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Essays on Time-Varying Risk and Investor Sentiment: Evidence from the U.S. And G-7 Countries Using Multivariate GARCH Modeling

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ESSAYS ON TIME-VARYING RISK AND INVESTOR SENTIMENT: EVIDENCE FROM THE U.S. AND G-7 COUNTRIES USING MULTIVARIATE GARCH MODELING

A Dissertation

by

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ABSTRACT

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This dissertation investigates the effects of investor sentiment on asset prices in both the U.S. equity market (chapter III) and international market (chapter IV). It employs a conditional version of the CAPM using a parsimonious generalized autoregressive conditional heteroskedasticity (GARCH) model in which the risk premia, betas, and correlations are time-varying. Investor sentiment is presented from two direct measures (surveys) and one indirect measure as conditional information variables; whereas, previous studies used macroeconomic fundamentals. Furthermore, investor sentiment is not assumed to be fully irrational. It is decomposed into its rational and irrational components. Both rational and irrational components are tested as conditioning information variables in several models. Results are compared with the macroeconomic fundamentals model.

Chapter III provides evidence U.S. investor sentiment contains information is priced in the U.S. equity market. In chapter IV, we find no evidence U.S. investor sentiment, either total or irrational, is related to the world market price of risk. These findings are important because it provides evidence U.S. investor sentiment does not significantly affect international asset pricing. This implies there are generally no transmission effects of U.S. sentiment across international markets.

DEDICATION

Without the help, support, and encouragement of my family, the completion of my doctoral studies would not have been possible. For this reason, I dedicate this dissertation to my mother Mary Whitmer, my daughter Ivanna, siblings Tracy, Daniel, and Jennifer, and brother-in-law Wayne who provided great support in my pursuit of this degree. I also would like to thank Idalia for her great patience, understanding, and encouragement throughout the whole process. Thank you all.

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CHAPTER I

INTRODUCTION

The purpose of this study is to examine whether investor sentiment is related to the market price of risk. Researchers show uninformed investors often make irrational choices, especially when risk is involved. Seminal works in this area include, among others, Kahneman and Tversky (1979), Shefrin and Statman (1985), and Shleifer and Vishny (1997). Continuing efforts to model these irrational choices in asset pricing models could provide better understanding of the extent these irrational choices affect security prices. This is of great interest to the investor public, academicians, analysts, and regulators.

An increased understanding of what affects the market price of risk has several practical applications. Two important areas of research are market contagion and international diversification. Increased understanding of irrational investor behavior could yield new insights into both areas of research.

Irrational investors create noise trader risk and are priced in the market, shown in De Long, Shleifer, Summers, and Waldmann (1990). Shleifer and Vishny (1997) show noise traders are often too risky for short-term arbitrageurs to bet against. The resulting lack of arbitrage causes prices to divert from fundamentals. This allows irrational investors to bear a disproportionate amount of risk, which causes higher expected returns than those of rational investors.

Studies on investor sentiment and its impact on security pricing include Lee, Jain, and Indro (2002), Baker and Wurgler (2006), (2007), Verma, Baklaci and Soydemir (2008), Verma and Verma (2008), and Baker, Wurgler, and Yuan (2012). Many studies decompose sentiment into its rational and irrational components (explained and unexplained). However, based on the literature review, the effect of the investor sentiment, either the explained or unexplained components, have not been explored in a multivariate conditional CAPM framework with GARCH-in-mean parameterization, in which the betas and risk premia are time-varying. The aim of this study is to conduct such an examination.

Previous studies have implemented the conditional CAPM in their research, e.g. Giovannini and Jorian (1989), Harvey (1991), Chan, Karolyi, and Stulz (1992), and Hansson and Hordahl (1998). These studies use the economic fundamentals as information variables. Ho and Hung (2009) find evidence investor sentiment plays an important role in capturing asset pricing anomalies (size, value, momentum, liquidity) in several asset pricing models including the conditional CAPM. Their study constrains beta values to be constant (as opposed to time-varying) using a two-pass methodology.

De Santis and Gerard (1997) and Soydemir (2005) allow the risk premia, betas, and correlations to be time-varying using a conditional CAPM with parsimonious multivariate GARCH modeling with the

parameterization of Ding and Engle (2001). This study extends their methodology by using investor sentiment as a proxy for the information set available to the investors in time t-1 as opposed to traditionally used economic fundamentals such as the term premium, change in dividends, and the default premium.

Chapter III tests the relationship between United States investor sentiment and the United States market price of risk. The S&P 500 is used as a proxy for the market portfolio. The seven largest Global Industry Classification Sectors (GICS) are captured as S&P 500 price indexes. The sectors listed in order from largest to smallest according to market capitalization are: 1) information technology, 2) financials, 3) consumer staples, 4) health care, 5) industrials, 6) energy, and 7) consumer discretionary. As of September 2010 this portfolio of seven GICS sectors netted about 90% of the S&P 500 by adjusted market capitalization (see Figure 1.1). The data is weekly in frequency starting from the first week of 2000 through the last week of 2010, yielding 574 observations. Observations start at the first week of 2000 in order to capture the dynamics of the dot-com bubble and subsequent market crash.

Chapter IV tests the relationship of United States investor sentiment to the world price of market risk. The global and individual country markets are captured using the Morgan Stanley Capital International (MSCI) total return world indices. The individual country portfolios are the member countries of the G7. These economies are the largest in the world as measured by gross domestic product (GDP). The G7 accounts for 45.26 % of the average GDP from 1995 through 2003 according to Jorgenson and Vu (2005). The International Monetary Fund world economic outlook database for April 2011 shows the portion of the G7's GDP to the world total is 49 %[1]. The G7 consists of the following countries, listed in order from the largest to the smallest: 1) United States, 2) Japan, 3) Germany, 4) United Kingdom, 5) Italy, 6) France, and 7) Canada. Additional countries were considered for this study, but not included in interest of model parsimony. Limiting the number of country portfolios to seven also avoids the two difficulties of computational expense and convergence problems in the estimation of the parameters using

[1] Data was retrieved from: http://bit.ly/fcv318 (on June 3, 2011)

maximum likelihood. Data is retrieved from *Datastream.* The sample data spans from January 1990 to March 2010 for a total of 243 monthly observations. Investor sentiment data availability issues constrain the start date to January 1990.

Two primary investor sentiment measures are used for both chapter III and IV. The first is the Investors Intelligence Advisors' Sentiment Index (II). Because most of the participants in this survey are current or past market professionals, II is widely considered to be a proxy for institutional investor sentiment (Wang, Keswani, & Taylor, 2006). The second is the sentiment index from the American Association of Individual Investors (AAII). Researchers often use AAII as a proxy for individual investor sentiment.

An indirect (non-survey) measure of investor sentiment, the call-put ratio is included as an additional information variable in models 1 and 3 in chapter III[2]. Standard terminology is "put-call" ratio, but in order to show a direct relationship to bearish sentiment, the ratio is reversed. Thus, in this dissertation it is called the "call-put" ratio. Historic put-call ratio data is available online from the Chicago Board Options Exchange (CBOE).

Following Verma, et al. (2008), all sentiment measures are decomposed into explained and unexplained components (rational and irrational sentiment prospectively). The total and decomposed sentiments are then introduced via several models as information variables. A traditionally used set of economic fundamental variables are also introduced in a separate model for comparison in both chapters III and IV. The set of economic fundamentals consist of the term premium, default premium, and the change in dividend yield in excess of the risk free rate.

