, H_{t-1}B$$

| | Canada | France | Germany | Italy | Japan | UK | USA |
|---|---|---|---|---|---|---|---|
| $\lambda_{m,0}$ | 0.9520 | 0.6082 | 1.0034 | 0.5560 | 0.3148 | 0.4464 | 0.7236 |
| | (2.837)** | (0.859) | (1.891)* | (0.799) | (0.655) | (0.940) | (1.710)* |
| $\lambda_{mm}$ | -0.0050 | 0.0072 | -0.0060 | 0.0097 | -0.0068 | 0.0121 | 0.0040 |
| | (-0.581) | (0.402) | (-0.488) | (0.814) | (-0.455) | (1.877)* | (0.203) |
| $\lambda_{mh}$ | -0.8247 | 0.8762 | -1.3573 | 0.7568 | -3.4460 | 0.7550 | 0.3740 |
| | (-1.004) | (0.614) | (-0.553) | (1.858)* | (-1.981)** | (0.683) | (0.446) |
| $\lambda_{h,0}$ | -0.0470 | -0.0313 | -0.0442 | -0.0148 | -0.0040 | -0.0848 | 0.0003 |
| | (-1.312) | (-0.933) | (-2.082)** | (-0.389) | (-0.142) | (-1.728)* | (0.014) |
| $\lambda_{hm}$ | -0.2680 | 0.0907 | -0.0466 | -0.0515 | 0.2050 | 0.3428 | -0.2921 |
| | (-2.752)** | (0.918) | (-0.318) | (-1.547) | (1.456) | (3.237)** | (-3.721)** |
| $\lambda_{hh}$ | 0.0773 | 0.2548 | 0.2183 | 0.0679 | 0.1224 | -0.0216 | 0.1032 |
| | (1.457) | (2.687)** | (3.022)** | (1.115) | (1.319) | (-0.170) | (1.832)* |
| | | | **Model with Zero Constants** | | | | |
| $\lambda_{mm}$ | 0.0111 | 0.0197 | 0.0128 | 0.0177 | 0.0011 | 0.0158 | 0.0340 |
| | (1.698)* | (1.919)* | (1.778)* | (2.726)** | (0.129) | (3.131)** | (3.586)** |
| $\lambda_{mh}$ | -2.0292 | 0.3920 | -2.5248 | 0.7955 | -3.8034 | 1.5052 | 0.3997 |
| | (-2.856)** | (0.299) | (-1.060) | (1.968)** | (-2.304)** | (1.966)** | (0.476) |
| $\lambda_{hm}$ | -0.2350 | 0.1363 | 0.0423 | -0.0529 | 0.2136 | 0.2688 | -0.2919 |
| | (-2.495)** | (1.587) | (0.301) | (-1.599) | (1.681)* | (2.770)** | (-3.844)** |
| $\lambda_{hh}$ | 0.0460 | 0.2058 | 0.1453 | 0.0542 | 0.1147 | -0.1701 | 0.1036 |
| | (0.969) | (2.608)** | (2.290)** | (1.094) | (1.527) | (-1.802)* | (2.088)** |
| LM | 4.2885 | 3.1558 | 7.8051 | 2.2114 | 3.9172 | 5.8980 | 5.3774 |

Note: (**) and (*) denote significance at the 5% and 10% significance level.
The variance covariance matrix is estimated using the BEKK model. LM is the likelihood ratio test for the hypothesis that the constants are zero. It is distributed as a $\chi^2$ with 2 degrees of freedom. The 5% critical value is 5.99.

Specifically, we want to see whether the risk premium on market excess returns and hedging factor excess returns are functions of their corresponding conditional variances and the conditional covariance. The theoretical two-factor model of the Merton (1973) assumes that the intercept is zero [see Equation (3.1)]. Scruggs (1998) points out that the intercept could be justified if there are market imperfections such as taxes, transactions costs, or preferred habitats. To test for the significance for such imperfections, the dynamic bivariate model is estimated with and without intercepts. The estimated parameters for the conditional variances are similar to the estimates obtained in the univariate models and they are not reported to save space. Table 3.8 reports the results when the hedging instrument used is the excess returns on long term bonds. Focusing on the model with constants, we see that regarding the conditional market premium, the market conditional variance is insignificant across all countries. The conditional covariance between excess market returns and excess bond returns is significant for the UK (at the 5% level at least) and for the US (at the 10% level). The covariance term is also significant for the UK and the US in the case of the risk premium of the long term rate. Interestingly, the conditional variance of the long term rate is significant in the cases of Canada, Germany and the UK even though for Germany the sign is negative. When the constants are restricted to be zero, the market conditional variance becomes significant for the market premium in the cases of Italy and the UK whereas the covariance term is significant for Canada, the UK and the US. The results are more interesting for the conditional risk premium of the long term rate. For example, the covariance term becomes significant for all countries with the exception of Germany. Similarly, the conditional variance term of the long term rate is significant with the only

exception being France. On the basis of the likelihood ratio test, the restriction that the constants are zero cannot be rejected across all countries with the exception of Germany and using a 5% level of significance.

Contrasting these findings with those of Scruggs and Glabanidis (2003) it can be said that the results here are more favorable for the two-factor dynamic model than their findings. It should be pointed out that these authors investigated only the US financial markets, whereas the evidence presented here covers the G-7 industrialized nations.

Table 3.9 reports the empirical findings when the industrial production is used as the hedging asset. The model with the constant shows again that the market conditional variance cannot consistently and reliably explain variations in the market premium. When the model is estimated with constants restricted to zero, we then begin to see that it can better explain variations in investors' risk premium. In particular, the conditional variance parameter becomes significant for France, UK and the US, while intertemporal risk exhibits significance for Italy, Japan, UK and the US. Such an empirical observation provides support for the theoretical ICAPM of Merton (1973) that markets are in equilibrium on aggregate and that model estimation does not require inclusion of a constant term. Again, this is corroborated with the results from estimation of the likelihood ratio statistic which supports the model without a constant, with only the exception of Canada in this case.

Table 3.10 reports the results when the hedging instrument used is changes in the slope of the yield curve. The results with the constants are similar to the earlier findings when the long term rate or, industrial production was used. The restricted model however shows some intriguing results regarding the market risk premium. As reported here and in

numerous other studies, the market variance fails in most cases to explain variation in the market premium. The results in Table 3.10 show that in the restricted model, the market conditional variance is a significant determinant of the market risk premium in six out of the seven markets (the exception being Japan). This is clearly a one finding and one that supports the use of the dynamic two factor model with the hedging factor being the shape of the yield curve. The covariance factor is also significant in four out of the seven cases. For the conditional risk premium of the hedging factor, the covariance is significant for Canada, Japan, UK and the US, and the variance is significant for France, Germany, UK and the US.

Overall the results show that the two factor model is doing a good job in explaining the risk premium dynamics of the excess market returns and the hedging instrument returns. Specifically, the long term rate and the industrial production do a better job in explain the risk premium of the hedging factor and the changes in the slope of the yield curve does a better job in explaining the market risk premium.

The strong message however that this empirical investigation conveys is that it is important for researchers to consider the importance of the hedging factor when examining the behavior of the dynamic risk premium and the nature of the intertemporal risk-return tradeoff. As Cochrane (2001) points out, the ICAPM has been sitting on the shelf and has not received rigorous empirical attention, at least not in its two-factor form which postulates that the dynamic risk premium is a function of the conditional market variance and its covariance with investment opportunities which shift stochastically through time. The findings in this chapter suggest a positive risk-return tradeoff as did the findings of the second chapter. However, in this case, the methodological exploration in trying to uncover

this relationship is different in that this chapter focused on the importance of including intertemporal risk in our modelling.

## 3.5. Concluding Remarks

Merton's (1973) intertemporal capital asset pricing framework serves as a paradigm for our understanding of how investors maximize their utility in a continuous-time economy that experiences stochastic changes. A large body of empirical literature applies some variant of this model to explore the intertemporal nature of the risk-return relation; this is, after all, one of the cornerstones in modern financial theory.

Most empirical work that theorizes on this relation applies some technique to either estimate a *simple* or *partial* equation expressed in Equation (3.2) and Equation (3.3), respectively. The second chapter of this thesis discusses literature that models the *simple* tradeoff between risk and return. This literature, as was discussed, tends to implement some form of (G)ARCH modeling to estimate the conditional second moments of aggregate stock returns. GARCH-in-mean modeling is particularly popular since it simultaneously links the conditional first and second moments of stock returns in order to form a *simple* estimate of investors' aggregate degree of risk aversion. Evidence from these studies offers conflicting inferences as to the nature of this important tradeoff; some find it to be positive, others negative and, still others, find it to be statistically indistinguishable from zero.

Volatility feedback is reputedly responsible for the conflicting results whereby an increase in volatility leads to an increase in the required rate of return and, subsequently,

a drop in the underlying asset's price. The second chapter makes the case that the earnings-yield is the required rate of return demanded by investors and should be regressed against the conditional variance series derived from the asymmetric GJR-GARCH to form a simple estimate of investors' aggregate level of risk aversion. International evidence from this procedure suggests a positive and significant short- and long-run intertemporal risk-return tradeoff.

This chapter however presents literature and evidence to suggest that, perhaps, the reason why empirical tests of this important relation yield contradictory results is because they omit the so-called "hedging" component from their analysis. The hedging component, as is defined by Merton (1973) reflects the investment opportunities and conditions which have some bearing on all investors. As Merton (1973) suggested, the long-term government bond yield may be useful in interpreting as a hedging factor and to use in order to motivate his two-factor ICAPM. Scruggs (1998) proceeds with this premise, yet makes the weak assumption that the conditional correlation between the market and long-term government bond yield is time-invariant. Recent research however argues that the correlation between market returns and bond returns is not 'static' but dynamic and time-varying (see for example Cappiello, Engle and Sheppard, 2006).

This chapter makes a contribution to extant literature by relaxing this assumption and exploring the intertemporal risk-return tradeoff on an international level utilizing alternative factors as the hedging component. Allowing the covariance parameter between the state factor and the market portfolio to be time-varying is more intuitively realistic since the interaction between the investment opportunity set and the market

portfolio undoubtedly changes through time (especially during changes in the business cycle).

When Scruggs and Glabadanidis (2003) relax this assumption they are unsuccessful in explaining variations in the dynamic market risk premium and in detecting a positive intertemporal risk-return tradeoff. As I argue in this chapter, it is important to understand that the long-term government bond yield, despite the information content it embodies regarding cost of capital, ease of obtaining credit and macroeconomic conditions at large, it is a factor which is influenced to a large extent by central banks. As such there are alternative factors that merit consideration. However, we need to be careful when doing this in order to avoid criticisms made by other researchers that the ICAPM may inaccurately be viewed as a "fishing license" (see Fama, 1991) whereby researchers "fish" for state factors that may yield empirically desirable results.

The hedging factors used in this empirical chapter are motivated by theory and on the basis of what these factors truly represent. An argument that is made here is that, since the long-term government bond yield is to a large extent correlated with central banks' policies regardless of which market you look at, it may be necessary to investigate the viability of other hedging factors. So far in the literature we know that volatility feedback is reputedly responsible for the conflicting findings in studies investigating the simple intertemporal risk-return tradeoff. This is illustrated in the second chapter. In this chapter, I cite evidence that perhaps omission of the hedging component is responsible for the conflicting findings since it is necessary to account for intertemporal risk. Despite this, evidence is still inconclusive.

Up until now, there has not been a clear reason why Scruggs (1998) and Scruggs and Glabadanidis (2003) find conflicting evidence and whether implementing a two-factor ICAPM can uncover a positive risk-return tradeoff. This chapter sheds new light into this and shows that future research needs to focus on identifying other state factors that can proxy for the investment opportunity set and which reflect real conditions in the economy that impact all investors.

# - Chapter Four -

# An Intertemporal Capital Asset Pricing Model with Heterogeneous Expectations

## 4.1. Introduction

The economic theory of uncertainty and its role on investor behavior is a foundation for much of modern empirical finance. A utility-maximizing agent must make decisions and constantly adjust their exposure to risk based on the distribution of investment opportunities and economic conditions which shift randomly through time. Several important asset pricing theories have emerged which attempt to delineate this and to explain the dynamics of expected stock returns based on risk.[22] A key assumption to such models, however, is that investors are rational and carry homogeneous expectations about risk, returns and the future distribution of potential outcomes regarding market conditions. Such an assumption forms the underpinning for the efficient market hypothesis (see Malkiel, 2003). From the previous two chapters, we know that most of asset pricing literature makes the assumption that investors are homogeneous in terms of their expectations and investment decisions. Now, in this chapter, I investigate the impact of heterogeneous traders in the stock market.

In practice, however, it seems implausible to believe that individuals somehow reach identical conclusions regarding risks and expected rewards in the stock market. The very essence of uncertainty implies, after all, that rational individuals differ in their

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[22] The single-period CAPM, for example, is a milestone in finance and the basis of much empirical work among academics and practitioners, who rely on this model for asset valuations (see Bruner *et al.,* 1998; Graham and Harvey, 2001).

expectations and preferences. The assumption of rationality is equally dubious. Some of the most tragic moments in human history arise from irrationality, greed, and 'herd-like' behavior; where people move together in herds instead of thinking independently.[23]

The stock market booms and busts of 1929 and 1987, respectively, resemble history in the sense that during the buildup of each crash, investors (and people at large) were in a state of euphoria. The media and other pseudo financial 'gurus' all but catered to this ecstasy by feeding investors with what they want to hear in order to gain popularity in the press. As investors falsely extrapolated their good fortunes linearly into the future, more and more investors jumped on the bandwagon and mimicked what the 'crowd' was doing, pushing prices further away from their fundamental value. At the peak of this mania, market participants closely watching fundamentals began to withdraw from the stock market and prices fell precipitously amid growing fear and hysteria among investors and institutions (see Shiller, 2000).

The burst of the "dot-com bubble" in 2000 tells a quite similar story. Prior to the crash, there was much excitement and overly zealous sentiment in the market. Although the technology sector constitutes a small fraction of the total market capitalization, it was the main driver behind upsurges in stock market prices. Ofek and Richardson (2002, 2003) estimate an implied P/E ratio of over 600 for internet stocks in 1999; in plain language, investors were somehow *expecting* these stocks to earn supernormal returns in the future which far exceed those of any individual stock which may have existed in the past. Shiller (2000) argues this crash was the result of frenzied investors who believed they can keep earning higher and higher returns, without regard for fundamental value. In

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[23] Shleifer (2000) and Sornette (2003) provide interesting discussions of human behavior and its effects on the market, citing infamous examples such as the Dutch Tulip mania of the 1620s and South Sea Bubble of 1720, and their present-day implications.

particular, he makes reference to how the P/E ratio can be used by participants to see if prices are too high (or low) relative to earnings. As pointed out be Ofek and Richardson (2002, 2003), the P/E ratio could predict that prices in the technology sector of the market were disproportionately high relative to earnings. Therefore, this class of investors, known as 'fundamental investors' is important and we want to know how their behavior impacts stock price dynamics. We further want to see what types of fundamental factors they potentially use to evaluate the stock market. Most recently, Chau, Deesomsak and Lau (2011) look at the issue of investor heterogeneity in the context of ETF contracts and finds that sentiment is important in driving investment behavior and this is of relevance to regulators and investors at large. This view is echoed by the investment community. Recently, a *New York Times* article highlighted the concern that regulators have regarding the behavior of various investors, some of which may be short-run high-frequency investors.[24]

Aforementioned events of this nature are irreconcilable from the viewpoint of the efficient markets hypothesis and traditional asset pricing theories mentioned in the previous two chapters. In particular, according to the efficient markets hypothesis, any asset mispricing induced by market fads or investor sentiment should be *immediately* corrected by a sufficiently large number of rational and well-informed arbitrageurs. This view dates back to Friedman (1953b) and has been debated and challenged vigorously in the literature; Black (1986) argues that investors trade on noise as if it were information and that their impact in the stock market may be long-lasting (see De Long *et al.*, 1991).

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[24] See the article by Nancy Folbre which appeared in the August 22, 2011 issue of the *New York Times* titled "A Sales Tax on Wall Street Transactions."

A widely-held view against the efficient market hypothesis is that arbitrageurs are constrained in terms of their ability to exploit asset mispricing stemming from noise traders. De Long *et al.* (1990a) and Shleifer and Summers (1990) argue that at least two types of risk act to limit their positions; fundamental risk and noise trader, or resale price, risk. Fundamental risk is the possibility that news may change regarding fundamentals (i.e. dividends and/or earnings) thus affecting the arbitrageur's initial position. Since the arbitrageur is risk-averse to some degree and has a finite investment horizon, this reduces their willingness to take a position against noise traders. Figlewski (1979) argues that the survival of noise traders persists indefinitely since arbitrageurs bear fundamental risk. Wurgler and Zhuravskaya (2002) argue that since stocks are imperfect substitutes, it is nearly impossible to eliminate fundamental risk. This ultimately constrains arbitrageurs and limits their aggressiveness against noise traders.

The second type of risk entails unpredictability in noise traders' opinions. For example, if an arbitrageur takes a short (long) position when bullish (bearish) noise traders have pushed prices too high (low), they must keep in mind that noise traders may continue to drive prices further from fundamentals in the future. This poses a threat to them especially if they must exit their position before the price recovers (see Black, 1986).

Other authors cite additional constraints facing arbitrageurs. Shleifer and Vishny (1997) illustrate theoretically the limits to arbitrage as a result of limited resources. Abreu and Brunnermeier (2002, 2003) argue that arbitrageurs face synchronization risk; since an individual arbitrageur is incapable of correcting mispricing in the stock market, they must somehow coordinate their efforts and trade as one. This is inherently difficult and can

allow bubbles to persist over extended periods because holding costs deter individual arbitrageurs from acting alone too soon against noise traders.

Probably one of the most destabilizing forms of noise trading that is responsible for the bubbles and crashes we have experienced throughout history is known as positive feedback trading (see De Long *et al.*, 1990b). Agents that engage in this type of trading are depicted as trend chasers (i.e. 'herding investors') and buy (sell) when prices move upwards (downwards). This type of trading may be the result of irrationality, fads, word-of-mouth enthusiasm, overly zealous extrapolative expectations, portfolio insurance strategies such as stop-loss orders, or margin call forced liquidations. Investment behavior or strategies that manifest into this type of trading exert a self-reinforcing influence on prices; fluctuations in price are augmented and independent of any rational valuations placed on fundamentals or mean-variance considerations. This exacerbates mispricing and allows it to persist.

The effect of noise traders on stock market prices is difficult to counter given some of the aforementioned risks arbitrageurs face. However, it is quite possible that, in addition to such risks, arbitrageurs may be disinclined to attack mispricing right away simply because it is not in their best interest to do so. In fact, they may find it optimal to 'ride' bubbles with the rest of the herd in order to reap any short-term gains. This induces price instability and only reinforces the impact of positive feedback investors; Hong and Stein (1999, p.2167) observe that "…a number of large and presumably sophisticated money managers use what are commonly described as momentum approaches…" George Soros, the successful investor and author of the controversial book, *Alchemy of Finance*

(1987), argues that the key to success is not to counter herding investors, but instead to ride the wave along with them and sell out near the top.

In light of this research, there is ample evidence to suggest that the trading patterns of different investors exert a significant influence on stock market prices. This evidence may also dispel the previously dominant notion that markets are efficient and that asset mispricing is transitory. Recent chaotic events in financial markets only seem to corroborate this view. In fact, policymakers have begun to assess the destabilizing impact of noise traders, the causes of market bubbles and crashes and plausible monetary policies to protect financial markets (see Bernanke, 2002).

The intent of this chapter is to model the trading patterns of three types of investors in several industrialized markets and to see to what extent their behavior is manifested in the time-varying dynamics of stock market returns. Namely, it extends the work of Sentana and Wadhwani (1992) and Cutler *et al.* (1990) and contributes to extant studies by producing a feedback trading framework that models the actions of (a) rational risk-averse expected utility maximizers (i.e. 'smart money' investors, (b) positive feedback traders, and (c) fundamental traders. Whereas rational investors trade on the basis of mean and variance considerations in the context of the equilibrium CAPM, positive feedback traders chase trends or utilize momentum strategies which extrapolate past performances.[25] Note that the important work of Cutler *et al.* (1990) considers rational investors, fundamental traders and feedback traders, however, there are differences between the model here and the model by Cutler *et al.* (1990). Firstly, the

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[25] It is important to note that the term 'rational' is used here consistent with the way it is used in extant academic studies. Namely, rational investors make decisions only on the basis of mean-variance considerations. In other words, they look at the first and second moments of assets' return distributions in order to form portfolios which maximize mean returns with respect to variance. Such an approach is consistent with the early work of Markowitz (1952) which is discussed in the second chapter of this thesis and states that only mean and variance matter in investors' portfolio formation decisions. Any other type of strategy that differs from this has been loosely referred to as 'non-rational' behavior in the literature.

work herein considers different measures of fundamental value to see which measure can explain the behavior of fundamental traders. The work by Cutler *et al.* (1990) assumes that the fundamental value evolves the way a random walk would and thus include a lagged term (see page 6 of their work). Secondly, Cutler *et al.* (1990) assume a constant required rate of return of zero by investors who form rational forecasts of the market (see page 7 of their work).

Fundamental traders believe in mean reversion of stock prices toward a long-run average, or fundamental, value. These traders decrease (increase) their demand for risky assets when prices are high (low) relative to fundamentals. In order to gain an understanding of the behavior of fundamental traders and to see whether integrating heterogeneous investors into the ICAPM of Merton (1980) can better explain the risk-return tradeoff, this chapter uses three proxies for fundamental value. The first one is based on the P/E ratio and the second on the dividend-yield. The literature behind such proxies was mentioned more extensively in the second chapter (see Campbell and Shiller, 2001; Shiller, 2000). The third proxy is based on the so-called Fed Model that was also mentioned in the second chapter which consists of the spread between the market earnings-yield and the long-term government bond yield (see Lander, Orphanides and Douvogiannis, 1997; Shiller, 2000; Campbell and Shiller, 1998 and 2001; Thomas and Zhang, 2008).

The findings from this chapter are of interest to practitioners and academics and pave the way for future research into this field. In particular, in terms of explaining the intertemporal risk-return tradeoff, the empirical evidence provided here corroborates the arguments made in the preceding two chapters; namely, it provides support for the Merton (1973) theoretical notion that the conditional variance and intertemporal risk are the sole

determining factors of investors' risk premium. This evidence also suggests that integrating the behavior of heterogeneous investors does not help to better explain variations in the intertemporal risk premium. Instead, the findings shed new light which has not been identified before and raises additional insights which merit further exploration. These findings are of interest to practitioners who seek valuation methods for the stock market and for academics who further want to explore into this field.

Firstly, there is empirical evidence here that fundamental traders drive, to some extent, movements in stock prices. This shows that valuation ratios, such as the earnings-yield and dividend-yield, may prove useful to practitioners who want to measure stock market performance and predict future market movements. In particular, the evidence here shows that fundamental traders increase their demand for stock shares when prices are low relative to their fundamental value and vice versa. In terms of gauging fundamental value, the ratios proposed here seem to be good indicators of whether stock prices as over- or under-valued. These results confirm the arguments made in the second chapter and the arguments of other researchers (see Shiller, 1996; Lander, Orphanides and Douvogiannis, 1997; Shiller, 2000; Campbell and Shiller, 1998 and 2001; Thomas and Zhang, 2008, to name a few).

A second major empirical finding which merits future research is that it appears positive feedback trading is not statistically evident when exploring monthly frequency data. This result does not imply a rejection of the notion that there exist heterogeneous groups of investors in the stock market, it instead suggests that feedback traders are present but only in the short run. These results are in contrast to those by Sentana and Wadhwani (1992), Koutmos (1997), and Antoniou, Koutmos and Pericli (2005). This of course may be due to

the fact that these studies are using daily data. In this case an argument can be made in favor of the notion that positive feedback trading is present in the short run, but it becomes insignificant in the longer run. It is also possible that there are also negative feedback traders so that the net result becomes insignificant over the longer-run and when looking at lower frequency data such as monthly stock market returns. This suggests that high-frequency traders and institutions may drive prices in the short-run but in the longer-run, negative feedback traders and fundamental traders push the prices back to their equilibrium values.

The remainder of this chapter is structured as follows. Section 4.2 presents a review of relevant literature. Section 4.3 presents the methodology and empirical model. Section 4.4 describes the data and procedure for variable construction. Section 4.5 discusses the major empirical findings and, finally, Section 4.6 concludes this chapter.

## 4.2. Review of Literature

What drives asset prices? This is an enduring question in financial economics and, rightly so, has received rigorous attention over the years. Although much significant advancement in asset pricing theory and econometric modeling has emerged as a result, the answer to this question still remains open and is hotly debated.

Perhaps the traditional path of asset pricing literature has been to take the following approaches; the first is an attempt to link the movements of asset prices to shifts in systematic risk and investors' degree of risk aversion. Such an approach is implicit in the Capital Asset Pricing Model (CAPM) as well as its intertemporal variant, the ICAPM. The intuitively straightforward prediction of these models is that increases in systematic risk ought to lead to an appropriate rise in investors' expected returns.

The second approach has been to link asset prices to fluctuations in the aggregate financial economy. Multifactor models that take on this approach, such as the Arbitrage Pricing Theory (APT), attempt to identify these set of risk factors which affect individual companies, industries, and even segments of the aggregate economy. This approach is carried out using cross-sectional regression techniques in an attempt to find which macroeconomic factors, if any, have an impact on stock market returns or the returns of certain portfolios and industries. The intuition behind this is that if there are factors which have an impact on firms' operating activities and cash flows, they need to be identified since they will also impact stock prices. For example, a certain company may be naturally sensitive to fluctuations in a certain macroeconomic factor (such as interest rates). If this is the case, then the returns for that company's stock must reward an appropriate risk premium to its investors for being exposed to this non-diversifiable risk (see Chen, Roll and Ross, 1986).

Taking into consideration these two established approaches, there is a relatively new approach which is recently gaining more and more recognition and comes from a field in finance known as 'behavioral finance.' This relatively new and growing field argues that researchers need to also consider investors' emotions and that perhaps it is erroneous to make the strong assumption that they behave rationally all the time. This was alluded to in the second chapter; particularly about how seemingly unrelated factors can have an impact on investors' perceptions and their behavior. These factors defy rational expectations by any account yet, as will be explored further, play an influential role on investors' decisions and, consequently, movements in stock prices (see De Long, Shleifer, Summers and Waldmann, 1990b; Shiller, 2000).

This section explores some of the many issues regarding behavioral finance, why investors act irrationally and why, contrary to the intuitively appealing assumptions of market efficiency, arbitrageurs are constrained and may (un-)willingly allow asset mispricing to persist (see De Long *et al.,* 1990a; Shleifer and Summers, 1990; Shleifer and Vishny, 1997; Shiller, 2000; Abreu and Brunnermeier, 2002 and 2003). These issues are very important not only from a behavioral finance perspective but will help us to better explain the dynamics of stock returns as a result of investors' behavior. Finally, it is the intent of this chapter to focus on the intertemporal risk-return tradeoff from a behavioral finance perspective, taking into account the actions of three different groups of investors; namely, rational, fundamental, and feedback investors (or traders). The contribution of this chapter to existing studies is to emphasize the importance of incorporating the actions and behavior of these three types of investors in order to explore the nature of the intertemporal tradeoff between risk and return. Perhaps, as is argued further later on, it is because we are not considering the significant impact of these investors that we cannot detect a statistically discernable risk-return tradeoff.

To examine some of these issues, this section will begin by providing an overview of the much acclaimed Efficient Markets Hypothesis (EMH) and evidence, both historic and recent, which seriously challenges this well-established proposition. It further examines why is it that investors do not make 'optimal' investment decisions on the basis of mean-variance considerations and what are some of the other factors, both psychological and external, which influences their thinking. One rather notable observation is that investors tend to 'herd' in the sense that they all move and invest in the same direction. This is known as feedback trading. This type of herding behavior has

been branded as the culprit (or is at least partially responsible for) the creation of stock market bubbles and other empirical anomalies, which are in turn discussed here. If this type of behavior exerts a significant impact in markets, as existing literature argues it does, then it is important to incorporate these investors' (miss-)behavior into a framework which allows us to explore the intertemporal risk-return tradeoff. Contrary to the traditional view that financial intermediaries (such as investment banks and money management firms) serve to minimize the problem of information asymmetry, this section further presents evidence that many of these institutions also engage in feedback behavior and herd with one another. I present below some of the many reasons why this happens and why it is so important that these factors are examined in order to better estimate the risk-return tradeoff.

### 4.2.1. The Efficient Market Hypothesis

Support for the Efficient Market Hypothesis (EMH) from well-known studies such as Fama (1965) and Malkiel (1973) contend that prices are 'correct' in the sense that they reflect all available information and is accessible to all investors. Thus, no one can (persistently) take advantage or 'time' the market to earn returns in excess of those that can be achieved from passively holding the market portfolio.[26]

If assets were in fact efficient and reflected all available information, there would be at least three characteristics reflected in stock market prices; firstly, opportunities and abnormal returns would be undetectable and no econometric model would be useful to

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[26] A very vivid illustration of the EMH is illustrated in Malkiel (2003) which gives an old proverbial joke among economists and academics evocative of the EMH and the notion that assets' prices are efficient where a student and his finance professor are walking together and suddenly the student notices a $100 bill on the ground. When the student goes to pick it up, the professor tells him "Do not even bother. If it were a real $100 bill, it wouldn't be there." This story is often told in finance classes by professors when introducing the EMH to students and is intended to illustrate what economists and academics connote when they say that markets are 'efficient;' namely, asset mispricing does not exist and, if there is any mispricing, it is temporary and will be eliminated by arbitrageurs immediately. Thus, there are no free '$100 bills' lying around waiting to be picked.

traders. If this is the case, then the investor is better off simply holding the market index. Now, if this were true, then the study of historical stock prices to predict movements in future prices (i.e. technical analysis) would be fruitless. The only thing that would really matter to 'rational' investors would be their degree of risk aversion and would make portfolio allocation decisions on the basis of mean-variance considerations. This is discussed in the second chapter where investors make 'optimal' or 'efficient' decisions on the basis of mean-variance considerations in the context of Markowitz (1952).

Secondly, stock market returns are tied to real economic factors which influence the macroeconomy at large such as the rate of inflation, unemployment, interest rates, the money supply, and the price of natural resources such as oil, to name a few examples. This premise formed the basis for the Arbitrage Pricing Theory of Ross (1976), which is discussed in greater depth in the second chapter and which is explored further by Chen, Roll and Ross (1986).

Thirdly, if markets are in fact efficient, then professional money managers and traders will not be able to consistently reap abnormal profits. The EMH makes the argument that information travels quickly and unrestrictedly and is accessible to all market participants at any given point in time. Thus, information is instantaneously reflected in stock prices and, therefore, expending time and resources to gather and analyze the information will not lead to any payoffs in the future. If an investor does happen to reap higher returns relative to his peers, this is only as a result of chance and is short-lived and is not the result of their abilities.

The EMH is also commonly linked to the idea that stock prices follow a 'random walk.' This phrase was popularized by Malkiel (1973) in his acclaimed book, *A Random*

*Walk Down Wall Street*, where he argues that future prices are random and unpredictable on the basis of historical prices. He jokingly likens the selection of stocks to a blindfolded chimp throwing darts and makes the argument that the chimp is just as likely to select a successful portfolio as an 'expert' money manager is. Investors are therefore better off just holding the market portfolio and not engaging in costly active management strategies which can eat up their wealth in the form of transactions fees.

In light of recent findings and events, however, there is enough evidence which seriously challenges the EMH and merits consideration when applying conventional asset pricing theories to study the dynamics of stock returns (see Black, 1986; De Long, Shleifer, Summers and Waldmann, 1990b; Shiller, 2000). In particular, we want to know why investors make suboptimal investment decisions and the impact this has on stock returns. If there are irrational investors present in the market which trade on emotions or other (seemingly) ad hoc factors unrelated to mean-variance considerations, then it is necessary to see what impact their actions have on stock prices and whether this can shed new light on the intertemporal risk-return tradeoff.

### 4.2.2. Investor Irrationality and Noise

The long-standing belief that investors are rational forms the basis for the EMH and the notion that stock prices fully reflect all available information. Thus, capital markets are "efficient" in the sense that these prices already incorporate all available information and there is no mispricing or opportunities for a 'free lunch' by arbitrage investors. The role of capital markets is, after all, the efficient allocation of scarce investor resources across competing production-investment alternatives by firms. Hence, prices of securities, which

represent ownership to firms' operations, serve as a signal to investors and reflect the investment-production possibilities that exist and the risks they entail.

However, the established paradigm that markets are efficient and that investors are rational agents has come under scrutiny, especially in light of recent financial chaotic events and the proliferation of Ponzi schemes which have snared investors and have undermined public confidence in financial institutions. In his seminal paper, Black (1986) observes that investors trade on 'noise' as if it were information. In this context, trading on so-called 'noise' is a meaning given to investors who trade on the basis of emotions, instincts, or of the haphazard advice of friends and so-called financial planners. Trading on noise ignores fundamental factors related to the firm's prospects, such as earnings or, as Black (1986) indicates, firms' P/E ratio.

The observation that investors trade on the basis of noise is not a new phenomena. Nearly seventy four years ago, John Maynard Keynes referred to this noise as 'animal spirits' to refer to a situation where investors trade on whimsical factors instead of relying on real economic reasoning in order to evaluate their investment decisions (see Keynes, 1936). Such whimsical factors may include things such as emotions, 'gut feelings' about where the market is going, advice from friends or so-called financial gurus, and information from other media outlets.

The media, such as popular investment television shows and other on-line investment forums, are an exemplary illustration of a source of noise which seems to have a profound influence on investors' decision-making and may even drive stock market volatility – at least in the short-run. For example, Antweiler and Frank (2004) study nearly 1.5 million message posts on the popular Yahoo! Finance and Raging Bull

sites about forty five companies for which posts were made. They report statistically significant evidence of a relationship between the degree of message activity and stock market volatility. In a similar vein, DeMarzo, Vayanos, and Zwiebel (2001) find that investors place strong emphasis on opinions with people they talk to. Such a finding suggests it may be profitable to become an influential agent in order to try and move stock market prices. The greater the numbers of people who listen to you, the more influential you become. Shiller (2000) further highlights the importance of conversations in influencing investors' decision-making when they pick stocks. In one of his previous studies, he found direct evidence that many individual investors pick stocks on the basis of what friends and acquaintances suggest to them (see Shiller and Pound, 1989).

More recently, Hong, Kubik, and Stein (2005) provide further support for how important word-of-mouth information is. In particular, they examine the portfolio holdings of mutual fund managers located in the same city with other mutual fund managers to see whether or not their trades are correlated. After looking at the holdings of some major funds in major respective cities in the U.S., they find that mutual fund managers in the same city tend to execute similar trades and hold similar portfolios. This may be the result of word-of-mouth transmission of information, whereby mutual fund managers located in the same city with one another are likely to meet with each other – for example, either through social events or investor conferences – and communicate with one another about what they are doing and where they think markets are going. Although we cannot preclude the possibility that they may consult with similar sources specific to the city they live in – for example, their local newspaper or a TV station – it is

still in spirit with the word-of-mouth transmission mechanism since the fund managers receive information from someone that is 'close' to them.

Word-of-mouth, regardless of whether it has any economic basis, also appears to have a strong effect in other market settings and circumstances in history. For example, Kelly and Grada (2000) examine two prominent banking panics in the 1800s and find that bad news of banks' woes spread by word-of-mouth in neighborhoods. This study is interesting because it looks at this phenomenon from an early time period where financial institutions were not as intricate and advanced as they are today. However, the findings from this study corroborate the observation made by Shiller (1995, p.181) and so many other researchers that "People who interact (...) regularly tend to think and behave similarly." This has even been explored in various other contexts unrelated to finance. For example, Banerjee (1992) introduces a model whereby he examines people's decision-making as they try to find the best restaurant. All the prospective customers in this model have imperfect information regarding the quality of the restaurants. Although the first individual may select a restaurant on the basis of their own imperfect information, the remaining successive individuals may very well substitute their own information and follow their predecessor. Thus, there is what is referred to in behavioral finance as 'herding' and this has resulted from noise, which agents in this case have perceived as information.

Evidence of this kind of behavior is well-established in studies, and its reasons are discussed more in the following sections. However, the observation that individuals make decisions on the basis of noise explains why we see this type of herding behavior. Oftentimes, individuals place more emphasis on what others do (even if it is noise)

instead of relying on their own knowledge and information. The study by Asch (1952) demonstrates that when individuals are placed in a group, they place more emphasis and credibility in others' actions instead of relying on their own knowledge. In particular, his study asks participants individually a series of basic question involving the length of line segments. The questions are obvious in nature and are easily answered by the subjects when they are being interview on an individual basis. The subjects were then placed into groups and asked the same questions. The members within this group however were confederates and, without the knowledge of the subjects, would purposefully give wrong answers to the questions. Thus, when a question was being posed, the confederates would purposefully give the wrong answer and, as Asch (1952) reports, the participants in the group would display signs of anxiety since they had a keen sense that the answer was wrong, yet would go along with the rest of the group. In effect, as Black (1986) indicates, the subjects were reacting to the 'noise' given from the confederates and placing more emphasis on its validity instead of relying on their own knowledge and experience.

The effect of word-of-mouth effects in driving herding behavior is prevalent in other fields of research as well. For example, Duflo and Saez (2002) investigate if staff members across Universities make decisions regarding their retirement accounts because they are being influenced by the decisions of their co-workers. The study finds that a staff member's decision to invest in a particular account is correlated with what others are doing within their department. Of course, this may be the result of the fact that University Professors may have a higher propensity to save, but it also does not preclude the possibility the many of the staff members within the department talk with one another and thus influence each others' decision-making.