[2] Other variables found in the literature are also considered as indirect measures of investor sentiment. They include The University of Michigan Consumer Sentiment Survey and the VIX. Models using these variables, and extracting the first principle component of the indirect sentiment measures, a methodology used by Ho and Hung (2009), do not converge. For this reason they were not included in this study.

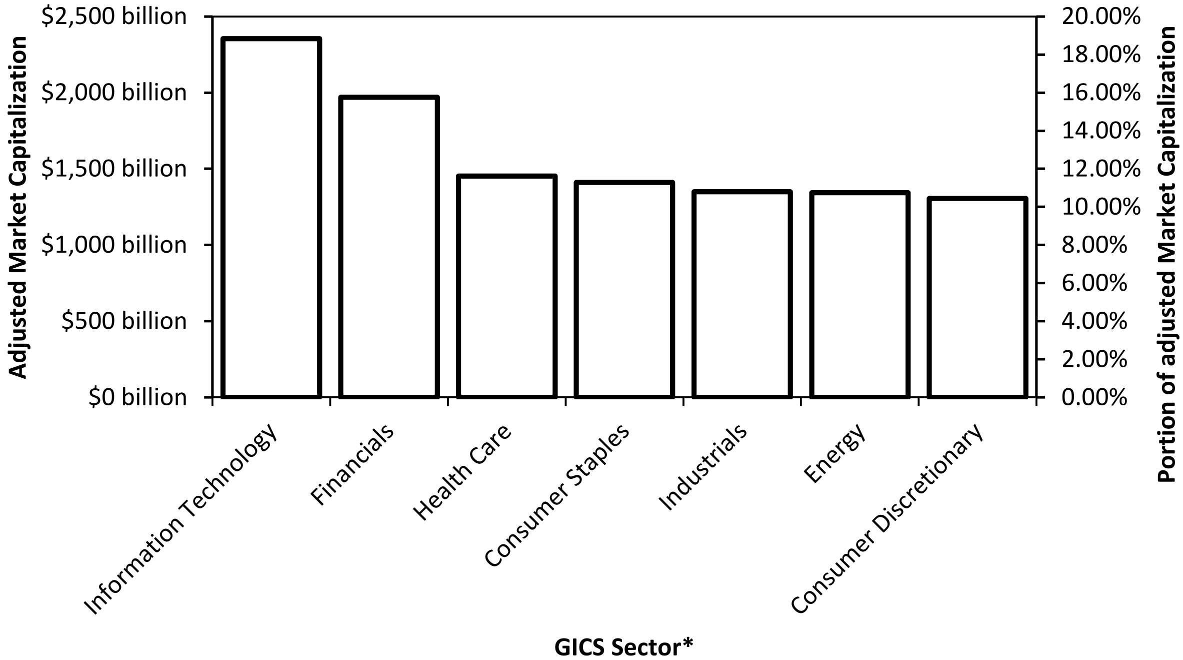
The strengths of the methodology (conditional CAPM with parsimonious multivariate GARCH) used in this study are: 1) it allows the risk premia, betas, and correlations to vary through time; 2) this methodology is parsimonious; thus more assets can be included in the model; and 3) there is much support for the conditional CAPM in existing literature. Hansson and Hordahl (1998) show strong support for the conditional CAPM, and indicate a multivariate GARCH-M might be improved if the market price of risk is allowed to be time-varying.

The weaknesses of this methodology are: 1) it can be difficult to get the maximum likelihood function to converge as the number of portfolios and informational variables increase the number of parameters to be estimated; 2) at this time there are no off-the-shelf programs available to do the analysis; and 3) this model may be considered to not be entirely an equilibrium model. The additional GARCH components added to the conditional CAPM may be considered by some to make the ad-hoc as opposed to being a true equilibrium model.

In chapter III it is found irrational sentiment, which is considered to be noise, contains information that is related to the market price of risk, which in turn is related to asset prices. Furthermore, in one model only the irrational component of the uninformed investor individual investors has a significant relationship to asset pricing. The irrational component of the informed institutional investors does not significantly differ from zero.

In chapter IV no evidence is found U.S. investor sentiment, either total or irrational, is related to the world market price of risk. These findings are important because it shows U.S. investor sentiment does not significantly affect international asset pricing. This implies there are no transmission effects of U.S. sentiment across international markets.

Figure 1.1 Summary of Global Industry Classification Standard (GICS) sectors



Data Source: http://bit.ly/6KG61q (September 24, 2010).
Fig. 1 does not include three GICS sectors: Utilities, Telecom and Materials; their total portion of the adjusted market capitalization is about 10% of the total.

CHAPTER II

LITERATURE REVIEW

Investor Sentiment is typically considered to be in the realm of behavioral finance. Section (2.1) discusses investor sentiment and provides a brief history of irrational behavior in finance. Section (2.1.3) discusses the literature on the decomposition of investor sentiment into its irrational and rational components. Section (2.2) begins with a history of the use of the CAPM in asset pricing and ends with a discourse of the conditional CAPM model used in this dissertation. Figure 2.2 provides a graphical depiction of the evolution of methodology and studies covered in this chapter, with the dotted line illustrating this dissertation's main contribution.

2.1 Irrational Behavior and Investor Sentiment

2.1.1 A Brief History of the Study of Irrational Behavior in Finance

In the 1950's most researchers in the subject areas of finance and economics were predicated on normative investor behavior. This focus on normative behavior is well defined by Elton, Gruber, Brown, and Goetzmann (2009), as they discuss the many chapters in their textbook which outline normative theory, "*that is, they are concerned with how investors should make choices*" (pg. 845). They go on to say "*In practice however, many people make suboptimal economic or financial decisions*" (pg. 845). Finance and economic research has since evolved; it has gradually incorporated positive theory (how individuals do make choices). Elton, et al. (2009) provide two good reasons for this evolution:

> "*If there are a few basic mistakes that investors make repeatedly, it may be possible through education, training, and communication to reduce or eliminate these tendencies*" and "*to the extent that certain forms of behavior are pervasive in the market, they may influence security prices*" (pg. 845).

Smith (1990) , in the introduction to his book, provides another good explanation:

> "*The logical structure of decision making implies that better answers to normative questions are likely to occur when decision makers have a richer set of positive theories that provide a better understanding of the consequences of their choices*" (pg. 3).

The rational expectations hypothesis, credited to John Muth (1960) is normative in nature. It assumes the future price an agent assigns to a security is equal to its expected value. The expected value is calculated by adding the probability weighted prices of all possible future outcomes. This raises the question, are all agents really good at such complicated statistical calculations? Thaler (1980) asks the same question:

> "*How does the normative theory hold up in more complicated situations? Consider the famous birthday problem in statistics: if 25 people are in a room what is the probability that at least one pair will share a birthday? This problem is famous because everyone guesses wrong when he first hears it.*" (pg. 40)

Simon (1957) observes:

"*The capacity of the human mind for formulating and solving complex problems is very small compared with the size of the problems whose solution is required for objectively rational behavior in the real world -- or even for a reasonable approximation to such objective rationality.*" (pg. 198)

These questions seem especially relevant for individual investors, for example those managing 401(k) accounts or day traders. These types of investors, who are mostly making decision alone, might not have the training or expertise necessary to consider all information rationally. Can we really expect them to rationally and correctly formulate, assign probabilities, and calculate expected values? As Lusardi and Mitchell (2011) suggest, many investors who manage their own retirement accounts don't even understand the extremely important concept of portfolio diversification.