In a different context, Coval and Shumway (2001) examine, quite literally, the impact noise has on stock market volatility. They actually analyzed the ambient noise level in the 30-year bond futures trading floor at the Chicago Board of Trade (CBOT). They found that the ambient noise levels made by traders contained useful information about the future prospects of the market. In particular, after controlling for factors such as volume of trade, announcements of news, and lagged changes in price, they find that the level of sound in the trading pit was a good forecaster of future volatility and presage other important occurrences in the market. For example, an increase in the level of sound, which was measured using microphone equipment, presaged increases in subsequent stock market volatility. This is because it would be during these periods that traders were feeling nervous and were extremely eager to execute their trades. As more and more traders begin to feel nervous and shout more in order to quickly execute trades, this will undoubtedly have an impact on the rest of the traders in the pit since they now must adjust their positions.

The studies which look at the impact of 'noise' on investors' behavior are in no way perfect depictions of reality. However, these studies do show the importance one's environment and what impact this has on individuals within this environment. As is discussed in the next subsection, the effects of noise and herding behavior have profound effects in stock markets. The study by Black (1986) goes a long way in describing our behavior and how this manifests itself in the stock market.

One very recent and substantial example of trading on noise via word-of-mouth was a case involving a New Jersey teenager in 2000 who was subject to enforcement actions by the SEC for conducting "Internet Fraud." This case featured prominently in the

press and an analysis of the court document is provided by Walker and Levine (2001). According to legal documents, the accused teenager, Jonathan Lebed, would purportedly purchase stock in small and thinly-traded tech companies and, afterwards, log in to various investment websites via multiple web addresses and usernames, and create a 'buzz' over those stocks and eulogize over how well they will perform in the future. According to sources related to the case, Mr. Lebed would consistently execute his fraudulent strategy by beginning to post basic (seemingly) accurate information pertaining to the company. Then, would create hype over the stock by making overly zealous recommendations such as "the next stock to gain 1000%" or "most undervalued stock..." (see Walker and Levine, 2001). This irrationally exuberant hype would temporarily drive the stock's price up, at which point Mr. Lebed would sell the stock and reap easy profits. Such a strategy would cause the type of positive feedback trading that was mentioned earlier as more and more investors buy the stock, without understanding what they are doing, in hopes that the price will appreciate more and more in the future.

After some time, this teenager had amassed hundreds of thousands of dollars in trading profits. The SEC stepped in to stop him because he had reputedly earned a strong influence in on-line trading forums and investment websites. As part of the settlement with the SEC, he was required to pay some fines but was able to retain much of his money. However, this case has much to teach us about the role of the media in influencing our decisions. What is the advice we are getting and whose interest is it serving? This is an important question which tends to be ignored. Today, there is a proliferation of so-called investment gurus and investment advisors which are syndicated in popular magazines, on the internet, and practically everywhere you look.

Why is it that people then continuously rely on this 'noise' to make investment decisions? As Black (1986) points out, investors may trade on noise for several reasons. One reason is that they simply may enjoy doing so. Another is that there is so much noise around that they are no longer capable of distinguishing it from real information.

### 4.2.3. Positive Feedback Trading, Irrational Exuberance and Market Bubbles

Trading on the basis of noise can manifest itself into what is known in the literature as 'positive feedback trading.' This type of trading is essentially a "trend chasing" or "momentum" type of strategy which entails buying (selling) a risky asset if during the last trading intervals it exhibited positive (negative) returns (see De Long, Shleifer, Summers and Waldmann, 1990b). This type of trading may be the result of portfolio insurance strategies such as stop-loss orders, or margin call forced liquidations, or it may be the result of herding and irrational exuberance caused by fads, word-of-mouth enthusiasm, and the media which may tout certain types of investing or certain asset classes (see Shiller, 2000).

Positive feedback trading is a destabilizing form of noise trading since it is independent of any rational valuations placed on fundamentals and is driven by fads and bandwagon effects, whereby investors copy each other and play along because everyone else seems to be doing the same. This form of trading is destabilizing in the sense that it pushes assets' prices further from their true fundamental value since investors are essentially buying overpriced stocks and selling underpriced stocks. This type of trading, as is described in the following section, is also prevalent among 'sophisticated' investors such as money managers and institutions. For example, the popular strategy of "window

dressing," which involves selling the embarrassing losers from the portfolio and replacing them with winners, is common among portfolio managers to coax investors that they are picking stocks which have done historically well. However, this strategy, despite the fact that it may on the surface appear clever, is merely a form of positive feedback trading. As is discussed further, with time, such a strategy is bound to fail at some point and may pose a significant risk to all parties involved.

It is important to understand that positive feedback trading can arise from investors' false presumptions that past trends are likely to persist. Therefore, if an asset has done well in the past, investors falsely perceive that it will continue to do so in the future (see Andreassen and Kraus, 1990). Thus, future movements in stock price as a result of this positive feedback trading become a self-reinforcing process which is independent of rational valuations or considerations of the firm's fundamental value. As this process continues indefinitely, investors who have been eyeing fundamentals start to withdraw from the market, future upswings in price cease, and expected returns on any future success of the stock quickly deteriorate and diminish, resulting in a burst of an inflated bubble or some form of a market crash.

Positive feedback trading can also arise from other psychological factors that influence investors and are discussed more elaborately and in turn in Section 4.2.5, "Investor Psychology and Finance." The three prominent factors however widely cited in behavioral finance literature are "overoptimism," "overconfidence," and a so-called "availability bias." Overoptimism, as its name suggests, describes investors that are in a state of euphoria whereby they assign unrealistically high probabilities that a certain event (or investment) will be successful. These overly optimistic emotions are

undoubtedly amplified by word-of-mouth effects where investors share their unrealistic optimism with other investors, thereby creating a (fragile) investment environment which is sharply driven by enthusiastic emotions instead of reasoning or a much warranted fundamental valuation (see De Long and Shleifer, 1991).

Overconfidence is yet another behavioral factor which can lead to positive feedback trading and describes a situation where (noise) traders essentially overestimate their abilities in the stock market and attribute past successes to their talents and dismiss the possibility that their past successes were the result of sheer luck. The seminal study by De Long, Shleifer, Summers and Waldmann (1991) presents a theoretical model which shows that noise traders may persist indefinitely and may not lose immediately to arbitrageurs and rational investors as previously thought. In fact, they may even dominate the market for some time and will attribute their past successes to their talents and abilities instead of considering the possibility that they were just lucky and trading on noise.

The premise that individual human beings credit their past success to their 'skills' and dismiss the possibility that there may have been some luck at play is not a new concept in social sciences. For example, Langer (1975) finds that humans possess an "illusion of control" over events that are otherwise fortuitous in nature and uncontrollable regardless of the skill set possessed by the subject in question. Such findings corroborate those of previous psychologists in earlier works. Most notably, Henslin (1967) studied the dice playing behavior of subjects and found that these players behave as if they are in control of the outcome that the toss would bring. In particular, they exercised care and were gentle when throwing the dice in hopes of getting low numbers yet would be more

aggressive and throw the dice harder in hopes of high numbers. As Langer (1975) points out, all these seemingly irrational behaviors may seem quite rational if one believes that skill is at play and not luck. Thus, subjects who participate in betting games may also bet with others who exude the most confidence. Noise traders persist in the market for these very same reasons. They will 'bet' where the markets are going based on past performance and what others are doing as well. Despite the predictions of the EMH that forecasting market performance is a fruitless endeavor, noise traders will use word-of-mouth methods to derive information from their social circles and acquaintances. Positive feedback trading is also linked to the findings of Langer (1975) in the sense that feedback traders copycat one another and if they see that other investors appear confident in their investment decisions and they have earned strong returns, they will quickly mimic them and copy their investment portfolio (i.e. add winners and drop losers). This only exacerbates stock prices' deviations from their fundamental value and may lead to stock market bubbles and subsequent crashes, as is discussed further.

Finally, the so-called availability bias argues that more recent events have a greater bearing on investors' decision-making and on their risk calculations (see Tversky and Kahneman, 1974). Therefore, market booms and the excess returns of other investors entice noise traders to jump in on the bandwagon and to overestimate the prospects for these investments. Likewise, if a stock market correction or crash happened in the distant past and is not fresh in the minds of investors, it tends to be forgotten and may lead to complacency among investors, and they will discount the likelihood that they might very well lose on their investments in the future (see Herring and Wachter, 1999).

Thus, these three types of behavior, when aggregated together, can lead to severe volatility in the stock market and deviations of stock prices from their fundamental values. In fact, Soros (1987), arguably one of the most effective investors in the world, describes his strategy of taking advantage of these psychological factors in order to reap profits. In particular, Soros describes that his strategy is not to trade on the basis of fundamental valuations, but instead on the future behavior of the crowd. For example, he describes how he took advantage of conditions during the 1960s conglomerate boom and the 1970s real estate investment trust (REIT) booms, respectively. According to Soros (1987), during the 1960s he saw that many noise traders were becoming excited over the apparent rise in earnings by conglomerates and were investing their money in this growing market. Whereas fundamental traders may have seen, as did George Soros, that this market may become overvalued, they probably would have taken short positions and wait until prices in this market corrected. However, as Soros argues, the trick is to know where the crowd is going and to trade in anticipation of their future behavior. For example, instead of shorting and waiting for a market correction, Soros invested in this booming market, anticipating that more positive feedback traders will do the same. The initial upswings in price therefore stimulated the enthusiasm of other investors because it generated a trend of rises in stock prices and high returns. This created further overoptimism among investors that this trend will continue and overconfidence for existing investors who believed that their skills were the reason for their (temporary) fortunes. The availability bias is also at play here since investors were myopically seeing current returns and downplaying risks in their estimations for future movements in the market.

Whereas it is quite possible that fundamental traders brought prices back down to appropriate levels warranted by fundamentals, Soros made money as prices appreciated by selling out at the peak of this mania, when conglomerates' earnings could not keep pace with noise traders' unrealistically high expectations. Therefore, Soros' strategy is one that involves 'timing' the behavior of crowds and trading (initially) along with noise traders and then exiting right before the bubble bursts.

This view is in accordance with what was mentioned before in section 4.1 that market bubbles are a self-reinforcing process and are fed by the irrational exuberance of investors. This view is well-rooted in academic literature and dates back to at least the work of Bagehot (1872) who observed that savers would "rush" into any investment that promised to deliver a high return (regardless of whether this investment was able to really provide such a return). After these savers realized that such investments can be sold at a higher profit, this stimulated their appetite to invest even more. The first taste (for a high promised return) then became dwarfed by the prospects that these investments can be sold for gains. This "mania" continued as irrational investors fed the bubble and falsely believed that these unsustainably high returns will persist into the indefinite future.

The prominent work of Kindleberger (1978) is written a century after that of Bagehot (1872) yet embodies similar themes and lessons. In particular, he sheds light into some of the tricks that are played by an elite group of investors who bet their money based on where the crowds are going. Initially, there is a group of "insiders" who destabilize prices by driving them upwards, thus stimulating the appetites of other investors who are unaware of the agenda of the "insiders," and they also go in and invest in hope of reaping similar rewards. When enough noise traders have jumped in on the

bandwagon and have over-inflated prices, the insiders then withdraw from the market and take positions which force prices back to fundamentals. While the insiders reap huge rewards, the amateur noise traders suffer from the hangover effects of the bubble. In the words of Kindleberger (1978), "[...] insiders initially destabilize by exaggerating the upswings and the falls, while the outsider amateurs who buy high and sell low are [...] the victims of euphoria, which infects them late in the day."

### 4.2.3.1 The Dutch Tulip Mania

In addition to the aforementioned 1960s conglomerate boom and the REIT boom of the 1970s, there are now numerous examples throughout the course of human history of when irrational exuberance, fueled by noise traders, led to the creation and bursting of stock market bubbles. Although these examples take place in different settings, they all share striking similarities in terms of how they start and how they end. Arguably the earliest documented case of a stock market bubble and crash is the so-called "Dutch Tulip Mania," which has since then been an exemplar of the devastating impact feedback trading and irrational exuberance has in the economy.

The Dutch Tulip Mania is often cited by researchers examining the importance of behavioral finance and how it applies in stock markets today (see Sornette, 2003). This mania began with a fascination for tulips among the upper class elitists of the time. Tulips were considered a rare and highly sought after flower which was originally brought over from Turkey to the Dutch in 1593. After some time, the tulips contracted a peculiar harmless virus which altered their color and gave them an exotic kind of look. This increased the rarity of the tulips and increased the premium that people were willing to

pay to buy these types of flowers. Tulips then became considered an investment vehicle among businessmen instead of a luxury item as was previously considered before. Thus the real money was being made through speculation instead of the actual cultivation of the tulips. The word-of-mouth effects only amplified the overconfidence and overoptimism that investors felt and there was no doubt in their mind that the price would ever fall. Thus, investors began to pour all their money and savings (and even sold off their property) to buy more and more. Prices soured to the equivalent of tens of thousands of dollars in today's present value terms (see Sornette, 2003) and many investors dismissed the possibility that such gains will be short-lived.

On February of 1637 negative news emerged that the tulips were too expensive and possibly difficult to sell and investors tried to cash out all at once. From then until May of the same year, major suppliers and businessmen tried desperately to coordinate their efforts to keep prices propped high, yet, by the end of the month, the prices for tulips collapsed and so did the wealth of all these noise traders who had invested everything in this market. At the peak of the mania, a bulb of tulip could buy an estate. After the bubble burst, it could only buy what it was really worth – a bulb of onion.

### 4.2.3.2 The English Stock Market Boom of the 1690s

The 1690s is an interesting period in England because it was at this time that markets were being established to permit the trading of shares in joint stock companies (see Chancellor, 1999). Given that these types of markets were new, there was a large class of uninformed and inexperienced investors who were willing to try their luck to earn quick riches. This class soon became easy quarry to insiders who were in cahoots with one

another and implemented some of the shady aforementioned tactics, such as those of Jonathan Lebed who would make baseless claims about the future prospects of stocks he would buy in order to entice other investors and spread a false sense of overoptimism in the market.

In particular, given that the stock market in England was at its nascent stages in the 1690s with really no regulation there were many "sham" companies which emerged to suck up investors' funds and the systematic manipulation of stock prices was rampant in order to benefit a select group of insiders (see Banner, 1998). Another strategy which was used extensively to prey on these amateur investors is known today as "pump and dump" whereby confederates spread false rumors about stocks which they have purchased and, after pumping up the stocks' prices, they sell off and reap rewards while others eventually lose their investments.[27] This type of strategy can be explained from the perspective of behavioral finance because it plays off investors' irrational behavior and, as is described more elaborately in Section 4.2.5, can be explained by the systematic psychological biases which individuals make and which materialize in their investment decisions.

Such a strategy, coupled with investors' irrationality, is also the source of positive feedback trading in markets, whereby investors falsely presume that just because stock prices have experienced recent appreciation they will continue to do so in the future. This type of feedback leads to the herding behavior previously mentioned and bandwagon effects, whereby investors copy others instead of conducting rational valuations and having a healthy sense of skepticism about what is really going on.

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[27] The "pump and dump" scheme is also referred to by the SEC as a "hype and dump manipulation" whereby investors are misled into buying stock falsely believing the fraudsters who create this mania either via internet messages and newsletters or other word-of-mouth means of communication (see SEC: http://www.sec.gov/answers/pumpdump.htm). When the price is "pumped up" the fraudsters exit their positions reaping easy rewards while others absorb the downfall.

The years before the summer of 1696 – when the bubble eventually burst and an economic crisis emerged – many of the powerful insiders had managed to artificially pump up prices and amass fortunes by feeding on the unsophisticated noise traders (see Chancellor, 1999). In response to the chaos and the strong outcries for regulation, Parliament passed regulations in 1697 to limit the number of brokers, all of whom had to be licensed by the City of London (see Banner, 1998).

### 4.2.3.3 The 1920s Boom and Bust

The years leading to the ultimate crash of 1929 were referred to by economic historians as the "roaring twenties" for the unprecedented industrial growth and overoptimism in the stock market. It was a time in America when the First World War had been declared a victory and the industrial sector was producing luxury items that had never been seen before or so readily available to the public (see Fraser, 2005). Thus, it was a time rampant with overoptimism and overconfidence and these emotions undoubtedly played out in the stock market. Namely, there was a large class of unsophisticated investors who believed that this trend will indefinitely continue and that there were no risks associated with investing in the stock market (see Shiller, 2000). They became overly trusting that favorable conditions would persist and, as in England's case, insiders were quick to capitalize off peoples' exuberance and irrationality.

Lax regulation and a Wall Street-friendly political environment only exacerbated matters and paved the way for insiders to commit financial deceit and to play on peoples' irrational emotions to realize huge gains (see Fraser, 2005). In particular, big players on Wall Street conjured up fraudulent strategies which enticed positive feedback trading among unsophisticated and uninformed investors. Such strategies consisted of methods to

manipulate stock prices in order to promote positive feedback trading among investors. To achieve this, insiders held pools of investment capital and would buy and sell stocks among each other. For example, one confederate would buy shares from their accomplice and then sell them back to their accomplice for a slightly higher price. This strategy would persist until investors would falsely believe that the prices of stocks were rising and they too would irrationally jump on the bandwagon and purchase these stocks in hopes of reaping high and easy returns.

When the bubble burst, as it has in the past, the effects were so devastating and long-lived that Congress created the Securities and Exchange Commission to serve as a watchdog and protect the public from fraudulent and deceptive practices. It also passed several measures of regulation, such as the Securities Act of 1933 and the Securities Exchange Act of 1934 which serve to provide the public with more information and make it considerably more difficult for insiders to engage in some of the deceitful tactics mentioned here.[28]

### 4.2.3.4 The Stock Market Crash of 1987

The stock market crash of October 1987 is strikingly similar in terms of the events and psychological factors culminating to this massive financial calamity. In the vivid words of Shleifer and Summers (1990, p.19) "[...] stock in the efficient markets hypothesis [...] crashed along with the rest of the market on October 19, 1987." This event is oftentimes cited by proponents of behavioral finance as a strong case against stock market efficiency given that there were many "insiders" who profited from the downfalls of the plethora of investors who exhibited the type of irrational herding behavior that leads to bubbles (see Shiller, 2000).

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[28] For more information refer to http://www.sec.gov/about/laws.shtml at the SEC's website.

The years prior to the crash, equity markets had experienced strong gains and large appreciations in prices, which had outpaced the growth in earnings and raise the P/E ratio to above-average levels. Some market commentators were cautious in their appraisal of the market and even warned of the possibility that it may be overvalued (see Anders and Garcia, 1987). These steady and unprecedented appreciations in price lured many investors such as large pension funds and this helped to boost prices (see Shiller, 2000).

Although equity prices were also supported by favorable tax treatments given to companies which buyout other companies, such as permitting them to deduct interest expenses incurred by issuing debt to finance the buyout (see Presidential Task Force on Market Mechanisms in the Brady Report, 1988), much of what happened was also the direct result of positive feedback trading, which was alluded to the Introduction of this chapter. In particular, financial markets during this period saw a popularization of a method involving programmed trading whereby computers would trade a block of stocks based on a set of predetermined conditions (see Shiller, 2000). Generally speaking, these so-called strategies would produce "optimal" portfolio allocations between stocks and other instruments whereby they increase the weight of the allocation in stocks during market upswings and pull out of stocks during market downturns.