Rational expectations theory is the foundation for the famous efficient market hypothesis by Fama (1970). The efficient market hypothesis, where the security prices are valued according to the information available to the agents (in strong, semi-strong and weak form), suggests rational expectations on the part of said agents. In this information age one can question how it is possible for agents to examine all relevant information and make an informed decision on the future price of a stock. Research evidence of asset mispricing under new information is found throughout financial research literature. A good example is the Shiller (1981) study, that shows stock prices often differ too much from their long-run trends when dividends are announced.

Other economists, who are puzzled over gambling behavior, questioned why supposedly rational individuals make bets when the expected value of the gamble is negative and developed utility theory (Markowitz (1952)) and the concept of risk preference. Risk preference can be defined as how an individual relates the utility of expected wealth and the expected utility of wealth, thus determining if he/she is risk averse, neutral, or loving (risk-loving individual would take the negative expected value gamble). Thus, both risk averse or risk loving individuals would be considered irrational, while risk neutral individuals could be considered rational. At this point it should be mentioned throughout this dissertation the words irrational sentiment are often used. Irrationality used in this context only implies these marginal investors are irrational in the narrow sense their view of the bullish or bearish sentiment doesn't follow the macroeconomic fundamentals. In this context it does not imply said agents are wholly irrational; when some psychological studies show it is normal behavior to make suboptimum decisions in certain cases. How can one say someone is irrational when they are risk loving or they are effected by previous losses when making risky decisions? It may be part of their genetic makeup, brain chemistry, upbringing or they were just born that way. Damodaran (2007) says it well:

> "*Finally, we should resist the temptation to label these behaviors as irrational. Much of what we observe in human behavior seems to be hard wired into our systems and cannot be easily eliminated (if at all)*" (pg. 14).

He also goes on to mention a study in which it was shown people who are emotionally disabled made more profitable gambles (13 percent higher returns) than the "normal" control group.

Kahneman and Tversky (1979) published a key research paper which studied the psychological aspect of choices about risk They find individuals often make decisions based a point of reference, for example, their neighbors wealth in comparison to theirs, or the purchase price of an asset in comparison to its value now. They found an individual's utility function can change, depending on where they are in relation to their reference point. They called their model of decision making under uncertainty "Prospect Theory." Elton, et al. (2009), in chapter 20 of their book, summarize several "heuristics" which Kahneman and Tversky additionally discovered in their psychological studies. These heuristics include: 1) representativeness - individuals will jump to conclusions, establishing probabilities based on limited information or small sample sizes; 2) anchoring and adjustment - one anchors his/her opinion on something then makes small adjustments based on it, marketers often use this to their advantage by marking up the price on a product and putting it on sale; 3) availability - when an individual uses only recent history to make a decision instead of looking for patterns to make predictions on future outcomes; and finally 4) overconfidence - a decision maker is hubristic in behavior, overestimating their ability to correctly take into account all the probabilities and outcomes of a gamble.

The disposition effect, a term coined by Shefrin and Statman (1985), is the irrational tendency of investors to keep holding an investment after a loss. They do this hoping to recover their losses. A rational investor will not become attached to a particular investment and only make the investment decision to buy or sell it based on tax consequences and relevant information of the future value and risk of the investment with respect to other investment opportunities and market information. Odean (1998) tests the disposition effect using data from 10,000 trading accounts, and finds:

"*These investors demonstrate a strong preference for realizing winners rather than losers. Their behavior does not appear to be motivated by a desire to rebalance portfolios, or to avoid the higher trading costs of low priced stocks.*" (pg. 1775)

Barber and Odean (2000) find in a study of over 85,000 accounts from 1991 to 1996, small investors in common stock underperform the stock market by about 6-1/2%. Their findings indicate it is due to high trading levels and overconfidence of the small investor. Barber and Odean (2001) examine excessive trading and gender. They partition the account data by gender on trades of commons stock from over 35,000 households from February 1991 through January 1997. They find men trade more excessively than women and the costs of their excessive trading reduces their net return by 2.63% compared with a 1.82% reduction for women's trades.

2.1.2 Irrational Investors and Asset Prices

Irrational investors, who create noise trader risk, have been well documented in various studies as being priced in the market. Delong, Shliefer, Summers and Waldmann (1990) show noise traders are often too risky. Many rational arbitrageurs are reluctant to bet against them due to their short-term performance requirements. This resulting lack of arbitrage causes prices to divert from fundamentals and allows irrational investors to bear a disproportionate amount of risk. The disproportionately higher risk then creates higher expected returns for those irrational investors.

Shleifer and Summers (1990) hypothesize limits of arbitrage and suggest investor sentiment (noise traders) mispricing and arbitrageur fear may play a role in an alternative theory to the efficient markets. They say in their conclusion:

> "*We have shown that the assumption of limited arbitrage is more general and plausible as a description of markets for risky assets than the assumption of perfect arbitrage which market efficiency relies on*." (pg. 31)

Shliefer and Vishny (1997) test the hypothesis noise traders can effect market prices enough to push arbitrageurs out of the market. They find arbitrageurs do, in fact, have time constraints which represent a risk which often outweigh any benefits of betting against a noise trader (even if they know the security is not at its fundamental value).

Lee, Jiang and Indro (2002) use the Investors' Intelligence sentiment index, in a univariate GARCH-in-mean specification to test the impact of noise trader risk on conditional volatility and expected returns. They show sentiment is a "*systematic risk which is priced*" (pg. 2277) and "*excess returns are contemporaneously positively correlated with shifts in sentiment*" (pg. 2277). They also find increasing changes in bullish (bearish) sentiment causes decreases (increases) in volatility and increases (decreases) in excess returns. Their study provides evidence investor sentiment may have significant effects on cross-sectional stock prices. Baker and Wurgler (2006) investigate how investor sentiment effects cross-section of stock returns. They predict investor sentiment will have larger effects on difficult to value assets because they are more difficult to arbitrage. They find when their proxy for sentiment is high (low) the returns are high (low) in stocks with the following characteristics: small, young, high volatility, unprofitable, non-dividend paying, extreme growth, and distressed stocks.

Kumar and Lee (2007) test co-movement between retail investors and asset prices using a database of more than 1.85 million transactions from 1991 to 1996. While controlling for macroeconomic movements and analyst forecasts, they find there is co-movement between systematic trading and asset returns on high retail concentration stocks. Their findings support the theory investor sentiment plays a role in pricing assets.

Baker and Wurgler (2007) describe the “top down” and the “bottom up” approach. The top down approach is the use of market or economic measures of sentiment. Some top down measures of investor sentiment are: 1) dividend premium - the premium for dividend-paying stocks is inversely related to investor sentiment; 2) trading volume (NYSE turnover) - often considered a proxy for market liquidity, which in-turn is considered to be directly related to positive investor sentiment; 3) the closed-end fund discount - an increase in the discount premium is related to a positive or bearish investor sentiment; 4) number of IPO’s and 5) first day return of IPO’s - both of which are positively related to bearish investor sentiment; and finally equity share in new issues (both debt and equity total), if companies are using equity to finance their capital project it is a sign of bearish investor sentiment. Other surveys commonly used as secondary or indirect measures of investor sentiment are the Conference Board Consumer Confidence and Michigan Consumer Sentiment Surveys.