As was mentioned in the Introduction briefly, portfolio insurance strategies were also at play during this stock market bubble whereby investors would try to protect themselves from downside risk. This strategy entails buying stock market index futures when the market is faring well and selling during downturns. Such a strategy, albeit avoids direct trading of stock, is essentially a positive feedback trading strategy which exacerbates price movements in either direction and drives them farther from their

fundamental value. As a matter of fact, there were anticipatory concerns just days before the crash that such positive feedback strategies can lead to a large number of investors selling their stocks and futures all at once (see Garcia, 1987). The October 12th article by the Wall Street Journal mentioned that the use of these strategies can result in a considerable "[...] rout for stocks" (see Garcia, 1987).

The few days preceding the crash were marked by a series of unfavorable pieces of news concerning financial markets; firstly, the U.S. House of Representatives filed for legislative measures to erase any tax benefits and interest rates were beginning to rise (see Securities and Exchange Commission (SEC) Report, 1988). This began to put downward pressure on stocks' prices since when interest rates rise, so does the discount factor (or required rate of return) investors assign to discount future expected dividends (see Koutmos, 2010 and references therein).

By Thursday the 15th, the investment environment became saturated with anxiety and many of the large institutional investors were pulling out of the stock market and into safer instruments such as bonds. By Friday the 16th, anxiety worsened as positive feedback traders continued to sell stocks given that their computer models were signaling them to continue to decrease their portfolio weights in the stock market. By the end of the trading day on that Friday, the S&P 500 index had fallen around 9% for that week amid investors' positive feedback behavior to continue to sell (see SEC Report, 1988).

On Monday the 19th, events had reached an irreversible state where there was very little policymakers could do to lessen the impact of the positive feedback traders. The unprecedented trading volume had besieged computers at the New York Stock Exchange (NYSE) that the Exchanged was forced to delay its opening (see SEC Report,

1988). While many of the specialists of the NYSE tried to lessen the impact of the positive feedback traders by buying stocks, they were unable to do so given the large quantity of investors (small and large) all selling at the same time (see SEC Report, 1988; Shiller, 2000). On that day alone, the DJIA, NYSE and Wilshire 5000 had fallen between approximately 19% and 23% (see Katzenbach, 1987; SEC Report, 1988).

**4.2.3.5 The Bursting of the Tech Bubble in the Late 1990s**

The bursting of the tech bubble tells a similar story whereby its creation and demise were brought forth by irrational herding and positive feedback investors. During the buildup prior to this crash, the availability bias had already taken effect in the sense that investors had, to some extent, forgotten the crash of October 1987. Furthermore, there was a lax feeling on Wall Street given that it had pressured Congress and lawmakers at Washington D.C. to make it more difficult to pursue lawsuits against financial intermediaries and issuers of securities (see Coffee, 2002). One such reform passed by policymakers was the much debated Private Securities and Litigation Reform Act of 1995 which made it increasingly difficult to file class action lawsuits against financial firms (see Coffee, 2002). Another landmark ruling was in 1999 when Congress and policymakers at Washington, D.C. decided to repeal the Glass-Steagall Act, which was originally enacted after the Crash of 1929 to separate investment banking from depository banking.

These events started to set the stage for overoptimism and overconfidence that Wall Street later experienced which led to the bubble and subsequent crash of the tech bubble in 2000. In particular, as in the case of the other aforementioned bubbles and crashes, upward trends in the market during the years preceding the crash enticed many

investors to engage in "trend chasing" (i.e. positive feedback) strategies in Nasdaq 100 stocks (see Griffin, Harris, and Topaloglu, 2003) which kept pushing prices of tech stocks further from their fundamental value. In fact, Ofek and Richardson (2002) estimate an implied P/E ratio of over 600 for internet stocks in 1999; in plain language, investors were somehow *expecting* these stocks to earn supernormal returns in the future which far exceed those of any individual stock which may have existed in the past. Shiller (2000) corroborates this point and argues that this crash was the result of frenzied investors who believed they can keep earning higher and higher returns, without regard for fundamental value. Shiller (2000) also blames an emphatic media seeking to maximize their viewership and ratings by constantly feeding investors with pseudo-news and investment advice which contributed to much of the hype.

Finally, as in the aforementioned market crashes, when investors with an eye on fundamentals began to withdraw from the market, prices fell precipitously and, as Ofek and Richardson (2002) report, the required return on these tech stocks remained at 0% for the next few years.

**4.2.3.6 Ponzi Schemes and Herding Behavior**

Now more than ever, we hear in the financial press of so-called Ponzi schemes; a fabricated story about how returns are made for investors whereby, in actuality, these returns are made by taking money from one investor and giving it to money invested by successive investors. This fraudulent formation of returns is essentially a pyramid scheme (or a money circulation scheme) which persists as long as there are future investors interested in investing with the fraudster and as long as the scheme goes undetected.

Real-world cases of this show that the problem of finding new investors is not a daunting task for the fraudster given some of the irrational behavior which investors display such as herding and positive feedback trading. For example, initially when investors hear of high returns, instead of considering the means by which the portfolio manager earned these returns, they immediately become very excited and it generates enthusiasm and overoptimism among investors. Thus, more and more investors want to partake in this and entrust the fraudster with their hard-earned money. As Shiller (2003) describes, these schemes persist as a result of the word-of-mouth effects, the media, and the social networks which people rely on for information, and the "envy" they get by seeing others' successes and fortunes.

Ponzi schemes are an example of positive feedback trading since more and more investors want to invest their money with the fraudster just because they presently see high returns, yet, when the scheme is uncovered and investors are losing money, they all want to withdraw out of this game immediately. Famous contemporary cases of Ponzi schemes abound in the news today. One most notable case was that of Bernard Madoff who is accused of running a $50 billion Ponzi scheme.[29] Given that Ponzi schemes exist (and can persist for some time) in countries with industrialized economies and established legal frameworks, it is no surprise that such schemes are widespread in other parts of the world which lack proper legal checks and balances. For example, from 1996 through 1997 there were many Ponzi schemes in Albania which collectively were so large in magnitude that amounted to a half of a year's GDP and even led to civil war (see Jarvis, 2000).

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[29] The litigation document which outlines the charges and facts against Bernard Madoff is publicly available at http://www.sec.gov/litigation/complaints/2008/comp-madoff121108.pdf

As Shiller (2000) argues, Ponzi schemes are akin to market bubbles fueled by irrational exuberance in the sense that high current returns incite overconfidence and overoptimism and, spreading via word-of-mouth enthusiasm and the media, entice more and more investors. Thus, the bubble (or Ponzi scheme) persists until it is uncovered and investors begin to ask questions or they suspect that something is awry. In this case, as in the other aforementioned cases, this type of investor behavior leads to positive feedback trading and it is therefore of interest to see if this kind of feedback trading is evident in the behavior of stock prices (see De Long *et al.*, 1990a; Shleifer and Summers, 1990; Shleifer and Vishny, 1997; Shiller, 2000).

**4.2.4 Financial Institutions and Herding Behavior**

The examples of stock market bubbles and irrational investor behavior just cited here are in no way comprehensive. For there are many more examples which have not been cited here yet the above examples are sufficient in terms of illustrating what happens when investors allow their greed and overconfidence to cloud their decision-making abilities. It also shows that these factors can lead to positive feedback behavior which, although in the short-run may lead to substantial gains, will almost always fail in the long-run.

A good question to ask however is why financial institutions do not prevent these events from happening and why they do not attack bubbles before it is too late. Economics textbooks often talk about financial institutions' role in financial markets and, one such role, is to limit the information asymmetry among the various class of investors and to ensure that markets are an equal playing field for everyone (see Mishkin, 2005). Given the examples cited above, along with casual observation of financial markets, there

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is ample evidence to suggest that such institutions may also very well engage in the types of irrational investing just described. In particular, they may be as prone to positive feedback trading and irrational exuberance just like individual investors are.

Academic literature has identified this problem and it is cited frequently as a grave concern and something that policymakers should be aware of as well. For example, hedge funds, which are viewed as being a sophisticated class of investors, have been found to engage in the types of positive feedback investment strategies mentioned here. For example, Brunnermeier and Nagel (2004) find that hedge fund managers did not trade in order to correct prices during the technology bubble, which was described in section 4.2.3.5 of this chapter. Instead, many of them captured much of the upturn by being heavily invested in tech stocks while reducing their weight considerably when the market bubble burst. The perceptive reader may ask, why do financial institutions herd and that they do not trade in order to correct mispricing?

There are several reasons why institutions and large "sophisticated" investors engage in positive feedback strategies and herding. Firstly, the simplest reason they do not correct mispricing is because it is not in their interest to do so. They may benefit from the irrational upswings in price and therefore see no reason to take opposing positions and wait until the market corrects in order for them to reap rewards. This is certainly the case for many of the hedge funds that Brunnermeier and Nagel (2004) were talking about in their study.

Secondly, investment managers are oftentimes evaluated based on their relative performance to some benchmark. This benchmark may consist of the market index or it may consist of the performance of the manager's peers. This has been referred to as

"compensation-based herding" in the literature and arises when financial institutions mimic each other and disregard their own information and intuition for fear that if they make a mistake, they will look bad relative to their peers and it will be shameful in the eyes of the investors and senior management. However, if everyone does poorly, then this can be blamed on other factors such as a weak economy which negatively impacts all investments (even the good ones). This premise is embodied in a famous quote by Keynes (1936) who makes the observation that "it is better […] to fail conventionally than to succeed unconventionally."

Maug and Naik (1996) introduce a theoretical model of an agent whereby their compensation is determined by the relative performance of their peers. Specifically, the agent's compensation increases (decreases) if they perform well (poorly) relative to their benchmark. Given this, it is important to note that the agent, as well as other agents who serve as the benchmark, have imperfect information regarding the market and may rely on their own unique data sources. They find that when benchmark investors make their investment decisions, an agent will observe these actions and make investment decisions which imitate the benchmark investors. Thus, in effect, the agent's investment portfolio moves closer to the portfolio of the benchmark. Given the compensation system in place, this provides the incentive to copy what the benchmark is doing.

Scharfstein and Stein (1990) extend this logic and argue that when a money manager invests in a poor investment decision, this outcome comes to light ex ante and if other managers did not invest in the same project or asset. If many other managers had also done the same and the investment turned sour, then this can be blamed on macroeconomic factors which affect everyone and not on managers' decision-making

capacity. As a result, even very good managers can resort to following the herd instead of taking the risk and investing in something unique for fear that it may be a wrong decision and it will reflect negatively on them in relation to what their peers are doing. This corroborates the statement by Keynes (1936) that it is better to fail along with everyone else than to take the risk of trying to succeed in isolation.

Graham (1999) argues that the principle of herding applies not only to financial institutions but even to investment newsletters. In particular, investment newsletters, and especially ones with lower reputations, are more likely to follow relatively more established newsletters in terms of investment advice and content. Thus, they herd on investment advice and follow the leaders in order to show that they too are producing high quality advice and research just like the leaders are. This is very similar to a strategy known as "window dressing" which is essentially a positive feedback strategy whereby investment managers remove losing stocks from their portfolios and replace them with winning stocks to make their portfolio "look better."

It is important to mention however that more research in this area is called for in order to see the true effects of financial institutions' influence on the market. The reason for this is there are mixed views in the literature concerning the role of financial institutions and if their herding is rational or irrational. For example, Lakonishok, Shleifer, and Vishny (1992) present at least three competing views on the behavior of institutions. The first such view is that institutions exert a destabilizing effect on the prices of stocks, pushing prices further from their fundamental value and inducing long-term volatility. This view rests on the premise that financial institutional holdings in the stock market far exceed those of individual investors and, therefore, when their buying

and selling activity is correlated this can have a large impact on prices. In light of the stock market crash of 1987, one fund manager described financial institutions as follows: "Institutions are herding animals [...] we watch the same indicators and prognostics [...] like lemmings, we tend to move in the same direction at the same time" [see Wall Street Journal, (October 17, 1989)]. This view also rests on many of the arguments made earlier by other researchers that managers' compensation is linked to their performance relative to that of their peers. Thus, there is a tendency for them to herd.

The second (and opposing) view is that institutions are cool and level-headed and only will herd together if they receive the same information and construe it in the same way. They may also exhibit herding behavior if they attack the same kind of mispricing or investor biases at the same time. This view, in contrary to what many of the other aforementioned studies argue, suggests a negative feedback strategy of selling overpriced assets and buying ones that are underpriced.

Finally, the last view is more neutral than the other two viewpoints and affords a more open-ended answer to this question. It argues that financial institutions are heterogeneous agents and utilize a broad range of portfolio strategies and indicators. Thus, their trades are uncorrelated and, in the long-run, cancel each other out.

**4.2.5 Investor Psychology and Finance**

What are some of the behavioral theories which seek to explain herding behavior and feedback-type investment strategies? To answer this question, we turn to some experimental evidence done by researchers in the field of psychology. In addition to some of the aforementioned theories such as overoptimism, overconfidence, and the

availability bias, there are several prominent psychology experiments and theories which have direct application here in behavioral finance and have gained credence over the years.

The notion that investors act on the basis of emotions and ways which are irrational is not new in finance or social psychology; for example, Keynes (1935) likens the stock selection process of investors as a mere "newspaper beauty contest" whereby they select stocks on the basis of which one they think will get the most votes. Since then, there has been much experimental evidence and theories which suggest investor psychology plays a large role in the stock market and may even lead to suboptimal decision-making and feedback trading. In particular, Andreassen and Kraus (1988) find that when they give subjects a sequence of historical stock prices (which the subjects knew were real) and asked to trade, they behaved in a fashion that is consistent with positive feedback trading. More specifically, despite the fact that there was no fundamental information available, they would pick out trends they thought existed and would buy more when prices appeared to be rising. This evidence is corroborated by later studies that look at investor behavior and try to link it with the rise of stock market bubbles (see Marimon, Spear and Sunder, 1993).

Feedback trading is also supported by evidence in the field of cognitive psychology which argues that investors (and human beings in general) make decisions on the basis of the "representativeness heuristic" which lead to systematic biases in their assessment of future possible events (see Kahneman and Tversky, 1974). In particular, they seek to find patters and associations in things and observations without regard for realistic probabilities. In their experiment, Kahneman and Tversky (1974) asked

participants to guess what occupation an unknown person had on the basis of their description, personality and interests. In general, participants in the experiment would guess occupations not considering the likelihood of the occupation and how often you come across someone with this type of occupation. A rational individual taking this experiment would guess unexceptional occupations since most people are in these occupations regardless of their interests or hobbies. Extending this logic further, investors may have a tendency to classify stocks into various categories based on their historical trends. They may, for example, classify stocks that have done well previously as "hot stocks" regardless of fundamentals or underlying factors of market risk.

Bem (1965) and Daniel, Hirschleifer and Subrahmanyam (1998) postulate that a so-called "self-attribution bias" may exacerbate the effects of feedback trading. This bias results from a common observation embedded in human behavior whereby individuals attribute fortunes to their skill (without considering the element of chance may be at play) and attributing their misfortunes to factors such as bad luck or factors beyond their control. Many readers at this point can probably call to mind situations in social circles where they have been in conversations where individuals boastfully talk about their investment successes and attribute it on the basis of their skills. In a similar fashion, other individuals may be inclined to attribute their misfortunes to exogenous bad conditions that everyone faces and may make the argument that "everyone is in the same boat."

It is important to see that this type of mindset is what leads to feedback-type trading patterns in stock prices. In particular, the conjectures set forth by Bem (1965) and Hirschleifer and Subramanyam (1999) lead to the overconfidence and overoptimism that was discussed previously. This kind of unrealistic and wishful thinking is prevalent not

only in the finance profession but in everyday life; for example, most participants believe they have above average abilities in everyday life such as driving a car or having good relationships with others (see Weinstein, 1980). In a more recent study, Buehler, Griffin and Ross (1994) find that participants were overconfident in their abilities and mentally planned that they could complete projects sooner than they were actually able to.

Finally, it is worth noting that much of the findings reported here in this section also explain why many investors lack sufficient diversification in their portfolios. For example, as was mentioned in detail in section 2.2.4.2 of this thesis, some investors simply invest in the company they work for or local companies near them because this is what they are familiar with (see Huberman, 2001). Overconfidence can manifest itself into poor diversification since investors feel unrealistic confidence about what they are familiar with instead of taking into account the fact that there are many possible aggregate stock market risks that cannot be hedged through investing myopically. A good example of this is individuals who invest in local companies despite the fact that the value of their real estate is tied to the success of the company.


## 4.2.6 Limits to Arbitrage

The EMH holds true when arbitrage opportunities are riskless and traders are willing to take chances to reap excess profits. In reality however, and in light of some of the arguments made before, markets are not entirely 'complete' in the sense that there are perfect substitutes for mispriced assets. They may not also be as efficient as the EMH suggests. Therefore, arbitrageurs almost certainly face many risks when trying to execute trades and these risks may constrain them severely in terms of their ability to correct

mispricing. Despite the standard view, which dates back to Friedman (1953), that arbitrageurs stabilize prices, there are arguments which claim that arbitrageurs are possibly constrained in terms of their ability to execute trades and stabilize prices. In fact, as is argued previously, there may even be an incentive for arbitrageurs to ride waves and follow herding investors in order to reap profits before attacking the bubble.

However, conventional literature in this field generally takes the position that arbitrageurs intend to take corrective roles in the market and to attack mispricing which is developed through the actions of noise traders. In general, the literature cites three types of risks which limit the corrective actions of arbitrageurs. The first two are known as fundamental risk and noise trader risk and are initially discussed in the seminal studies by Figlewski (1979) and De Long *et al.* (1990a, 1990b, 1991). The former of these two risks can be illustrated by this simple example: Suppose an arbitrageur buys undervalued stocks of a hypothetical company whose fundamental value is $30 but has been pushed down to $25 by pessimistic noise traders. The obvious imminent threat to arbitrageurs is that a bad piece of news may arrive regarding this company and it may push the price even further down. A natural way to hedge this risk is to buy shares from substitute companies (i.e. companies in the same industry perhaps). However, this sort of strategy may provide protection if there is bad news relating to the entire industry but still leaves open the possibility that bad news can arrive regarding the specific company's shares. Thus, it is not possible to eliminate fundamental risk in its entirety.

The second type of risk their study mentions is known as noise trader risk and is different from fundamental risk in the sense that arbitrageurs may attack mispricing but may do so somewhere at the midpoint of the feedback wave and, as such, mispricing may

persist and exacerbate in the near future. Thus, arbitrageurs may be forced to liquidate their positions and suffer losses as feedback traders continue to push prices further from their fundamental value.

A third type of risk is known as synchronization risk and is perhaps the reason arbitrageurs face the two aforementioned risks (see Abreu and Brunnermeier, 2002 and 2003). This risk results from the inability of arbitrageurs to successfully coordinate their actions to attach mispricing. For example, arbitrageurs may be aware of mispricing at an individual level but may not act for fear that they are acting alone. Therefore, there is a synchronization problem in the sense that they cannot coordinate to attack mispricing as a whole. If they cannot time their actions, then arbitrageurs who act alone may face the two aforementioned risks and suffer losses to their portfolio.

Of course there are other types of risks arbitrageurs face that stem from these three risks and which limit their abilities. Abreu and Brunnermeier (2002), for instance, argue that arbitrageurs face holding costs in their attempt to exploit mispricing. Consider for example a hypothetical arbitrageur who sells short an overpriced stock. Short-selling incurs several holding costs; they must hold the proceeds from the short sale in a low- or zero-bearing interest margin account. In addition, given the conditions of the margin account, it may be necessary for them to put more money in into this account and this presents an opportunity cost for alternative investments opportunities that are missed.

Therefore, the implication of these events is that there exist feedback traders and fundamental traders who may have a significant impact on the behavior of stock prices and who drive the direction of the aggregate market. It is the intent of this chapter to model the behavior of these types of investors and to see whether their actions are

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manifested in the movements of stock prices. Although some of the aforementioned instances are rather extreme in terms of their nature and improbable in terms of their frequency, they do illustrate some rather important aspects of investor behavior and emphasize the arguments of Black (1986), De Long *et al.* (1990a), Shleifer and Summers (1990), Shleifer and Vishny (1997) and Shiller (2000) that there are heterogeneous investors in the marketplace and it is therefore of interest to investigate the intertemporal risk-return tradeoff by incorporating their behavior in our empirical models.

## 4.3. The Model

In light of the aforementioned arguments, there is evidence to suggest the presence of investors with heterogeneous trading patterns which influence the movement of stock prices. As mentioned, stock price dynamics may be driven by emotions in the stock market and also by investors who base their decisions on fundamental factors. Thus, it is important to consider these groups of investors when trying to uncover the forces which drive stock prices. The ICAPM of Merton (1973) provides an intuitive formulization yet is based on the premise that investors are utility maximizers which make decisions on the basis of mean-variance considerations when selecting optimal portfolios. Such a generalization is consistent with the groundwork theory laid forth by Markowitz (1952) which was discussed more in-depth in the second chapter of this thesis. However, as is argued by other researchers and as is discussed in the previous section, perhaps it is important that we consider the fact that there exist heterogeneous investors which, through their trading behaviors, influence the movements in stock prices.

The model used to describe the presence of heterogeneous trading patterns is based on the works of Shiller (1984), Sentana and Wadhwani (1992), and Cutler, Poterba and Summers (1990). The model postulates three types of traders: (a) rational risk-averse investors who make decisions on the basis of mean-variance considerations; (b) positive feedback, or, momentum traders, who are trend-chasers and buy (sell) when market prices rise (fall); and finally, (c) fundamental traders, who base their expectations on prices relative to fundamentals.

The demand for shares by rational risk-averse investors is consistent with the axioms which govern utility maximization theory. These investors are holding a greater fraction of shares when they forecast higher expected returns relative to the required returns. The demand function for this group can be written as:

$$S_{1,t-1} = \frac{[E_{t-1}(R_t) - r_f]}{\theta \sigma^2_t} \; ; \; \theta > 0 \qquad (4.1)$$

where, $S_{1,t-1}$, is the fraction of shares held by group 1, at time t-1. $E_{t-1}(R_t)$ is the conditional expectation of the return as of time t-1, $r_f$, is the risk-free rate, $\theta$ is the coefficient of relative risk aversion and $\sigma^2_t$ is the conditional variance as of time t-1. This demand function is identical to the one used by Sentana and Wadhwani (1992) and it can be reduced to the one used by Cutler, Poterba and Summers (1990) with suitable parameter restrictions.

Fundamental traders form expectations of future returns of the basis of fundamental values. When prices are low relative to fundamental values, they increase their demand and vice versa. Their demand function is given by:

$$S_{2,t-1} = \beta(f_{t-1} - P_{t-1}); \; \beta > 0 \qquad (4.2)$$

where, $S_{2,t-1}$ is the demand for shares held by group 2 at $t$-$1$, and $f_{t-1}$ and $P_{t-1}$ are the fundamental value and the price respectively.

Finally, feedback traders base their demand on past returns (i.e., they raise their demand following price increases and lower it following price decreases). This may be due to the use of stop-loss orders, technical analysis, overconfidence and overoptimism, trading on the basis of noise, or even portfolio insurance strategies. The demand function that captures this behavior is given by,

$$S_{3,t-1} = \delta\left(R_{t-1} - r_f\right); \; \delta > 0 \tag{4.3}$$

where, $S_{3,t-1}$ is the fraction of shares held by group 3 and $\delta$ is the feedback parameter, expected to be positive assuming that positive feedback trading far outweighs any negative feedback trading. This is similar to the model presented by Sentana and Wadhwani (1992) in the sense that investor demand for shares at time $t$ is a function of what prices are in time $t$-$1$. The notation I use here is different from that of Sentana and Wadhwani (1992) in the sense that demand at time $t$ is a function of returns on the stock market in excess of the risk free rate, i.e., $R_{t-1} - r_f$. It is important also to note that the main distinction between the model used here in this chapter and the model by Sentana and Wadhwani (1992) is that the latter looks at the behavior of only rational investors and feedback investors.

In equilibrium, all shares will be held, so that we can write:

$$S_{1,t-1}+S_{2,t-1}+S_{3,t-1} = 1. \tag{4.4A}$$

or, alternatively,

$$\frac{[E_{t-1}(R_t)-r_f]}{\theta\sigma^2_t} + \delta\big(R_{t-1}-r_f\big) + \beta\big(f_{t-1}-P_{t-1}\big) = 1 \tag{4.4B}$$

Setting $R_t - r_f = r_t$, and $E_{t-1}(R_t) - r_f = r_t + \varepsilon_t$ we get:

$$r_t = \theta\sigma_t^2 - \delta(\theta\sigma_t^2)\big(r_{t-1}\big) - \beta(\theta\sigma_t^2)\big(f_{t-1}-P_{t-1}\big) + \varepsilon_t \tag{4.5}$$

Equation (4.5) can be recast in a simplified form as follows:

$$r_t = b_0 + b_1\sigma_t^2 + b_2\,[\sigma_t^2\big(f_{t-1}-P_{t-1}\big)] + b_3\,[\sigma_t^2\big(r_{t-1}\big)] + \varepsilon_t \tag{4.6}$$

where, $b_0=0$, $b_1=\theta$, $b_2=-\beta\theta$, and $b_3=-\delta$. Based on this model, the presence of fundamental traders implies that $b_2$ is negative and statistically significant. Similarly, if there is positive feedback trading it implies that $b_3$ is also negative and statistically significant.

Finally, the conditional variance is modeled as an EGARCH(1,1) process as follows:

$$ln(\sigma^2_t) = \alpha_0 + \alpha_1\big(\big|z_{t-1}\big| - E\big|z_{t-1}\big| + \lambda z_{t-1}\big) + \alpha_2 ln(\sigma^2_{t-1}) \tag{4.7}$$

where, $ln(.)$ are natural logarithms and $z_t = \varepsilon_t/\sigma_t$ are standardized residuals. The EGARCH specification is advantageous in that it allows the conditional variance to behave asymmetrically in response to positive and negative innovations of equal magnitude. In other words, this is consistent with Campbel and Hentschel (1992) which argues that 'bad' news leads to more volatility than 'good' news. Furthermore, a first order lag structure is adopted since, consistent with existing evidence, lower-order GARCH models have

proven sufficient in terms of effectively modeling the time-series properties of stock returns (see Bollerslev, Chou and Kroner, 1992).[30]

The model described by Equations (4.1) through (4.7) nests both the Sentana and Wadhwani (1992) and Cutler, Poterba and Summers (1990) models. For example, if the conditional variance is constant over time, the model reduces to that of Cutler, Poterba and Summers (1990). When we assume that the conditional variance is time-varying but the fundamental traders are not present, (i.e. $\delta=0$) then the Sentana and Wadhwani (1992) model holds.

There is no general agreement on what is an appropriate proxy for the fundamental value. Cutler, Poterba and Summers (1990) find that a constant multiple of dividends works well for stocks. Jiang and Lee (2009) use both dividends and earnings. Furthermore, there is a large body of academic and practitioner literature that use the so-called Fed model, whereby the fundamental value is equal to earnings discounted by the long-term government bond rate. This model was described in greater depth in the second chapter and now will be used again here.

To assure robustness of the results this chapter use three different measures for fundamental value; the first is based on earnings, the second is based on dividends and, finally, the third is based on the Fed model. These three measures are calculated using current earnings and dividends as well as normalized earnings and dividends based on two-year moving averages.

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[30] For robustness, the heterogeneous model was also estimated using, instead of the EGARCH model in Equation (4.7), a GJR-GARCH model as was described in the second chapter in Equation (2.24b). The findings (not reported here for the sake for brevity) find qualitatively analogous results as those reported in Tables 4.2 through 4.8. Consistent with diagnostic tests performed, this suggests that both the GARCH-based models here provide a similar estimate for volatility since they both account for the asymmetric impact of news. Since the results are qualitatively similar, this then highlights the need for focusing more research on considering other proxies for fundamental value, as this may help to better explain the behavior of such fundamental investors.

## 4.4. Data and Variable Construction

The data used to test the model refer the stock markets of the group of seven industrialized nations, G-7. By examining international stock markets, useful information can be gained as to their respective risk-return characteristics and whether heterogeneous investors are present in such markets. The frequency of the data is monthly since fundamental factors such as the price-earnings ratio are available on a lower frequency basis. The sample ranges and descriptive statistics are identified in Table 4.1.

In particular, the data used in this study include the monthly observations for the stock price indices of the Group of Seven nations (G-7); namely, those of Canada, France, Germany, Italy, Japan, the UK, and the US. These countries are chosen to examine the presence of heterogeneous investors and to see to what extent their actions possibly drive stock prices. In examining these markets, the following indices are used: Toronto 300 Composite (Canada), CAC industrial price index (France), DAX price index (Germany), Milano price index (Italy), Nikkei 225 (Japan), FT All Share Index (UK), and the S&P 500 (USA). The starting dates for each market are reported in Table 4.1 and are 1/1973 (for Canada), 1/1989 (for France), 1/1983 (for Germany), 1/1987 (for Italy), 1/1985 (for Japan), 1/1976 (for the UK), and 1/1968 (for the US). The ending date for all markets is 6/2009. The choice for the data ranges is determined by the availability of all data necessary to complete this investigation at the time this study was undertaken. It is important that the data came from a single source and I avoided splicing together data from different sources such as, for example, adjoining data from DataStream with data from the International Monetary Fund (IMF), the National Bureau of Economic Research (NBER), or other research divisions within various Central Banks. Thus, the data used for

this purpose are thus solely collected from DataStream, a well-respected source of financial and economic data used by practitioners and academicians alike. The sample ranges are dictated by data availability and contingent on the requirement that there be uninterrupted data, since I avoid splicing with other sources.

In contrast to studies that focus on the autocorrelation dynamics of higher frequency data to test for the presence of feedback traders, this chapter uses monthly observations to see in the longer-run whether such feedback trading is evident. In addition to this, fundamental traders use fundamental factors, such as the P/E ratio, which are generally available on a lower frequency basis.

The unconditional return series, $R_t$, for each market index is calculated in continuously compounded terms as $R_t = 100*\ln(P_{i,t} / P_{i,t-1})$. Dividends are factored into each index's return series by adding in the appropriate market's monthly dividend-yield. Descriptive statistics for each stock market's monthly returns that are provided in Table 4.1 include the mean ($\mu$) and standard deviation ($\sigma$), measures for skewness ($S$) and kurtosis ($K$). The monthly return series for all stock market indexes are negatively skewed and highly leptokurtic. This is consistent with asset pricing literature and the so-called 'volatility feedback' hypothesis of Campbell and Hentschel (1992) which argues that large negative shocks in market returns lead to more volatility than positive shocks of equal magnitude, as is mentioned in the previous chapters of the thesis.

Furthermore, these statistics show, as is described in the second and third chapters, evidence of so-called 'ARCH effects' in the volatility of the return series for each market and that negative innovations lead to more volatility than positive innovations of equal magnitude (see Engle and Ng, 1993). This is a reason for the

empirical observation that volatility tends to cluster together, as is illustrated in Figure

2.1 in the second chapter.

## Table 4.1: Sample Ranges & Descriptive Statistics

|  | Canada | France | Germany | Italy | Japan | UK | USA |
|---|---|---|---|---|---|---|---|
| *Sample start date:* | *(01/1973)* | *(01/1989)* | *(01/1983)* | *(01/1987)* | *(01/1985)* | *(01/1976)* | *(01/1968)* |
| *Sample end date:* | *(06/2009)* | *(06/2009)* | *(06/2009)* | *(06/2009)* | *(06/2009)* | *(06/2009)* | *(06/2009)* |
| **(A) *Monthly stock market returns*** | | | | | | | |
| $\mu$ | 0.8140 | 0.5115 | 0.8567 | 0.3188 | 0.0840 | 0.9981 | 0.7275 |
| $\sigma$ | 4.6630 | 5.6493 | 6.4487 | 6.2832 | 5.7588 | 4.9082 | 4.5079 |
| S | -0.9296 | -0.5284 | -0.8562 | 0.1360 | -0.3836 | -1.0134 | -0.6929 |
| K | 6.7175 | 3.4286 | 5.4387 | 3.6457 | 4.3500 | 7.4994 | 5.6112 |
| **(B) *Monthly stock market P/E ratio*** | | | | | | | |
| $\mu$ | 15.3000 | 14.5715 | 17.1610 | 17.5019 | 43.1289 | 14.5557 | 18.3181 |
| $\sigma$ | 4.9671 | 4.0321 | 3.6753 | 4.8044 | 13.4805 | 5.1737 | 10.1326 |
| S | 0.2086 | 0.9333 | -0.0020 | 0.6984 | 0.0887 | 0.5427 | 4.9849 |
| K | 2.7132 | 3.4962 | 2.4445 | 4.3257 | 2.1392 | 2.5136 | 49.9134 |
| **(C) *Monthly dividend-yield*** | | | | | | | |
| $\mu$ | 3.0597 | 2.9972 | 2.1179 | 2.9133 | 0.9353 | 4.1559 | 3.1784 |
| $\sigma$ | 1.0682 | 0.7833 | 0.5910 | 1.2900 | 0.3974 | 1.1895 | 1.2932 |
| S | 0.4401 | 1.4638 | 1.9143 | 2.3991 | 2.5230 | 0.3074 | 0.3319 |
| K | 2.4534 | 7.4498 | 9.2083 | 11.7000 | 11.5002 | 2.5035 | 2.2600 |
| **(D) *Monthly stock market earnings-yield*** | | | | | | | |
| $\mu$ | 7.4239 | 7.3524 | 6.1627 | 6.1871 | 2.5996 | 7.8769 | 6.6815 |
| $\sigma$ | 2.8199 | 1.8069 | 1.4280 | 1.9602 | 0.9887 | 2.9404 | 2.9477 |
| S | 1.0670 | 0.2659 | 0.8560 | 2.2532 | 1.6742 | 0.8237 | 0.8712 |
| K | 3.1606 | 2.8868 | 3.0556 | 10.8992 | 7.1103 | 3.2768 | 3.0458 |
| **(E) *Monthly long-term govt. bond yield*** | | | | | | | |
| $\mu$ | 8.3807 | 5.8337 | 5.8299 | 7.6738 | 3.2157 | 8.5848 | 7.2934 |
| $\sigma$ | 2.9178 | 1.9862 | 1.6105 | 3.9183 | 1.9156 | 3.3762 | 2.5355 |
| S | 0.4110 | 0.6949 | 0.1595 | 0.3663 | 0.5157 | 0.2456 | 0.8862 |
| K | 2.8012 | 2.1921 | 1.9198 | 1.4624 | 1.9003 | 1.9261 | 3.5745 |
| **(F) *Monthly short-term govt. bond yield*** | | | | | | | |
| $\mu$ | 6.9575 | 5.0188 | 5.2210 | 9.8739 | 1.3135 | 8.1842 | 5.7444 |
| $\sigma$ | 4.1654 | 2.9587 | 2.4735 | 5.4882 | 2.0588 | 3.5799 | 2.9000 |
| S | 0.8222 | 0.8381 | 1.0538 | 0.0221 | 2.1186 | 0.3986 | 0.8019 |
| K | 3.1680 | 2.3513 | 3.7224 | 1.8814 | 6.6245 | 2.2691 | 4.3733 |

*Note*: This table reports the sample statistics for each of the markets; $\mu$ – mean; $\sigma$ – standard deviation; S – skewness; K – excess kurtosis. The descriptive statistics indicate non-normality in the unconditional return series, as is observed in the second and third chapters of the thesis.

For each country the primary variables used are the stock price index, the dividend yield, the price-to-earnings ratio (P/E ratio), the short term (3-month) rate on Treasury Bills and the long-term (10-year) rate on government bonds. The dividend yield and the P/E ratio are used to calculate dividend payments $(D_t)$ and earnings $(E_t)$. As mentioned, the continuously compounded unconditional stock rate of return is calculated as $R_t=ln[(P_t+D_t)/P_{t-1}]$.

The three different proxies for fundamental value are calculated as follows and discussed in turn. The first proxy, $f_1$, is the long average earnings multiple:

$f_1$ =(*long-term average earnings multiple*) x $E_t$. It is calculated as the sample average of the P/E ratio. This type of fundamental is used rather routinely by researchers (see Fama and French, 2002). The second proxy, $f_2$, is based on a constant multiple of dividends. Even though dividends and earnings are highly correlated, especially for the aggregate market, the correlation is far from perfect. Thus, using a proxy based on dividends could produce additional insights. The calculation of the second proxy is done as follows:

$f_2$= *constant multiple x $D_t$*. On the basis of the constant growth model, the constant will be approximately equal to *1/(k-g)* where *k* is the required rate of return and *g* is the growth rate. It is also equal to the inverse of the long-term dividend yield. In constructing this proxy, I use the sample average of the inverse of the dividend yield. A justification for the use of this type of fundamental proxy can be found in Cutler, Poterba and Summers (1990) and is useful in comparing a fundamental factor, such as dividends, to the price of the asset.

Finally, the third fundamental proxy, $f_3$, is based on the Fed model that was discussed in the second chapter and which predicts that the earnings yield (E/P) should be

approximately equal to the long-term yield to maturity on government bonds. Thus, the calculation of the third fundamental proxy is done as follows: $f_3 = E_t / YTM_t$.

To make sure the results are not biased by short-run fluctuations in earnings and dividends, I recalculate the three proxies using two-year (24 month) moving averages for earnings and dividends. The proxies based on two year moving averages are denoted respectively as $f_1^*$, $f_2^*$ and $f_3^*$. The moving averages provide a more "smoothed" indicator of the fundamental value.