Two direct measures of investor sentiment are the American Association of Individual Investors (AAII) and Investors Intelligence (II) Sentiment Surveys. The AAII index is often thought of as sentiment survey which focuses primarily on uninformed or retail investors. The AA survey is viewed as one which generally provides the sentiment of informed or institutional investors.

Many studies, e.g., Baker and Wurgler (2007) , Bandopadhyaya and Jones (2006), Brown and Cliff (2004), Han (2008), and Kurov (2010) use the VIX as a measure of investor sentiment. The VIX is the Black Scholes implied volatility, based on option data from the Standard and Poor's 500 index. The VIX is often called the "fear index." It is generally theorized to be inversely related to bullish investor sentiment. In the top down approach these measures are often combined to make an investor sentiment index by applying principal components techniques. The first factor of the principal component is then used as a measure of investor sentiment in asset pricing and volatility models. Baker and Wurgler (2006) use this methodology.

The "bottom up" approach assumes certain investor behavior is based on psychology. An example of the bottom up approach is Barberis, Shleifer, and Vishney (1998), who develop an important model of investor sentiment based on conservatism, which produces overreaction and underreaction on stock prices based on good news and bad news events. Daniel, Hirshleifer, and Subrahmanyam (1998) develop a similar model on overreaction and underreaction based on the psychological biases of investor overconfidence (on the precision of private information) and self-attribution or hubris. They state "*individuals too strongly attribute events that confirm the validity of their actions to high ability*" (pg. 1842).

Baker, et al. (2012) investigate investor sentiment in both global and local markets using data from Siamese twin pairs (stocks that theoretically should be priced the same, even though they exist in different markets). They find investor sentiment is a contrarian predictor of market returns, and its predictability is economically significant. They also find local and global investor sentiment is independent, with global sentiment slightly more important than local sentiment. Thet also find sentiment is contagious.

Changsheng and Yongfeng (2012) test the Chinese stock market for the impact of investor sentiment on asset prices. A total sentiment index is constructed using the first and second principal components. The index is then first-differenced to build a change in sentiment variable. The following sentiment measures are used from the Chinese stock market: 1) the first day return of IPO's, 2) the closed-end fund discount, 3) the market turnover rate, and 4) the number of new stock accounts for each month. They control for the three Fama and French (1993) risk factors and the Carhart (1997) momentum factor. They find 1) investor sentiment is directly related to portfolio excess returns in hot stocks and value stocks, 2) Bullish (Bearish) sentiment is related to increases (decreases) in excess returns and 3) investor sentiment is a needed contributor to systematic risk in the Chinese market.

2.1.3 Decomposing Investor Sentiment into its Rational and Irrational Components

A study of the literature reveals the author's definition of investor sentiment can be grouped into two distinct types. The first type of investor sentiment is defined by Baker and Wurgler (2007) as:

> "*a belief about future cash flows and investment risks that is not justified by the facts at hand*" (pg. 129)
>
> or
>
> "*the beliefs about future cash flows or discount rates that are not supported by the prevailing fundamentals*" Baker and Wurgler (2006) (pg. 6), Lemmon and Portniaguina (2006) (pg. 1499), and Main and Sankaraguruswamy (2008) (pg. 1).

This first type of definition considers investor sentiment to be entirely irrational; from this point forward I will call this type of sentiment "irrational investor sentiment" or "irrational sentiment." Typically traders who exhibit irrational investor sentiment are called noise traders.

Barberis, et al., (1998) (pg. 307) provides an example of the second type of investor sentiment definition: "*how investors form beliefs*" . Baker and Wurgler (2007) (pg. 132) define it as "*simply optimism or pessimism about stocks in general*." This second type of definition, which in this paper I will henceforth call "total sentiment," makes no claim the investor's sentiment is not supported or not justified by the facts or fundamentals. From this viewpoint investor sentiment is neither irrational nor rational; it is just a statement of investors' beliefs about the future. Depending on the state of nature, these beliefs could turn out to be correct or incorrect. Total sentiment is often measured directly by taking surveys.

Many studies, such as Qiu and Welch (2004), Verma, et al. (2008), Verma and Verma (2008), Verma and Soydemir (2009), Verma and Soydemir (2010), and Zouaoui, Nouyrigat, and Beer (2011), decompose investor sentiment using multiple regression. They employ total sentiment as the dependent variable, and a vector of economic fundamentals as independent variables. This regression approach allows each total investor sentiment measure to be decomposed into two components (see Figure 2.1). The first component is the fitted values, which henceforth will be called "rational investor sentiment" or "rational sentiment." This component is related to the business cycles or the macroeconomic fundamentals. The second component is the error term, often considered the psychological component or a more "pure" form of investor sentiment. This component is a purer form of sentiment because it is unrelated to the macroeconomic fundamentals. Henceforth this second component will be called "irrational investor sentiment." This methodology allows researchers to separate and examine the relationship of both rational and irrational sentiment with asset prices.

2.2 Asset Pricing and the Conditional CAPM

2.2.1 The Capital Asset Pricing Model

The Capital Asset Pricing Model (CAPM) builds on optimal portfolio selection theory, or mean variance portfolio theory, developed by Markowitz (1952), and is widely used in business for asset pricing. The CAPM is often credited to some combination of the following scholars: Treynor (1961), Sharpe (1964), Lintner (1965), or Mossin (1966). Markowitz and Sharpe won Nobel prizes in economics for their aforementioned contributions. The CAPM states the expected excess return above the risk-free rate on an asset is a function of its market "beta" (the amount of risk, as measured by the covariance of the asset and the market divided by the market variance) times the return on the market in excess of the risk free rate (the price of risk, also called the market risk premium, or the market price of risk).

Giovannini and Jorian (1989) use a static CAPM to investigate whether the fluctuations, which are seen in the first and second moments of asset prices are consistent with the original CAPM. Their static CAPM model fails to explain the fluctuations of the conditional variances. They conclude further study is needed with more assets than they used, and a more complete specification of the second moments.

2.2.2 ARCH and GARCH Modeling in the CAPM

Engel and Rodrigues (1989) test restrictions on the international CAPM using the publicly held outstanding government debt (denominated in native currencies) of six countries: France, Germany, Italy, Japan, U.K., and U.S. They find allowing time-varying covariance in a multivariate ARCH process alleviates problems with heteroscedasticity in the CAPM error terms and improves the model. They still reject the CAPM over an alternatively hypothesized more general asset pricing model.

Bollerslev, Engle, and Wooldridge (1988) use multivariate generalized autoregressive conditional heteroskedastic (GARCH) modeling to capture the second moments (T Bollerslev, 1986) with the CAPM. They form a market portfolio consisting of quarterly returns of 6-month Treasury Bills, 20-year Treasury bonds, and NYSE value-weighted equity returns from the first quarter of 1959 through the second quarter of 1984. They find the conditional covariances vary greatly over time and are significant in determining time-varying risk premia. They also mention the betas are also time-varying, and one can forecast them. They find evidence their model may be underspecified, and other conditional variables, like innovations in consumption, might be included to improve the model.