## 4.5. Empirical Evidence

The empirical findings of the feedback model with the three types of investors described above are reported for each respective G-7 market in Tables 4.2 through 4.8, which are located at the end of this section. The estimation is based on nonlinear maximum likelihood techniques assuming that the error term is normally distributed.

Table 4.2 reports the results for Canada. The constant (i.e., parameter $b_0$) is insignificant across all models. The parameter $b_1$ is positive in most cases but statistically insignificant. As mentioned earlier, the presence of fundamental traders is captured by parameter $b_2$ and the model predicts that it should be negative. Interestingly, $b_2$ is negative and statistically significant at the 5% level of significance at least. This result holds irrespective of the way the fundamental proxy is defined, implying that the result is quite robust. There is no evidence of positive feedback trading as the relevant parameter $b_3$ is insignificant. These results are in contrast to those by Sentana and Wadhwani (1992), Koutmos (1997), and Antoniou, Koutmos and Pericli (2005). This may be due to the fact that these studies are using daily data. In this case an argument can be made in favor of the

notion that positive feedback trading is present in the short run, but it becomes insignificant in the longer run. It is also possible that there are also negative feedback traders so that the net result becomes insignificant. The parameters that describe the conditional variance are always significant proving that the conditional variance is indeed time-varying. More specifically, the estimate for conditional variance is a function of past standardized residuals and the past conditional variance itself. Moreover, in the case of Canada, the variance responds asymmetrically to past residuals (i.e., it rises faster when the residuals are negative compared to when the residuals are positive). This can be seen by the sign and significance of parameter $\lambda$.

I use the likelihood ratio statistic (LR) to test the significance of this extended model compared to that of Cutler, Poterba and Summers (1990). Since the latter model is nested, the LR statistic is appropriate. It is calculated as LR = -2*($L_0$-$L_1$) where $L_0$ is the value of the likelihood function under the null hypothesis, in this case, the Cutler, Poterba and Summers (1990) model, and $L_1$ is the value of the alternative hypothesis. The alternative hypothesis is the full model here. It follows chi-square distribution with degrees of freedom equal to the number of parameter restrictions required under the null hypothesis. In this case, the number of restrictions is 3 meaning that the critical values are 7.31 and 9.35 at the 5% and 1% levels. The estimated values of LR are well above the critical values at 1% suggesting that the extended model may provide further advantages. It is again important to note that the restricted model by Cutler, Poterba and Summers (1990) assumes a constant required rate of return of zero by investors who form rational forecasts of the market.

If we now turn to the findings from France (reported in Table 4.3) we find no evidence of positive feedback trading but convincing evidence of fundamental trading. The

strongest case for fundamental trading is made when the proxies used are $f_1$ and $f_1^*$. There is strong evidence that the conditional variance in France is asymmetric (i.e., parameter $\lambda$ is negative and significant). Furthermore, the LR test rejects the null hypothesis and suggests that the full model used here may have some additional advantages in describing investor behavior.

The results for Germany (Table 4.4) are similar in the sense that the positive feedback parameter is insignificant but the fundamental trading parameter $b_2$ is negative and significant in most cases. The strongest case for fundamental trading can be made when the proxy for fundamental value used is based on the P/E multiple (i.e., $f_1$). The conditional variance is also time-varying since the relevant parameters are significant and there is evidence of some asymmetry in the variance. Again, the LR statistic rejects the restricted model in favor of the full model that is used here.

The findings for the remaining four markets are qualitatively similar as those of the preceding aforementioned markets. Specifically, there is evidence of fundamental trading but not enough evidence to support the view that feedback trading is present. An exception appears to be the U.S. market, where there is some evidence of positive feedback trading when the proxy used is $f_1$. In the majority of cases the conditional variance is asymmetric, supporting the use of the EGARCH model. Furthermore, the LR test shows that the extended model performs better than the model by Cutler, Poterba and Summers (1990).

**Table 4.2: Presence of Heterogeneous Traders in Canada's Stock Market**

| Coeff. | $f_1$ | $f_2$ | $f_3$ | $f_1^*$ | $f_2^*$ | $f_3^*$ |
|---|---|---|---|---|---|---|
| $b_0$ | -0.1757 | 0.1655 | 0.3140 | 1.2578 | 0.7271 | 0.5635 |
| | (-0.165) | (0.221) | (0.389) | (1.167) | (0.790) | (0.636) |
| $b_1$ | 0.0310 | 0.0297 | 0.0015 | -0.0513 | 0.0061 | -0.0071 |
| | (0.559) | (0.763) | (0.038) | (-0.847) | (0.125) | (-0.159) |
| $b_2 * 10^4$ | -1.7214 | -0.6475 | -0.3957 | 1.4035 | -0.7174 | -0.4638 |
| | (-2.660)** | (-2.130)** | (-2.288)** | (-2.738)** | (-2.085)** | (-2.330)** |
| $b_3$ | 0.0014 | -0.0015 | 0.0009 | -0.0053 | 0.0068 | 0.0008 |
| | (0.471) | (0.984) | (0.516) | (-0.136) | (0.383) | (0.452) |
| $\alpha_0$ | 1.0863 | 1.0880 | 1.0144 | 0.7761 | 0.9410 | 0.9277 |
| | (3.014)** | (3.034)** | (2.941)** | (2.641)** | (2.823)** | (2.788)** |
| $\alpha_1$ | 0.2048 | 0.2117 | 0.2235 | 0.2780 | 0.2528 | 0.2617 |
| | (1.888)* | (1.639)* | (1.808)* | (2.567)** | (2.054)** | (2.164)** |
| $\alpha_2$ | 0.5767 | 0.5281 | 0.5996 | 0.6602 | 0.6110 | 0.6131 |
| | (4.647)** | (4.812)** | (5.141)** | (6.357)** | (5.410)** | (5.422)** |
| $\lambda$ | -0.2482 | -0.2620 | -0.2545 | -0.2182 | -0.2662 | -0.2594 |
| | (-5.003)** | (-4.811)** | (-4.809)** | (-4.203)** | (-4.901)** | (-4.826)** |
| LR | 19.92* | 20.76* | 22.42** | 20.72* | 21.30** | 22.14** |

<u>Note</u>: This table presents findings for the Canadian stock market whereby (*) and (**) denote significance at the 10% and 5% levels, respectively. It estimates the following feedback model: $r_t = b_0 + b_1\sigma_t^2 + b_2 [\sigma_t^2(f_{t-1} - P_{t-1})] + b_3 [\sigma_t^2(r_{t-1})] + \varepsilon_t$ whereby the parameters $b_0$, $b_1$, $b_2$, and $b_3$ are parameters to be estimated. This model is estimated with each of the respective fundamental proxies, $f_1$, $f_2$, and $f_3$, as well as the 2-year moving average in the earnings and dividends for these proxies, denoted as $f_1^*$, $f_2^*$, and $f_3^*$, respectively. The parameter $b_1$ measures investors' risk aversion and whether there is a risk-return tradeoff. Consistent with theory, this parameter should be positive and statistically significant. The parameter $b_2$ measures the presence of fundamental traders for each of the respective fundamental proxies and, if fundamental traders are present, the sign of this parameter should be negative and statistically significant. The parameter $b_3$ measures to what extent feedback traders exist in this market. If there are positive feedback traders, $b_3$ is expected to be negative and statistically significant. The conditional variance, $\sigma_t^2$, is estimated using an EGARCH(1,1) specification: $ln(\sigma_t^2) = \alpha_0 + \alpha_1(|z_{t-1}| - E|z_{t-1}| + \lambda z_{t-1}) + \alpha_2 ln(\sigma_{t-1}^2)$, whereby $ln(.)$ are natural logarithms and $z_t = \varepsilon_t/\sigma_t$ are standardized residuals. Finally, the likelihood ratio statistic (LR) is estimated to test the significance of this extended model compared to that of Cutler, Poterba and Summers (1990).

**Table 4.3: Presence of Heterogeneous Traders in France's Stock Market**

| Coeff. | $f_1$ | $f_2$ | $f_3$ | $f_1^*$ | $f_2^*$ | $f_3^*$ |
|---|---|---|---|---|---|---|
| $b_0$ | -0.0469 | -0.3885 | 0.4424 | 0.8280 | 1.2574 | 0.2848 |
|  | (-0.048) | (-0.443) | (0.455) | (0.783) | (0.642) | (0.243) |
| $b_1$ | 0.0215 | 0.0518 | 0.0341 | -0.0139 | 0.0097 | 0.0145 |
|  | (0.608) | (1.706)* | (0.109) | (-0.335) | (0.160) | (0.318) |
| $b_2 * 10^4$ | -0.3845 | -0.0973 | -0.0710 | -0.2299 | -0.0081 | -0.0010 |
|  | (-3.301)** | (-1.475) | (-0.872) | (-3.193)** | (-1.148) | (-0.116) |
| $b_3$ | 0.0001 | 0.0009 | -0.0003 | 0.0002 | 0.0009 | 0.0009 |
|  | (0.084) | (0.835) | (-0.246) | (0.086) | (0.403) | (0.338) |
| $\alpha_0$ | 0.4896 | 5.4712 | 0.5977 | 0.2056 | 0.2617 | 0.3308 |
|  | (1.488) | (7.619)** | (1.343) | (1.036) | (1.131) | (0.386) |
| $\alpha_1$ | 0.2290 | 0.8217 | 0.3482 | 0.2431 | 0.2545 | 0.3373 |
|  | (1.764)* | (0.677) | (2.083)** | (1.932)* | (1.909)* | (2.021)** |
| $\alpha_2$ | 0.7936 | 0.6246 | 0.7335 | 0.8781 | 0.8605 | 0.8157 |
|  | (7.125)** | (3.048)** | (5.090)** | (12.286)** | (10.231)** | (6.234)** |
| $\lambda$ | -0.1833 | -0.2194 | -0.1814 | -0.1430 | -0.1547 | -0.1292 |
|  | (-2.492)** | (2.334)** | (-2.162)** | (-2.343)** | (-2.516)** | (-1.742)* |
| LR | 22.08** | 19.04* | 24.47** | 20.98** | 22.12** | 19.28* |

<u>Note</u>: This table presents findings for the French stock market whereby (*) and (**) denote significance at the 10% and 5% levels, respectively. It estimates the following feedback model: $r_t = b_0 + b_1\sigma_t^2 + b_2 [\sigma_t^2(f_{t-1} - P_{t-1})] + b_3 [\sigma_t^2(r_{t-1})] + \varepsilon_t$ whereby the parameters $b_0$, $b_1$, $b_2$, and $b_3$ are parameters to be estimated. This model is estimated with each of the respective fundamental proxies, $f_1$, $f_2$, and $f_3$, as well as the 2-year moving average in the earnings and dividends for these proxies, denoted as $f_1^*$, $f_2^*$, and $f_3^*$, respectively. The parameter $b_1$ measures investors' risk aversion and whether there is a risk-return tradeoff. Consistent with theory, this parameter should be positive and statistically significant. The parameter $b_2$ measures the presence of fundamental traders for each of the respective fundamental proxies and, if fundamental traders are present, the sign of this parameter should be negative and statistically significant. The parameter $b_3$ measures to what extent feedback traders exist in this market. If there are positive feedback traders, $b_3$ is expected to be negative and statistically significant. The conditional variance, $\sigma_t^2$, is estimated using an EGARCH(1,1) specification: $ln(\sigma_t^2) = \alpha_0 + \alpha_1(|z_{t-1}| - E|z_{t-1}| + \lambda z_{t-1}) + \alpha_2 ln(\sigma_{t-1}^2)$, whereby $ln(.)$ are natural logarithms and $z_t = \varepsilon_t/\sigma_t$ are standardized residuals. Finally, the likelihood ratio statistic (LR) is estimated to test the significance of this extended model compared to that of Cutler, Poterba and Summers (1990).

**Table 4.4: Presence of Heterogeneous Traders in Germany's Stock Market**

| Coeff. | $f_1$ | $f_2$ | $f_3$ | $f_1^*$ | $f_2^*$ | $f_3^*$ |
|---|---|---|---|---|---|---|
| $b_0$ | 0.1246 | 0.1647 | 0.1884 | 0.1298 | 0.1055 | 0.2665 |
|  | (0.2413) | (0.303) | (0.355) | (0.231) | (0.193) | (0.482) |
| $b_1$ | 0.0894 | 0.0154 | 0.0523 | 0.0590 | 0.0205 | 0.0340 |
|  | (0.548) | (0.777) | (0.305) | (0.322) | (0.976) | (0.179) |
| $b_2 * 10^4$ | -0.1557 | 0.0959 | -0.0192 | -0.1014 | 0.1107 | -0.0156 |
|  | (-2.336)** | (1.744)* | (-0.711) | (-1.892)* | (1.749)* | (-0.662) |
| $b_3$ | 0.0005 | 0.0006 | 0.0006 | 0.0005 | 0.0006 | 0.0007 |
|  | (0.490) | (0.587) | (0.581) | (0.509) | (0.587) | (0.594) |
| $\alpha_0$ | -0.0217 | -0.0324 | -0.0163 | -0.0062 | -0.0213 | -0.0056 |
|  | (-0.283) | (-0.437) | (-0.209) | (-0.072) | (-0.242) | (-0.063) |
| $\alpha_1$ | 0.2569 | 0.2709 | 0.2704 | 0.2918 | 0.3048 | -0.3021 |
|  | (4.472)** | (4.467)** | (4.446)** | (4.384)** | (4.414)** | (-4.306)** |
| $\alpha_2$ | 0.9204 | 0.9507 | 0.9460 | 0.9391 | 0.9407 | 0.9368 |
|  | (42.033)** | (42.221)** | (39.572)** | (36.455)** | (35.651)** | (34.256)** |
| $\lambda$ | -0.0459 | 0.0145 | 0.0041 | -0.0024 | 0.0119 | 0.0256 |
|  | (0.164) | (0.529) | (0.151) | (-0.006) | (0.366) | (0.081) |
| LR | 52.58** | 55.94** | 54.64** | 52.60** | 55.32** | 55.76** |

Note: This table presents findings for the German stock market whereby (*) and (**) denote significance at the 10% and 5% levels, respectively. It estimates the following feedback model: $r_t = b_0 + b_1\sigma_t^2 + b_2 [\sigma_t^2(f_{t-1} - P_{t-1})] + b_3 [\sigma_t^2(r_{t-1})] + \varepsilon_t$ whereby the parameters $b_0$, $b_1$, $b_2$, and $b_3$ are parameters to be estimated. This model is estimated with each of the respective fundamental proxies, $f_1$, $f_2$, and $f_3$, as well as the 2-year moving average in the earnings and dividends for these proxies, denoted as $f_1^*$, $f_2^*$, and $f_3^*$, respectively. The parameter $b_1$ measures investors' risk aversion and whether there is a risk-return tradeoff. Consistent with theory, this parameter should be positive and statistically significant. The parameter $b_2$ measures the presence of fundamental traders for each of the respective fundamental proxies and, if fundamental traders are present, the sign of this parameter should be negative and statistically significant. The parameter $b_3$ measures to what extent feedback traders exist in this market. If there are positive feedback traders, $b_3$ is expected to be negative and statistically significant. The conditional variance, $\sigma_t^2$, is estimated using an EGARCH(1,1) specification: $ln(\sigma_t^2) = \alpha_0 + \alpha_1(|z_{t-1}| - E|z_{t-1}| + \lambda z_{t-1}) + \alpha_2 ln(\sigma_{t-1}^2)$, whereby $ln(.)$ are natural logarithms and $z_t = \varepsilon_t/\sigma_t$ are standardized residuals. Finally, the likelihood ratio statistic (LR) is estimated to test the significance of this extended model compared to that of Cutler, Poterba and Summers (1990).

**Table 4.5: Presence of Heterogeneous Traders in Italy's Stock Market**

| Coeff. | $f_1$ | $f_2$ | $f_3$ | $f_1^*$ | $f_2^*$ | $f_3^*$ |
|---|---|---|---|---|---|---|
| $b_0$ | 0.9809 | 1.6048 | -0.0715 | 0.8534 | 1.4061 | 0.0862 |
| | (1.274) | (2.451)** | (-0.735) | (1.148) | (1.791)* | (1.193) |
| $b_1$ | -0.0152 | -0.0137 | 0.0017 | -0.0179 | -0.0155 | -0.0175 |
| | (-0.825) | (-1.018) | (0.052) | (-0.867) | (-0.790) | (-0.897) |
| $b_2 * 10^4$ | -0.3463 | -0.1609 | -0.0949 | -0.1907 | -0.0001 | -0.0385 |
| | (-3.162)** | (-1.806)* | (-1.657)* | (-2.285)** | (-1.292) | (-0.671) |
| $b_3$ | 0.0001 | 0.0006 | 0.0004 | 0.0004 | 0.0013 | 0.0007 |
| | (0.129) | (0.653) | (0.527) | (0.369) | (0.989) | (0.589) |
| $\alpha_0$ | -0.0043 | 0.0628 | 0.0094 | -0.0221 | 0.1358 | -0.0683 |
| | (-0.026) | (0.389) | (0.052) | (-0.142) | (0.644) | (-0.409) |
| $\alpha_1$ | 0.3672 | 0.3797 | 0.3700 | 0.3329 | 0.3355 | 0.3378 |
| | (2.724)** | (3.621)** | (2.808)** | (2.326)** | (3.053)** | (2.383)** |
| $\alpha_2$ | 0.9193 | 0.9047 | 0.9154 | 0.9308 | 0.8906 | 0.9254 |
| | (17.833)** | (19.112)** | (16.833)** | (18.663)** | (13.802)** | (17.310)** |
| $\lambda$ | -0.0533 | 0.0001 | -0.0771 | -0.0961 | -0.0542 | -0.1025 |
| | (-1.041) | (0.003) | (-1.559) | (-1.880)* | (-1.332) | (-2.023)** |
| LR | 23.02** | 33.40** | 23.36** | 24.06** | 17.28* | 24.80** |

Note: This table presents findings for the Italian stock market whereby (*) and (**) denote significance at the 10% and 5% levels, respectively. It estimates the following feedback model: $r_t = b_0 + b_1\sigma_t^2 + b_2 [\sigma_t^2(f_{t-1} - P_{t-1})] + b_3 [\sigma_t^2(r_{t-1})] + \varepsilon_t$ whereby the parameters $b_0$, $b_1$, $b_2$, and $b_3$ are parameters to be estimated. This model is estimated with each of the respective fundamental proxies, $f_1$, $f_2$, and $f_3$, as well as the 2-year moving average in the earnings and dividends for these proxies, denoted as $f_1^*$, $f_2^*$, and $f_3^*$, respectively. The parameter $b_1$ measures investors' risk aversion and whether there is a risk-return tradeoff. Consistent with theory, this parameter should be positive and statistically significant. The parameter $b_2$ measures the presence of fundamental traders for each of the respective fundamental proxies and, if fundamental traders are present, the sign of this parameter should be negative and statistically significant. The parameter $b_3$ measures to what extent feedback traders exist in this market. If there are positive feedback traders, $b_3$ is expected to be negative and statistically significant. The conditional variance, $\sigma_t^2$, is estimated using an EGARCH(1,1) specification: $ln(\sigma_t^2) = \alpha_0 + \alpha_1(|z_{t-1}| - E|z_{t-1}| + \lambda z_{t-1}) + \alpha_2 ln(\sigma_{t-1}^2)$, whereby $ln(.)$ are natural logarithms and $z_t = \varepsilon_t/\sigma_t$ are standardized residuals. Finally, the likelihood ratio statistic (LR) is estimated to test the significance of this extended model compared to that of Cutler, Poterba and Summers (1990).

**Table 4.6: Presence of Heterogeneous Traders in Japan's Stock Market**

| Coeff. | $f_1$ | $f_2$ | $f_3$ | $f_1^*$ | $f_2^*$ | $f_3^*$ |
|---|---|---|---|---|---|---|
| $b_0$ | 0.8266 | 1.0542 | 0.5391 | 0.8557 | 1.0747 | 0.4367 |
|  | (1.711)* | (1.967)** | (1.211) | (1.819)* | (2.048)** | (0.996) |
| $b_1$ | -0.0312 | -0.0297 | -0.0171 | -0.0307 | -0.0291 | -0.0038 |
|  | (-1.365) | (-1.632)* | (-0.821) | (-1.353) | (-1.614) | (-0.178) |
| $b_2 * 10^4$ | -0.6369 | -0.5432 | -0.0410 | -0.6427 | -0.0048 | -0.0506 |
|  | (-2.239)** | (-2.396)** | (-0.379) | (-2.713)** | (-2.003)** | (-0.469) |
| $b_3$ | 0.0005 | -0.0014 | 0.0006 | -0.0015 | 0.0013 | 0.0009 |
|  | (0.375) | (-1.280) | (0.467) | (-1.423) | (-1.242) | (0.618) |
| $\alpha_0$ | -0.0180 | -0.0253 | -0.0368 | -0.0395 | -0.0363 | -0.0465 |
|  | (-0.291) | (-0.458) | (-0.632) | (-0.725) | (-0.664) | (-0.768) |
| $\alpha_1$ | 0.1972 | 0.1952 | 0.2187 | 0.2035 | 0.2015 | 0.2321 |
|  | (4.059)** | (4.099)** | (4.634)** | (4.087)** | (4.112)** | (4.747)** |
| $\alpha_2$ | 0.9561 | 0.9592 | 0.9573 | 0.9620 | 0.9614 | 0.9570 |
|  | (52.245)** | (60.305)** | (57.109)** | (69.191)** | (62.773)** | (56.009)** |
| $\lambda$ | -0.0393 | -0.0381 | -0.0295 | -0.0325 | -0.0359 | -0.0277 |
|  | (-1.453) | (-1.500) | (-1.065) | (-1.234) | (-1.377) | (-0.945) |
| **LR** | 48.38* | 50.56** | 34.36** | 50.14** | 53.48** | 55.40** |

<u>Note</u>: This table presents findings for the Japanese stock market whereby (*) and (**) denote significance at the 10% and 5% levels, respectively. It estimates the following feedback model: $r_t = b_0 + b_1\sigma_t^2 + b_2 [\sigma_t^2(f_{t-1} - P_{t-1})] + b_3 [\sigma_t^2(r_{t-1})] + \varepsilon_t$ whereby the parameters $b_0$, $b_1$, $b_2$, and $b_3$ are parameters to be estimated. This model is estimated with each of the respective fundamental proxies, $f_1$, $f_2$, and $f_3$, as well as the 2-year moving average in the earnings and dividends for these proxies, denoted as $f_1^*$, $f_2^*$, and $f_3^*$, respectively. The parameter $b_1$ measures investors' risk aversion and whether there is a risk-return tradeoff. Consistent with theory, this parameter should be positive and statistically significant. The parameter $b_2$ measures the presence of fundamental traders for each of the respective fundamental proxies and, if fundamental traders are present, the sign of this parameter should be negative and statistically significant. The parameter $b_3$ measures to what extent feedback traders exist in this market. If there are positive feedback traders, $b_3$ is expected to be negative and statistically significant. The conditional variance, $\sigma_t^2$, is estimated using an EGARCH(1,1) specification: $ln(\sigma_t^2) = \alpha_0 + \alpha_1(|z_{t-1}| - E|z_{t-1}| + \lambda z_{t-1}) + \alpha_2 ln(\sigma_{t-1}^2)$, whereby $ln(.)$ are natural logarithms and $z_t = \varepsilon_t/\sigma_t$ are standardized residuals. Finally, the likelihood ratio statistic (LR) is estimated to test the significance of this extended model compared to that of Cutler, Poterba and Summers (1990).

**Table 4.7: Presence of Heterogeneous Traders in the UK Stock Market**

| Coeff. | $f_1$ | $f_2$ | $f_3$ | $f_1^*$ | $f_2^*$ | $f_3^*$ |
|---|---|---|---|---|---|---|
| $b_0$ | 0.0545 | 0.2139 | 0.0704 | 0.2312 | 0.0223 | -0.0773 |
|  | (0.135) | (0.506) | (0.177) | (0.566) | (0.050) | (-0.192) |
| $b_1$ | 0.0088 | 0.0109 | 0.0094 | 0.0153 | 0.0013 | 0.0109 |
|  | (0.877) | (1.091) | (0.956) | (1.502) | (1.074) | (1.118) |
| $b_2 * 10^4$ | -0.8312 | -0.0516 | -0.0105 | -0.2643 | -0.0324 | -0.0177 |
|  | (-3.892)** | (-0.894) | (-1.209) | (-2.650)** | (-0.533) | (-1.479) |
| $b_3$ | 0.0014 | 0.0018 | 0.0012 | 0.0012 | 0.0012 | 0.0012 |
|  | (3.109)** | (2.902)** | (3.084)** | (2.896)** | (3.023)** | (2.995)** |
| $\alpha_0$ | -0.0361 | -0.0125 | -0.0309 | -0.0500 | -0.0249 | -0.0341 |
|  | (-0.529) | (-0.179) | (-0.425) | (-0.782) | (-0.364) | (-0.481) |
| $\alpha_1$ | 0.2992 | 0.2823 | 0.2979 | 0.2931 | 0.2856 | 0.2903 |
|  | (5.014)** | (4.811)** | (4.986)** | (4.891)** | (4.825)** | (4.878)** |
| $\alpha_2$ | 0.9423 | 0.9389 | 0.9411 | 0.9482 | 0.9421 | 0.9437 |
|  | (39.974)** | (38.368)** | (37.818)** | (43.777)** | (39.743)** | (39.075)** |
| $\lambda$ | -0.0401 | -0.0567 | -0.0423 | -0.0324 | -0.0492 | -0.0423 |
|  | (-1.434) | (-1.857)* | (-1.374) | (-1.205) | (-1.689)* | (-1.372) |
| LR | 98.54** | 97.66** | 96.84** | 96.26** | 95.14** | 94.26** |

Note: This table presents findings for the U.K. stock market whereby (*) and (**) denote significance at the 10% and 5% levels, respectively. It estimates the following feedback model: $r_t = b_0 + b_1\sigma_t^2 + b_2 [\sigma_t^2(f_{t-1} - P_{t-1})] + b_3 [\sigma_t^2(r_{t-1})] + \varepsilon_t$ whereby the parameters $b_0$, $b_1$, $b_2$, and $b_3$ are parameters to be estimated. This model is estimated with each of the respective fundamental proxies, $f_1$, $f_2$, and $f_3$, as well as the 2-year moving average in the earnings and dividends for these proxies, denoted as $f_1^*$, $f_2^*$, and $f_3^*$, respectively. The parameter $b_1$ measures investors' risk aversion and whether there is a risk-return tradeoff. Consistent with theory, this parameter should be positive and statistically significant. The parameter $b_2$ measures the presence of fundamental traders for each of the respective fundamental proxies and, if fundamental traders are present, the sign of this parameter should be negative and statistically significant. The parameter $b_3$ measures to what extent feedback traders exist in this market. If there are positive feedback traders, $b_3$ is expected to be negative and statistically significant. The conditional variance, $\sigma_t^2$, is estimated using an EGARCH(1,1) specification: $ln(\sigma_t^2) = \alpha_0 + \alpha_1(|z_{t-1}| - E|z_{t-1}| + \lambda z_{t-1}) + \alpha_2 ln(\sigma_{t-1}^2)$, whereby $ln(.)$ are natural logarithms and $z_t = \varepsilon_t/\sigma_t$ are standardized residuals. Finally, the likelihood ratio statistic (LR) is estimated to test the significance of this extended model compared to that of Cutler, Poterba and Summers (1990).

**Table 4.8: Presence of Heterogeneous Traders in the US Stock Market**

| Coeff. | $f_1$ | $f_2$ | $f_3$ | $f_1^*$ | $f_2^*$ | $f_3^*$ |
|---|---|---|---|---|---|---|
| $b_0$ | -0.5100 | -0.4491 | -0.5123 | 0.2789 | 0.1300 | 0.5382 |
|  | (-1.090) | (-0.941) | (-1.117) | (0.314) | (0.198) | (0.604) |
| $b_1$ | 0.0442 | 0.0475 | 0.0408 | 0.0553 | 0.0123 | -0.0148 |
|  | (-1.972)** | (1.697)* | (1.923)* | (1.614) | (0.357) | (-0.302) |
| $b_2 * 10^4$ | -0.1217 | -0.0235 | -0.3948 | -0.6898 | -0.0095 | -0.2989 |
|  | (-0.327) | (-0.456) | (-1.327) | (-1.890)* | (-0.283) | (-1.832)* |
| $b_3$ | 0.0027 | 0.0023 | 0.0021 | 0.0013 | 0.0025 | 0.0007 |
|  | (2.264)** | (2.019)** | (1.810)* | (0.386) | (1.169) | (0.213) |
| $\alpha_0$ | 1.4157 | 1.3189 | 1.5888 | 0.0701 | 0.0909 | 0.0784 |
|  | (5.362)** | (5.136)** | (5.553)** | (0.671) | (0.799) | (0.727) |
| $\alpha_1$ | 0.0965 | 0.1026 | 0.0767 | 0.2087 | 0.2046 | 0.2085 |
|  | (1.081) | (1.145) | (0.836) | (2.744)** | (2.678)** | (2.738)** |
| $\alpha_2$ | 0.4865 | 0.5182 | 0.4319 | 0.9214 | 0.9156 | 0.9187 |
|  | (5.529)** | (6.071)** | (4.527)** | (22.654)** | (21.214)** | (22.035)** |
| $\lambda$ | -0.3338 | -0.3243 | -0.3512 | -0.0872 | -0.1018 | -0.1002 |
|  | (-5.813)** | (-5.574)** | (-6.342)** | (-3.098)** | (-3.245)** | (-3.225)** |
| LR | 44.26** | 43.40** | 43.50** | 44.58** | 45.54** | 45.74** |

Note: This table presents findings for the U.S. stock market whereby (*) and (**) denote significance at the 10% and 5% levels, respectively. It estimates the following feedback model: $r_t = b_0 + b_1\sigma_t^2 + b_2 [\sigma_t^2(f_{t-1} - P_{t-1})] + b_3 [\sigma_t^2(r_{t-1})] + \varepsilon_t$ whereby the parameters $b_0$, $b_1$, $b_2$, and $b_3$ are parameters to be estimated. This model is estimated with each of the respective fundamental proxies, $f_1$, $f_2$, and $f_3$, as well as the 2-year moving average in the earnings and dividends for these proxies, denoted as $f_1^*$, $f_2^*$, and $f_3^*$, respectively. The parameter $b_1$ measures investors' risk aversion and whether there is a risk-return tradeoff. Consistent with theory, this parameter should be positive and statistically significant. The parameter $b_2$ measures the presence of fundamental traders for each of the respective fundamental proxies and, if fundamental traders are present, the sign of this parameter should be negative and statistically significant. The parameter $b_3$ measures to what extent feedback traders exist in this market. If there are positive feedback traders, $b_3$ is expected to be negative and statistically significant. The conditional variance, $\sigma_t^2$, is estimated using an EGARCH(1,1) specification: $ln(\sigma_t^2) = \alpha_0 + \alpha_1(|z_{t-1}| - E|z_{t-1}| + \lambda z_{t-1}) + \alpha_2 ln(\sigma_{t-1}^2)$, whereby $ln(.)$ are natural logarithms and $z_t = \varepsilon_t/\sigma_t$ are standardized residuals. Finally, the likelihood ratio statistic (LR) is estimated to test the significance of this extended model compared to that of Cutler, Poterba and Summers (1990).

Overall, the findings herein are of interest to practitioners and academics. Firstly, in the context of explaining the intertemporal risk-return tradeoff, the empirical evidence provided here corroborates the arguments made in the preceding two chapters; namely, it provides support for the Merton (1973) theoretical notion that the conditional variance and intertemporal risk are the sole determining factors of investors' risk premium. The findings herein provide support for this conclusion in the sense that, despite integrating the behavior of heterogeneous investors, this does not help in explaining variations in the intertemporal risk premium. However, in addition to this insight, the findings here identify new insights which merit further exploration. These findings are of interest to practitioners who seek valuation methods for the stock market and for academics who further want to explore into this field.

Firstly, the empirical evidence here suggests that fundamental traders drive, to some extent, movements in stock prices. Given this finding, it is perhaps of use for practitioners and policymakers to monitor ratios such as the price-earnings ratio, as this fundamental factor, among others, can give cues as to weather the stock market is over- or under-priced.

Given the empirical findings and the demand that fundamental traders exhibit in each respective countries' stock market, the evidence here shows that fundamental traders increase their demand for stock shares when prices are low relative to their fundamental value and vice versa. These results confirm the arguments made in the second chapter and the arguments of other researchers (see Shiller, 1996; Lander, Orphanides and Douvogiannis, 1997; Shiller, 2000; Campbell and Shiller, 1998 and 2001; Thomas and Zhang, 2008, to name a few).

A second major finding of this chapter is that it appears positive feedback trading is not statistically evident when exploring monthly frequency data, as is indicated by the parameter $b_3$ in Tables 4.2 through 4.8. This result does not imply a rejection of the notion that there different types of investors with different strategies and expectations, it instead suggests that feedback traders are present but it seems their actions exert an impact on stock prices only in the short run. These results are in contrast to those by Sentana and Wadhwani (1992), Koutmos (1997), and Antoniou, Koutmos and Pericli (2005). This of course may be due to the fact that these studies are using daily data. In this case, the argument can be made in favor of the empirical observation that positive feedback trading is present in the short-run, but it becomes insignificant in the longer-run. It is also possible that there are also negative feedback traders so that the net result becomes insignificant over the longer-run and when looking at lower frequency data such as monthly stock market returns. This empirical finding is evocative of the notion that high-frequency traders and institutions may drive prices in the short-run but in the longer-run, negative feedback traders and fundamental traders push the prices back to their equilibrium values.

## 4.6. Concluding Remarks

This chapter estimates a dynamic capital asset pricing model (CAPM) which characterizes the trading behavior of three types of market participants; namely, rational risk-averse investors, positive feedback traders and fundamental traders. Rational risk-averse investors' demand for risky assets is dictated solely by mean-variance considerations in the context of the equilibrium CAPM. Positive feedback (i.e. momentum) traders follow trends in the marketplace and buy (sell) stocks when prices

rise (fall). Such behavior is the result of irrationality, trading on noise or incomplete information, bandwagon effects, portfolio insurance strategies, or other extrapolative expectations, such as stop-loss orders. Fundamental traders believe in mean reversion of stock prices toward a long-run average, or fundamental, value. Their demand for risky assets is governed by the degree to which prices diverge from their fundamental value.

This chapter makes a unique contribution in the sense that it explores the nature of the intertemporal nature in a model that integrates the behavior of different types of investors. As mentioned, there is ample evidence to suggest that investors trade on other factors other than mean-variance considerations, which classical capital asset pricing theory suggests. In addition to incorporating the behavior of feedback traders, there are several fundamental proxies used here to capture the behavior of fundamental traders. One of the factors is based on the so-called "Fed model" which was discussed also in the second chapter of the thesis.

Furthermore, there are some key findings which merit attention. Firstly, despite the fact that this chapter integrates the trading behavior of fundamental and feedback traders, there is statistically unsubstantiated evidence of a positive risk-return tradeoff when estimating Equation (4.6). This finding may possibly be the result of the intrinsic shortcomings associated with using historical realized returns as an unbiased estimate of investors' expected returns, as is argued in the second chapter of this thesis and in Koutmos (2010, 2011 and references therein). If it is the case that historical returns are fundamentally inaccurate in describing expected returns, then a model such as Equation (4.6) which incorporates the behavior of heterogeneous investors may not alone be able to detect a positive risk-return tradeoff. It does however shed new light into how the

heterogeneous behavior of investors drives stock prices and to what extent this is statistically observable.

A second key finding in this chapter which merits attention and offers a contribution to literature is that it appears that feedback trading is not as evident using monthly data as it is when using higher frequency data (such as daily data). In this case, an argument can be made in favor of the notion that positive feedback trading is present in the short run, but it becomes insignificant in the longer run. It is also possible that there are negative feedback traders so that the net result becomes insignificant over the longer run.

In a contribution to the research literature, despite the fact that it seems that integrating heterogeneous investors into our model does not explain variations in the intertemporal risk premium, the inherent usefulness of fundamental factors – such as the price-earnings ratio – cannot be ignored. It is no surprise that during times leading to stock market bubbles, such as the build up and burst of the Tech Bubble in the late 1990s, there was excessive positive feedback and, as a result, the price-earnings ratio had deviated significantly from its long-run trend (see Griffin, Harris and Topaloglu, 2003; Ofek and Richardson, 2002). Therefore, it is worthwhile for policymakers and investors to consider such factors given that they may give an accurate picture of whether stock markets are over- or under-valued. This argument also supports the arguments made by Shiller (2000) of using this ratio as a gauge to see whether there is "irrational exuberance" in the market and where prices are relative to fundamentals.

A plausible direction that I am exploring is to apply the model in Equation (4.6) to test whether it can explain variations in investors' risk premium in industry portfolios. Koutmos (2011) finds that different portfolios have unique time-varying risk

characteristics and respond differently to shocks in the aggregate stock market. It will be useful to see to what extent feedback trading is prevalent in various industries, given each industries' unique characteristics, consumer demand, and risk exposure to the overall market. It will also be beneficial to evaluate whether fundamental proxies – such as the price-earnings ratio – can be used to explain variations in investors' risk premium when applying the model in Equation (4.6) which examines stock price dynamics in the context of heterogeneous traders.

# Chapter Five
# Summary and Conclusion

## 5.1. Overview of the Study

The motivation for this thesis stems for the inconsistent empirical findings regarding the intertemporal risk-return tradeoff. Despite the theoretical notion that investors are risk-averse agents and demand higher returns per unit of risk that they take, the conflicting evidence is overwhelming and prompts further debate and investigation into this important relationship. As mentioned, the risk-return tradeoff is important from a theoretical standpoint since it provides insights into investors' behavior and the behavior of stock prices. It seeks to answer the question of whether investors are risk-averse agents as is the classically held view in financial economics and which underpins much of asset pricing theory. From the perspective of practitioners, this relationship is also important as they consider various asset classes and investment possibilities and attempt to gauge their clients' degree of risk aversion and what investment vehicles are appropriate for them. In a different context, practitioners also need estimates of expected returns when conducting cost of capital approximations (see Graham and Harvey, 2001).