2.2.3 The Conditional CAPM with Multivariate GARCH Parameterization

Harvey (1991) uses a multivariate conditional CAPM to investigate the return behavior of seventeen country equity portfolios. His study consists of monthly data ranging from December 1969 to May 1989. Harvey uses the Morgan Stanley Capital International (MSCI) equity index data for the sixteen Organization for Economic Cooperation and Development (OECD) countries plus Hong Kong. Equation 1 expresses his model:

$$E\left[r_{jt}\middle|\Omega_{t-1}\right] = \frac{E[r_{mt}|\Omega_{t-1}]}{Var[r_{mt}|\Omega_{t-1}]} Cov\left[r_{jt}, r_{mt}\middle|\Omega_{t-1}\right], \tag{2.1}$$

where r_{jt} is the return on country portfolio; *j*, from the time t-1 to time t; Ω_{t-1} is the information set which investors use to determine their prices at time t-1; and $E\left[r_{jt}\middle|\Omega_{t-1}\right]$ is the expected conditional return. The ratio $\frac{E[r_{mt}|\Omega_{t-1}]}{Var[r_{mt}|\Omega_{t-1}]}$ is conditionally expected award per unit of risk (world price of covariance risk), where $r_{mt}$is the return on the market in excess of the risk-free rate and $Cov\left[r_{jt}, r_{mt}\middle|\Omega_{t-1}\right]$ is the amount of risk. Harvey finds evidence supports the conditional CAPM i.e. the covariance risk helps explain country performance. He also finds evidence the world price of covariance risk varies through time. These findings are similar to those found by Harvey (1989).

Chan, et al. (1992) investigate the risk premium in the U.S. market using a bivariate GARCH-in-mean process. They use daily data from the S&P 500 and the Nikkei 225 from January 3, 1980 to December 31, 1989. They find evidence there is significant foreign influence on the time-varying risk premium for U.S. equity assets. This provides evidence of international market integration over the time period which they sampled. They generally were not able to reject their model of the international CAPM at a 5 percent level.

De Santis and Gerard (1997) use monthly data from MSCI for the worlds eight largest equity markets (the countries in the G7 plus Switzerland) from January 1970 to December 1994. They use multivariate GARCH parameterization in conjunction with the conditional CAPM while restricting the market price of risk to be non-negative. Their model allows the market price of risk, as well as the covariances between the individual portfolios and the market, to vary though time.

Their findings support the conditional CAPM. They also find large market declines are contagious, but international diversification does somewhat shield the U.S. investor with an average gain of 2.11 percent over their sample period. Their parsimonious multivariate GARCH-in-mean parameterization is advantageous because it:

> "*makes the model applicable to relatively large cross-sections of assets, while preserving flexibility in the dynamics of the conditional second moments"*
>
> (pg. 1886).

Hansson and Hordahl (1998) test the conditional CAPM using a multivariate GARCH-M. They test the null hypothesis of the conditional CAPM against six competing GARCH-M models. They cannot reject the null with any of the competing models. They use a static market price of risk and suggest using a time-varying market price of risk could improve their models.

Soydemir (2005) employs a model similar to De Santis and Gerard (1997), but uses monthly price data from five Asian countries, U.S., U.K., and the world market to investigate the response of price shocks in Asian markets. He finds little evidence in favor of the static CAPM and strong evidence in favor of the conditional CAPM. He also finds emerging markets have higher time-varying price of risks and lower time-varying correlations than of developed economies. His study also shows the price of covariance risk is higher in the developed economies (U.S. and U.K.) and can be contagious.

Carrieri, Errunza, and Hogan (2009) employ a tri-variate GARCH model to investigate how market integration has evolved for eight emerging markets (6 South American and 2 Asian) from 1997 through 2000. They find none of the countries appear to be segmented and there are large cross-market differences in the degree of integration. Over their sample period the emerging markets seem to be moving towards market integration, while financial market policies play a large role in market integration.

2.2.4 Investor Sentiment as Information Variables in the Conditional CAPM

Ho and Hung (2009), incorporate investor sentiment as conditioning information in several asset pricing models, including the CAPM. They investigate if size, value, liquidity and momentum effects are captured by incorporating investor sentiment as information variables. They form a composite investor sentiment index by extracting the principle component from three different sentiment-related surveys. Their study uses a two-pass framework, where Betas are not allowed to vary through time. They find the size effect decreases in the conditional CAPM when sentiment is included as conditioning information.

2.3 How this Study Extends the Literature

This study extends the literature (please refer to the dotted arrow on Figure 2.2) by investigating if investor sentiment is related to asset prices in both the U.S. equity market (chapter II) and internationally (chapter III). First, it uses the methodology of De Santis and Gerard (1997), using a conditional version of the CAPM using a parsimonious GARCH model in which the risk premia, betas and correlations are time-varying. Second, investor sentiment is presented from two direct measures (surveys) and one indirect measure as conditional information variables; whereas previous studies used economic fundamentals. Finally, investor sentiment is not assumed to be fully irrational. The methodology of Verma et al. (2008) is used to decompose total sentiment into its irrational and rational components. Both irrational and rational components are tested as conditioning information variables in several models. Results are then compared with the economic fundamentals model. In addition, because this methodology provides information on the time-varying correlations and market price of risk, they are plotted in order to gain visual insight as how they react to U.S. recessions.

Figure 2.1 Decomposing Investor Sentiment

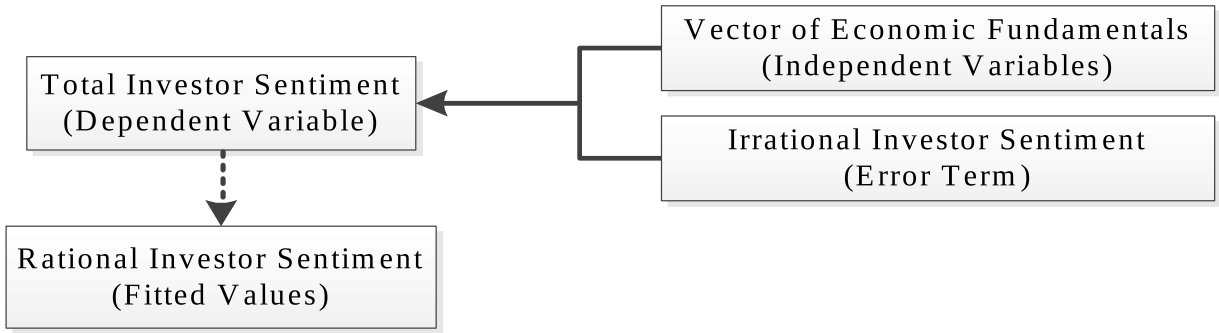
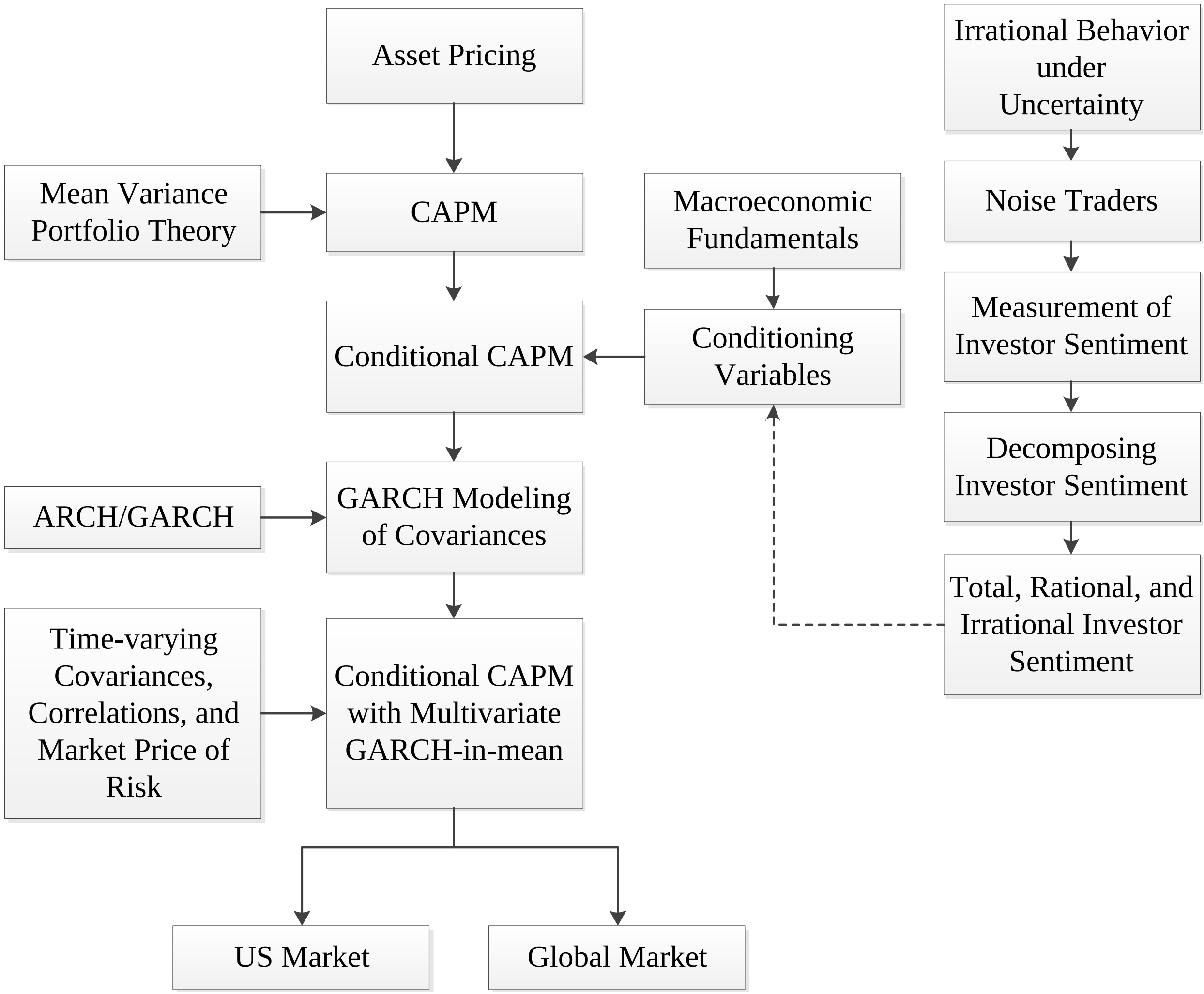


Figure 2.2 Literature Review – Evolution of the methodology and studies.



CHAPTER III

THE U.S. MARKET

3.1 Introduction

This chapter employs the methodology used by De Santis and Gerard (1997) and Soydemir (2005) to test whether sentiment is priced. It differs from theirs in several ways. First, it focuses on the U.S. market instead of the global market. Second, in addition to using economic fundamentals, several models using investor sentiment measures are introduced as the information available to the investor at time t-1. Third, it uses sample data which is weekly in frequency instead of monthly. Lastly, it extends the time-frame several more years to include the most recent U.S. recession.

De Santis and Gerard (1997) test the conditional CAPM for the eight largest equity markets in the world. Their sample is of monthly frequency and spans the time period from January 1970 through December 1994. Their results support most of the pricing restrictions of the CAPM, and they find although severe market declines are contagious, benefits of international diversification had not declined significantly over their sample period.

Soydemir (2005), uses multivariate GARCH modeling in conjunction with the conditional CAPM, allowing risk premia, betas and correlation to vary through time. He employs a vector autogression (VAR) to model impulse response functions of the time-varying price of covariance. His sample includes five Asian countries, the U.S. and the U.K. The data is monthly, ranging from June 1989 through October 2002. He finds the price of covariance risk is higher for emerging markets, and cross country correlations increase during the 1997 Asian crisis. His VAR estimations show contagion in the price of covariance risk in varying degrees.

We use the parameterization of Ding and Engle (2001) which allows the risk premia, betas, and correlations to vary through time. Literature shows this improves the conditional CAPM model. This parameterization also allows examination of the predictive performance of the time-varying correlations and risk premia over the last two U.S. recessions. This parsimonious GARCH process allows more GICS sectors to be analyzed simultaneously. Although the conditional density of asset returns are assumed to have a normal distribution, the quasi-maximum likelihood estimates for the standard errors are utilized in order to yield robust results to violations of the normality assumption.

We assume total investor sentiment is not entirely irrational. Following the methodology of Verma, et al. (2008), we decompose investor sentiment into its rational and irrational components. We decompose three different measures of total investor sentiment; two represent the informed investor and the other the uninformed investor. This allows testing of the following four null hypotheses:

1) Total sentiment of both informed and uninformed investors is not priced.
2) Rational sentiment of both informed and uninformed investors is not priced.
3) Irrational sentiment of informed investors is not priced.
4) Irrational sentiment of uninformed investor is not priced.

The extant literature shows investor sentiment is priced. Therefore we predict null hypothesis (1) will be rejected in favor of the alterative. A rational investor should incorporate the information about macroeconomic fundamentals into their investment decisions. Therefore hypothesis (2) should also be rejected in favor of the alternative. Null hypothesis (3) could have mixed results. Informed investors must have an irrational component, but it should be small in comparison to an uninformed investor; therefore it is predicted it will not be priced. Uniformed investors should by definition be noise traders, thus have a large irrational component. For this reason we predict null hypothesis (4) will be rejected and the irrational component of uniformed investors will be priced.

This chapter contributes to the literature in the following distinct ways. First, three measures of U.S. total investor sentiment are tested in a multivariate conditional CAPM. Second, investor sentiment is decomposed in order to test if rational and/or irrational sentiment is priced in the U.S. market. Finally, the predictive performance of the model is examined during the 2001 and 2008 U.S. recessions by plotting the time-varying market price of risk and correlations before, during and after the recessionary periods.

3.2 Measurement and Data Sources

3.2.1 Portfolio Price and Return Data

The price data which is used to proxy the market comes from the seven largest global industry classification standard (GICS) sectors from the S&P 500. Additionally, investor sentiment is used as an alternative to macroeconomic fundamentals as conditioning information available to the agent at time t-1. The primary investor sentiment survey data comes from two sources, Investors Intelligence (II) and The American Association of Individual Investors (AAII). The investor sentiment measures are further decomposed into their rational and irrational components following the methodology of Verma, Baklaci and Soydemir (2008). The total, rational, and irrational sentiment components, along with rational economic fundamentals are employed as information (conditioning) variables in various models in the conditional CAPM.