This thesis provides compelling evidence in favor of an intertemporal risk-return tradeoff and provides reasons as to why existing studies provide contradictory evidence. In addition to exploring variants of the Merton (1973) ICAPM, this thesis also explores relevant peripheral issues within asset pricing and econometrics; such as time-series modelling, the identification of macroeconomic factors which can proxy for investors' intertemporal risk, and feedback trading, to name only a few. Altogether, the chapters provide a contribution and foundation for future research into this issue.

The second chapter introduces some of the foundations of asset pricing theory and time-series modelling and the Merton (1973) ICAPM. It argues that the reason for existing conflicting findings is because studies are erroneously using *ex post* historical realized returns as an unbiased proxy for investors' forward-looking expectations of their expected returns. It thus provides arguments which highlight the limitations with using *ex post* historical realized returns as a proxy for investors' forward-looking expectation of returns. It contributes to existing literature by providing a forward-looking proxy of expected returns which is derived theoretically from the Gordon (1962) dividend constant growth model, something which, to my knowledge, has not been considered before.

The chapter is motivated by the 'volatility feedback hypothesis' of French, Schwert and Stambaugh (1987) and Campbell and Hentschel (1992) to motivate the argument that historical realized returns are unjustifiably used as a proxy for investors' forward-looking expectations of their expected returns. More specifically, the volatility feedback argument argues that negative shocks in stock returns lead to higher future volatility than positive shocks of equal magnitude. This proposition is consistent with the empirical observation that volatility is persistent and, as is described in Mandelbrot (1963) and Fama (1965), an increase in current volatility leads to more volatility in the future. The reason for this is, as Campbell and Hentschel (1992) argue, is because the negative effects associated with bad news in the stock market are more pronounced than good news and have a larger bearing on investors' investment decisions.

This argument can also be used to explain why extant studies find a negative or statistically insignificant risk-return relation; in particular, as Mandelbrot (1963) describes, since volatility is persistent, an increase in volatility today 'signals' that

volatility will be higher in the future. This raises investors' required rate of return and the discount factor they use to discount expected future streams of income. If we assume that corporate earnings and dividends are not rising while volatility rises, prices will obviously fall since investors sell off their positions and wait until expected returns rise again to the appropriate level. A graphical illustration of this is shown in Koutmos (2010) which illustrates the movements of implied volatility relative to the market price of the S&P 500 Index.

Whereas the second chapter considers a single-factor variant of the Merton (1973) ICAPM, which posits that expected returns are solely a function of conditional volatility, the third chapter introduces the two-factor ICAPM. This model posits that expected returns are, in addition to volatility, a function of their conditional covariance with investment opportunities that shift stochastically through time (see Scruggs, 1998; Scruggs and Glabadanidis, 2003). It proposes to use, in addition to the long-term government bond yield, the industrial production index and twists in the yield curve to proxy for shifts in the investment opportunity which shifts stochastically through time.

The fourth chapter contributes to literature by examining the intertemporal risk-return tradeoff but takes an innovative approach relative to existing studies in the sense that it integrates the trading behavior of heterogeneous types of traders; namely, the behavior of positive feedback traders and fundamental traders. The motivation for this chapter stems from the fact that, until now, empirical literature applies variations of the Merton (1973) ICAPM assuming that investors make decisions on the basis of mean-variance considerations in the context of Markowitz (1952) and that there is no mispricing of assets. A relatively new body of research however finds that, contrary to

the equilibrium notion that mispricing is transitory and that markets are efficient (see Malkiel, 2003), there is evidence that identifies many constraints which arbitrageurs face which limit their ability to attack mispricing and, therefore, stock market prices may deviate for some time from their equilibrium value (see De Long *et al.,* 1990a; Shleifer and Summers, 1990; Shleifer and Vishny, 1997; Shiller, 2000; Abreu and Brunnermeier, 2002 and 2003).

In an innovation to extant literature, the fourth chapter, given the extant findings which suggest the presence of heterogeneous investors, explores whether we should integrate this behavior in our models when estimating the intertemporal risk-return tradeoff. So far in the literature, existing studies only have only looked at variants of the Merton (1973) ICAPM using predominantly GARCH-type frameworks. There has not been an attempt yet to see whether we can better explain the risk-return tradeoff by incorporating the behavior of these heterogeneous investors in our model.

## 5.2. Summary of the Empirical Findings

This thesis makes its unique contributions by exploring the intertemporal risk-return tradeoff from different angles and affording explanations as to why extant findings are mixed. As already mentioned in the second chapter, the empirical findings lend credible support to the notion that we as investors are risk averse and therefore demand higher returns in order to take on higher risks. More specifically, the market earnings-yield, which serves as a proxy for investors' required rate of return in the stock market, varies positively with market volatility both in the short- and long-run when looking at international stock markets. There is also evidence of a positive long-run relation

between the earnings-yield and the long-term government bond yield. This relationship can be justified on grounds that as interest rates rise, the cost of firms' debt also rises and their ability to raise capital is impinged. Thus, the future prospects of the firm become relatively riskier and investors may assign a higher discount rate to its future cash flows (i.e. their required rate of return rises). Secondly, the stock market may simply become a less attractive investment as investors' opportunity cost rises and they move into more "risk-free" investments such as Treasury bills and bonds. Therefore, their required rate of return in the stock market rises commensurate to this risk. Such a relation is also consistent with extant literature which also documents a positive association between the market earnings-yield and the long-term government bond yield (see Gordon, 1962; Bleiberg, 1989; Fairfield, 1994; Greenspan, 1997; White, 2000).

The third chapter explores a two-factor version of the Merton (1973) ICAPM using, in addition to the long-term government bond yield, industrial production and twists in the yield curve as proxies for intertemporal risk. A major finding of the chapter is the empirical observation that intertemporal risk is important and this can consistently be seen to play a significant role across most of the G-7 markets here in the sample. This finding sheds new light on existing studies. Namely, up until now, studies have not made it clear whether conflicting findings are the result of econometric (miss-)specifications or because of omission of the second factor which serves to proxy for the investment opportunity state. Whereas Scruggs (1998) argues in favor of the two-factor ICAPM, Scruggs and Glabadanidis (2003) report empirical evidence to the contrary. The findings in the chapter, however, provide strong evidence in favor of the notion that intertemporal risk is an important ingredient in determining investors' risk premium in the stock market

and may be a possibly strong reason for extant conflicting findings in the literature. It is important to mention here that, given that industrial production shifts asymmetrically through time and, although relatively less pronounced, there is some evidence of the other proxies exhibiting asymmetric behavior, the model used to test the two-factor ICAPM is the BEKK model of Engle and Kroner (1995). This model is advantageous in that it allows the conditional variance and the covariance within the context of the ICAPM to respond asymmetrically to past innovations. Such a model, therefore, can accommodate the asymmetric time-series movements in factors and may provide a better description of intertemporal risk and investors' risk premium in the stock market.

Furthermore, consistent with the tests conducted in the chapter, the empirical evidence here supports the Merton (1973) theoretical view of the ICAPM without a constant term. This is conducted in the chapter via a likelihood ratio test to see whether restricting the constant to zero is supported. The findings here lend support to the theoretical ICAPM of Merton (1973) and to the second assumption in his seminal paper regarding capital market structure which is the foundation for intertemporal asset pricing; namely, transactions costs do not exist and there are no taxes or other constraints (see Merton, 1973, p.868). Before this thesis, the literature does not give a clear distinction as to whether the Merton (1973) theoretical two-factor model holds with or without a constant term. The findings here support the notion of the theoretical ICAPM and the empirical findings show that if we accept the assumptions that Merton (1973) establishes, the proposed state factors do a comparatively better job in explaining variations in investors' intertemporal risk premium relative to the model if we account for a constant term which attempts to capture such market inefficiencies.

Finally, consistent with the arguments made herein, another major finding in the chapter is that it appears that the long-term government bond yield may not be an appropriate proxy for investment opportunities, given that it does not exhibit consistently reliable empirical significance in terms of explaining intertemporal variations in investors' risk premium. This provides support to the argument made in the thesis that the long-term bond yield is a financial variable that is, to a large extent, controlled by the actions of central banks (see Mishkin, 2005) and may not accurately reflect investment opportunities. This may be a contributing reason why Scruggs and Glabadanidis (2003) do not find a positive risk-return relation when focusing on the U.S. market. However, the international evidence here corroborates the view of Guo and Whitelaw (2006, p.1435) that this does not "imply a rejection..." of the ICAPM, and contributes to literature by empirically showing the behavior of the intertemporal risk premium using proposed factors rooted in theory.

The fourth chapter explores whether integrating the behavior of different types of investors can help in explaining the intertemporal risk-return tradeoff. Namely, the evidence here corroborates the arguments made in the preceding chapters which provide support for the Merton (1973) theoretical notion that the conditional variance and intertemporal risk are the sole determining factors of investors' risk premium. The evidence from the fourth chapter suggests that integrating the behavior of heterogeneous investors does not help to better explain variations in the intertemporal risk premium. Instead, the findings shed new light which has not been identified before and raises additional insights which merit further exploration. These findings are of interest to practitioners who seek

valuation methods for the stock market and for academics who further want to explore into this field.

In particular, it is of interest to see that the empirical evidence suggests that positive feedback trading is not statistically evident when exploring monthly frequency data. This result does not imply a rejection of the notion that there exist heterogeneous groups of investors in the stock market. It instead suggests that feedback traders are present but only in the short run. These results are in contrast to those by Sentana and Wadhwani (1992), Koutmos (1997), and Antoniou, Koutmos and Pericli (2005). This of course may be due to the fact that these studies are using daily data. In this case an argument can be made in favor of the notion that positive feedback trading is present in the short run, but it becomes insignificant in the longer run. It is also possible that there are also negative feedback traders so that the net result becomes insignificant over the longer-run and when looking at lower frequency data such as monthly stock market returns. This suggests that high-frequency traders and institutions may drive prices in the short-run but in the longer-run, negative feedback traders and fundamental traders push the prices back to their equilibrium values.

## 5.3. Implications

This thesis provides academic researchers and practitioners many implications about the behavior of stock prices and the economy. For example, from the perspective of an investor, it is important to understand the nature of the risk-return relation because it directly impacts their decision-making and their willingness to bear more risk. If we have a better understanding of the nature of the risk-return tradeoff, then this will help

investors make better decisions and we can better understand whether the volatility of an asset plays a role in the expected returns of this very asset.

Some of the major implications of the second chapter have to do with the limitations with using *ex post* historical returns as a proxy for investors' forward-looking expected returns. Namely, it argues that there are at least three intrinsic shortcomings to using historical realized returns; firstly, current research indicates that the risk premium is time-varying and, therefore, any inferences drawn concerning *expected* returns using *ex post* returns may be highly sensitive to the sampling period under consideration (see Merton, 1973; Lundblad, 2007). Secondly, we as investors are forward-looking and thus form expectations of the required rate of return on the basis of current volatility, as well as news regarding future volatility in the stock market. This is consistent with the arguments made by Campbell and Hentschel (1992) that future volatility is a function of past news as well as any future news that may disseminate to investors. Finally, as Lundblad (2007) duly indicates, the belief that a long enough sample of historical returns will 'converge,' eventually, to expected returns is misplaced and inaccurate. More specifically, his study finds that nearly two hundred years worth of data is needed in order for us to see historical realized returns converge to investors' expected rate of return. This means that practitioners should possibly consider ex ante factors which can forecast future states of the economy and can proxy for expected returns.

When the market earnings-yield is used as a proxy for the required rate of return in the stock market, there are many implications which can be derived and can be of use to market participants. Namely, the research here provides information about the market earnings-yield and shows how this can shift as market volatility varies through time. In

particular, periods of heightened stock market volatility are associated with higher market earnings-yields. This empirical observation is consistent with the findings of Campbell and Shiller (1998, 2001) and Shiller (2000). Namely, the market earnings-yield, as well as its reciprocal – the price-earnings ratio – can serve as an indicator of future market conditions. In particular, when the market earnings-yield is relatively high, it generally corresponds to higher market volatility and that investors' required rate of return has risen. As a result, and consistent with the volatility feedback hypothesis of Campbell and Hentschel (1992), this will lead to a drop in stock prices as investors sell off their positions in the stock market and wait for expected returns to rise to the appropriate level (see Koutmos, 2010 and 2011). Thus, a relatively high earnings-yield serves to signal that returns will be higher in the future because investors' required rate of return has risen and thus future returns must rise to compensate them for increases in market volatility.

These findings are also consistent with the arguments made by Shiller (2000), who argues that a high price-earnings ratio (i.e. low earnings-yield) may be a signal of "irrational exuberance" in the stock market whereby investors are heavily invested in the stock market with an expectation that stock prices will continue to rise in the future. Under a scenario such as this one, investors do not foresee any imminent risks and feel comfortable with their investing and, thus, their required rate of return is low. In a scenario where the market price-earnings ratio is low (i.e. the earnings-yield is high), this may signal that many investors avoid investing in the stock market and stock prices are undervalued (see Shiller, 2000), possibly because of increased risks and market volatility. In such a scenario, their required rate of return (i.e. the market earnings-yield) is high and

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they demand higher returns to compensate them and in order to invest in the stock market.

The implications of the findings of the third chapter are of interest to both market participants and academicians. Namely, from the perspective of academic theory, the findings herein lend credible support to a positive intertemporal risk-return tradeoff in the context of the Merton (1973) ICAPM. These findings hold in international markets and suggest that perhaps conflicting extant findings are an artifact of omitting the second factor in the ICAPM which serves as a proxy for the investment opportunity set. In particular, the following important findings emerge from this chapter.

From the perspective of market participants the empirical findings illustrate a great deal about the properties of intertemporal risk which faces all investors and how this risk shifts through time. In particular, when examining the time-series dynamics of each of the proposed proxies for the investment opportunity set, it is interesting to see that their respective conditional variance estimates are a function of past volatility and innovations. Namely, for the long-term government bond yield, its conditional mean is positively linked with its conditional variance. This suggests a positive relation between its returns and its volatility. Furthermore, when examining the time-series properties of industrial production, it is interesting to see that, alike the other two proposed factors, it appears to respond asymmetrically to innovations across many of the market indices in the sample. In other words, negative shocks (declines in industrial production) lead to more volatility than positive shocks (increases in industrial production) of equal magnitude. Such an empirical observation can be supported by existing studies which examine the economic behavior of markets and what implications policy-making has on

output and economic performance. In this regard, Neftci (1984), Hamilton (1989) and Artis, Kontolemis and Osborn (1997) argue that industrial production reflects states in the business cycle and, namely, economic ups and downs exhibit asymmetry; whereby industrial production declines more in absolute terms during recessions than it rises during periods of economic prosperity. Such a finding is of interest to academics and practitioners and suggests that there is something similar to the so-called 'volatility feedback hypothesis' of Campbell and Hentschel (1992) which is present in economic cycles in our market.

In addition to these empirical findings, the chapter, apart from investigating the intertemporal risk-return relation, sheds light on what kind of factors investors ought to consider when assessing economic conditions and when trying to explain variations in expected stock market returns. In particular, the empirical findings reported here show strongest evidence for suggesting that shifts in the yield curve describe states in the economy. This finding provides some basis for using the yield curve in order to track market and economic performance and predict future states of the economy. These empirical findings thus provide further support to studies which argue of the economic information content embodied in the yield curve (see Estrella and Hardouvelis, 1991; Campbell, 1995; Estrella and Mishkin, 1998; Hamilton and Kim, 2002, to name only a few).

Finally, the fourth chapter provides some insights as to which types of investors tend to drive stock prices on a more long-term basis. In particular, the empirical evidence here shows that fundamental traders drive, to some extent, movements in stock prices. This shows that valuation ratios, such as the earnings-yield and dividend-yield proposed in this

thesis, may prove useful to practitioners who want to measure stock market performance and possibly predict future market movements. The evidence here shows that fundamental traders increase their demand for stock shares when prices are low relative to their fundamental value and vice versa. In terms of gauging fundamental value, the ratios proposed here seem to be good indicators of whether stock prices as over- or under-valued. These results confirm the arguments made in the second chapter and the arguments of other researchers (see Shiller, 1996; Lander, Orphanides and Douvogiannis, 1997; Shiller, 2000; Campbell and Shiller, 1998 and 2001; Thomas and Zhang, 2008, to name a few). Furthermore, the findings show that in the short-run, as some of the aforementioned studies indicate, although there may be extant evidence of feedback trading this tends to disappear over the longer-run as negative feedback traders and fundamental traders enter the stock market.

## 5.4. Future Research

As already mentioned, there are several important avenues that can be considered in order to expand on the findings and arguments made herein in order to better understand the risk-return tradeoff. Namely, this relationship is so important that it has been described as the "first fundamental law in finance..." (see Ghysels, Santa-Clara and Valkanov, 2005). This relation is important given that it is the cornerstone of financial economic theory and has many applications to market participants.

As such, there are several enhancements and extensions that can be undertaken in order for us to better understand the nature of this important relation. In particular, Koutmos (2011) investigates the time-varying nature of volatility in industries within the

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NYSE, NASDAQ and AMEX, and find that some industries exhibit higher systematic risk for investors relative to others. Thus, instead of focusing strictly on the intertemporal risk-return tradeoff in the stock market, future research can also investigate the nature of this important relation across various industries. The reason why this is important is because different industries have unique risk characteristics given that they produce respective goods and services and consumers exhibit varying degrees of elasticity in terms of their demands towards these goods and services. Thus, investors considering to invest in various industry sectors need to be aware of the risk-return characteristics and how they shift relative to shocks in the aggregate stock market.

In terms of the methodologies and techniques employed in the third chapter, as a suggestion for future research, there are many possible extensions that can be taken using the knowledge here in order to better our understanding of the financial world. These extensions need not necessarily pertain to asset pricing or the intertemporal risk-return relation *per se*. For example, we can use the tools here to investigate the dynamics of other asset classes such as fixed income securities. In particular, what is the interaction between various fixed income asset classes and the stock market? How does this interaction change in the presence of market shocks and is there an asymmetric response in terms of what happens to volatility in the presence of positive and negative shocks? Finally, are there any relevant state factors that can be considered when examining the expected returns of other asset classes such as bonds or derivatives?

Finally, given the methodology and findings of the fourth chapter, a plausible path for future research is to apply the model in Equation (4.6) to other investment environments other than stock market indexes to see how the model behaves and whether

feedback trading and a positive risk-return relation is evident. For example, there is work that has been done in the mutual fund industry by Hong, Kubik, and Stein (2005) which finds that fund managers in the same geographical location have a tendency to copy one another and this leads to herding. A good extension is to examine whether there is a positive risk-return tradeoff in this industry and how do investors respond when mutual fund returns become more or less volatile through time. This also raises the question of how this model behaves during up and down markets and what this tells us about investor behavior.

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