The data is retrieved from *Datastream*, unless specifically mentioned otherwise. There are 275 observations, weekly in frequency, beginning the last week of the year 1999 through the last week of 2010. Returns are calculated as continuous in percent form using the following equation:

$$R_{it} = \ln\left(\frac{P_{it}}{P_{it-1}}\right) X100 \tag{3.1}$$

Where P_{it} is U.S. dollar-denominated and i represents each of seven GICS sector portfolio from the S&P 500. The S&P 500 as a whole is the eighth portfolio, which is used as the market portfolio. The GICS sector price data is in total return form, thus it reflects prices with dividends being reinvested. The calculation of excess returns using Eq. (3.1) yields 274 total return observations starting week 1 of 2000 through week 52 of 2010. Referring to Figure 1.1, the GICS sectors included in this study are the seven largest by market capitalization. These seven sectors make up 89.5 percent of the adjusted market capitalization of the S&P 500 as of September 24, 2010. The seven sectors, ranked in order from largest to smallest are: information technology, financials, health care, consumer staples, industrials, energy and consumer discretionary. Three remaining sectors, each about 3 percent of the total market capitalization were not included. They were excluded from this study in interest of model parsimony, and to avoid the computational expense adding more sectors adds to the estimation the time-varying conditional covariance matrices.

The excess returns, R_{it}^{e}, are calculated as:

$$R_{it}^{e} = R_{it} - R_{ft}, \tag{3.2}$$

where R_{ft} is the weekly return on the 3-month U.S. Treasury bill, secondary market, middle rate, at time t, and R_{it} is defined in Eq. (3.1).

Table 3.1, Panel A reports the summary statistics for the excess returns. The portfolio with the largest mean excess return is the energy sector, with a value of 0.143 percent per week. Health care, consumer staples and the industrials sectors all have positive mean weekly excess returns. The information technologies, finance and consumer discretionary as well as the S&P 500 composite all have negative mean weekly excess returns over the sample period. The information technology sector has the lowest mean excess return at -0.156 percent per week. Comparing the mean excess returns and standard deviation between sectors, there appears to be little evidence of a linear relationship, or they are positively related as theory suggests. Similarly, a comparison of median excess return to standard deviation does not reveal a robust positive relationship.[3] All Jarque-Bera (1980) and Lilliefores (1967) goodness-of-fit tests show significant evidence in favor of rejecting the null hypothesis that the weekly excess returns are normally distributed. All kurtosis estimates are greater than 3, indicating the distribution is leptokurtic, or more peaked than a normal distribution. This is expected as “fat tails” are often observed in the distribution of return series. All eight excess return distributions are negatively skewed (mean < median), with skewness estimations ranging from -1.292 to 0.006.

Table 3.1, Panel B reports the autocorrelation of excess returns up to six lags. Nine of the 42 autocorrelations are highly significant with p-values less than one percent. Twenty-one autocorrelations are not statistically significance with p-values greater than ten percent. The information technology, health care, industrials, and consumer discretionary sectors have little statistical evidence of autocorrelation. The finance and consumer staples sectors have

[3] Regressing mean excess return and standard deviation gives a negative slope coefficient with a R-squared value of 0.2621, while similarly regressing median excess return gives a positive slope and a R-squared of 0.0386.

statistically significant autocorrelation at all six lags. This suggests an autoregressive term may be needed in the mean equation[4].

The summary analysis of the excess returns squared, is shown in Table 3.1, Panel C. This panel shows highly significant autocorrelation with p-values less than one percent for all six lags for all 8 portfolios. Thus multivariate GARCH (1, 1) parameterization in the second moments is deemed appropriate.

Table 3.1, Panel D reports the unconditional cross-sectional correlations for the excess returns. All correlations are significant at the one percent level. Most sector-to-sector correlations are below 0.7, with the exception of consumer discretionary – information technology, consumer discretionary – finance, and consumer discretionary – industrials, with Pearson's product-moment correlation coefficients of 0.710, 0.808 and 0.862 respectively. The correlation coefficient of industrials-finance is 0.788 and consumer staples-health care is 0.700, these two are the only other sector-to-sector correlations at or above 0.7. The Information technology, finance, industrials and consumer discretionary sectors all correlate highly with the S&P 500 composite index, having values of approximately 0.8 or greater.

Figures 3.1 through 3.8 depict the values of the excess returns of the individual GICS sectors and market portfolios over time. As expected the most volatile periods generally occur during the two U.S. recessionary periods.

3.2.2 Information Variables

Two general sets of information variables (z_{t-1} in Eq. (3.8)) are used in this study (see Figure 3.9). The first set is composed of, the traditionally used, economic fundamentals and the

[4] The M-GARCH model was first ran as designed in previous studies, without an autoregressive term in the mean equation. The subsequent residual analysis showed little or no significant autocorrelation (see Tables (3.7a), (3.7b), (3.7c), and (3.7d)). For this reason in interest of model parsimony an autoregressive term was not used in the mean equation.

second set is investor sentiment. The economic fundamentals variables are: the default premium (DP), which is the difference between the U.S. corporate bond yield in Moody's seasoned issued Baa and Aaa bonds; the term premium (TP),which is the difference in Baa and the risk free rate, and the change in the U.S. market dividend yield in excess of the risk free rate (CHDIV). These variables have been used frequently in asset pricing literature; additionally they are often employed in technical and fundamental analysis by investors. Moreover, they have been shown to carry non-redundant information in several studies including Bekaert and Hodrick (1992), Bekaert and Harvey (1997), and De Santis and Gerard (1998).

The second general set of measures is composed of two primary investor sentiment surveys and a secondary measurement. The first primary measure, $AAII_t$, is calculated from the weekly survey data from the AAII. The AAII Sentiment Survey attempts to measure, by polling among their membership, the proportion that is bullish, bearish, or neutral on the stock market for the next six months. AAII members are only allowed one vote per week.

The second primary sentiment measure, II_t, is calculated from the II. II is constructed by examination of in excess of one hundred independent market newsletters. They examine at each article and determine whether the author is bullish, bearish or neutral. II has historically used the same four editors when generating the report, and claim this keeps their historical data consistent over time. Because the AAII Investor Sentiment Survey is polled from individual investors, literature generally considers it to be more irrational than the professional advisors in the II Advisors' Sentiment Report.

Both $AAII_t$ and II_t represent bull-bear spreads, which are calculated by subtracting the percent bearish from the percent bullish. Thus, a positive spread indicates more investors are more bullish. This measure is often employed in the literature, for example see Brown (1999), Brown and Cliff (2004), (2005), Schmeling (2007), Han (2008), Verma, et al. (2008), and Verma and Verma (2008). Figures 3.10 and 3.11 depict the II and AAII bull-bear spreads respectively. The investor sentiment variables are further decomposed into rational and irrational components as described later in Section (3.3), Eqs. (3.9a) and (3.9b).

Two secondary or non-direct sentiment measures are considered for this are: the University of Michigan Consumer Sentiment Index; and the weekly average of the total volume of calls to puts ($CALL\_PUT_t$) from the Chicago Board Options Exchange (CBOE)[5]. Fisher and Statman (2003) find the University of Michigan Consumer Sentiment Index is related to individual investor sentiment, but not institutional investors. Meaning these investors, being less informed, should be more irrational than a more informed institutional investor. The University of Michigan Consumer Sentiment Index is monthly in frequency, so it was deemed inappropriate for this study.

The put-call ratio is a widely accepted bearish indicator [see Brown and Cliff (2004)]. In this study the ratio is reversed in order ease interpretation among the different sentiment parameter estimates. If $CALL\_PUT_t$ is greater (less) than unity it can be interpreted as bullish (bearish) investor sentiment. An increase (decrease) in magnitude of the call-put ratio indicates a more bullish (bearish) investor sentiment. Because the majority of calls and puts are traded by institutional investors, this secondary measure can be considered to be an institutional or informed investor sentiment indicator rather than a uniformed investor sentiment measure. The call-put ratio is decomposed into its irrational and rational components using the same methodology as the primary investor sentiment variables (Eq. (3.9c)). Figure 3.12 depicts the CALL_PUT ratio through time.

[5] Available from: http://www.cboe.com/data/PutCallRatio.aspx

There are ten macroeconomic fundamentals used as regressors for decomposing the investor sentiment measures ($AAII_t$, II_t, and $CALL\_PUT_t$) into their rational and irrational components. These regressors ($Fund_{jt}$ in Eqs. (3.9a), (3.9b). and (3.9c)) consist of the three Fama and French (1996) factors; 1) the high minus low book-to-price ratio (HML); 2) the small minus big market capitalization (SMB); and 3) the market risk premium (MKT-RF). Additional resgressors are 4) the momentum factor (MOM) of Jegadeesh and Titman (1993) and Carhart (1997); 5) the first difference of the return on the 1-month Treasury Bill[6]; 6) the economic risk premia [Campbell (1987); Ferson, Harvey, and Campbell (1991)] measured by the difference between the return on the 3-month and 1-month Treasury Bills; 7) the dividend yield [Harvey (1989); Litzenberger and Ramaswamy (1979)] measured as the first difference of the U.S. dividend yield; 8) the term premium [Fama (1990); Harvey (1989); Merton (1974)] measured as the first difference of the yield of the 10-year U.S. Treasury Bond in excess of the 3-month U.S. Treasury Bill; 9) the default premium as defined previously; and finally 10) the inflation rate in percent [Asprem (1989)].

The inflation rate, expressed in percent form, is calculated using the U.S. Consumer Price Index (CPI), all urban, seasonally adjusted value from the U.S. Department of Commerce, Bureau of Economic Analysis. U.S. CPI data is only available in monthly frequency, using it requires conversion to weekly frequency. It is converted to weekly using a cubic spline interpolation [Al Awad and Goodwin (1998); De Boor (2001)].

The irrational components of AAII, II and CALL_PUT are AAII_IRR, II_IRR, CALL_PUT_IRR respectively (see Eqs. (3.9a), (3.9b), and (3.9c). Similarly the rational

[6] Weekly data on HML, SMB, MKT-RF, MOM and return on the one-month Treasury Bill are obtained from the Kenneth French data library located online at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. Weekly MOM is calculated with a rolling sum of five daily observations, while the other variables are available as direct downloads in weekly form.

components are henceforth labeled as AAII_RAT and II_RAT. These components are simply the fitted values, and can be considered to be the rational future expectations of the individual and institutional investors respectively.

Table 3.2, Panel A shows the descriptive statistics for the two groups of information variables. All information variables reject the null hypothesis of normality at the 5 percent level or less. Table 3.2, Panel B shows the correlations to be particularly low, thus confirming the information variables carry mostly non-redundant information.

3.3 Model Specification and Econometric Methodology

The pricing is modeled utilizing the following, commonly used, conditional asset pricing CAPM benchmark model:

$$\mathrm{E}(R_{it}|\mathfrak{I}_{t-1}) - R_{ft} = \delta_{t-1}\,\mathrm{COV}(R_{it}, R_{mt}|\mathfrak{I}_{t-1})\ \forall_i \tag{3.3}$$

Where R_{it} is the return on the risky asset i (in this chapter, a GICS sector portfolio of equity returns) between times t and $t-1$; R_{ft} is the risk free rate at time t; δ_{t-1} is the price of covariance risk (market price of risk); R_{mt} is the return on the market between times t and $t-1$; and $\mathfrak{I}_{t-1}$ is the information set available to the agents at time $t-1$. Equation (3.3) can be tested using:

$$\mathbf{R}_\mathrm{t} - \mathrm{R}_\mathrm{ft}\boldsymbol{\iota} = \delta_\mathrm{t-1}\mathbf{h}_\mathrm{Nt} + \boldsymbol{\epsilon}_\mathrm{t} \qquad \boldsymbol{\epsilon}_\mathrm{t}|\mathfrak{I}_\mathrm{t-1} \sim \mathrm{N}(0, \mathbf{H}_\mathrm{t}) \tag{3.4}$$

Where $\boldsymbol{R_t}$ is a (N X 1) vector, (in this chapter N is the number of GICS sectors plus one for the total S&P 500 or market) of returns; $\boldsymbol{\iota}$ is a (N X 1) vector of ones; $\boldsymbol{H_t}$ is the (N X N) conditional covariance matrix; and $\boldsymbol{h_{Nt}}$ is the Nth column of $\boldsymbol{H_t}$ containing the covariance of each GICS sector return with the S&P 500 return variance at time t. The restrictions for the second moments are modeled by the following parsimonious multivariate generalized autoregressive conditional heteroscedasticity (GARCH) extension of a univariate GARCH (1, 1):

$$\boldsymbol{H}_t = \boldsymbol{H}_0 * (\boldsymbol{\iota}\boldsymbol{\iota}' - \boldsymbol{a}\boldsymbol{a}' - \boldsymbol{b}\boldsymbol{b}') + \boldsymbol{a}\boldsymbol{a}' * \boldsymbol{\epsilon}_{t-1}\boldsymbol{\epsilon}'_{t-1} + \boldsymbol{b}\boldsymbol{b}' * \boldsymbol{H}_{t-1} \tag{3.5}$$

In the Eq. (3.5), for the first iteration $\boldsymbol{H}_0$ is an (N X N) unconditional covariance matrix (sample covariance matrix). It is updated to the covariance matrix of the residuals from the mean equation each iteration thereafter. The "*" symbol denotes the Hadamard matrix product (an element-by-element multiplication). The $\boldsymbol{a}$ and $\boldsymbol{b}$ are each (N X 1) vectors of parameter estimations. The log-likelihood function to be maximized is:

$$\ln L(\theta) = -\frac{TN}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T} ln|H_t(\theta)| - \frac{1}{2}\sum_{t=1}^{T} \boldsymbol{\epsilon}_t(\theta)' H_t(\theta)^{-1}\, \boldsymbol{\epsilon}_t(\theta), \tag{3.6}$$

where θ is the vector of unknown model parameter estimates. The model is tested using quasi-maximum likelihood (QML) due to non-normality (see Bollerslev and Wooldridge (1992)). The optimization algorithm is that of Berndt, Hall, Hall and Hausmann (BHHH) (1974),.

In conditional asset pricing models the price of covariance risk (δ_{t-1}, Eqs. (3.7) and (3.8)) can be allowed to vary through time as a linear function of a set of instruments (vector $\boldsymbol{z}_{t-1}$ in Eq. (3.8)). However, as Merton (1980) discusses, the price of covariance risk is often negative using this methodology, which works against theoretical predictions. He shows a non-negativity restriction can be added to the model to achieve unbiased estimates of the market price of risk. In this study δ_{t-1} is constrained to be non-negative by employing an exponential function [Bekaert and Harvey (1995), De Santis and Gerard (1998), and Soydemir (2005)]:

$$R_{it} - R_{ft} = \delta_{t-1}\,\mathrm{COV}(R_{it}, R_{mt}|\Im_{t-1}) + \varepsilon_{it}\ \ \forall_i \tag{3.7}$$

$$\delta_{t-1} = \exp(\lambda + \boldsymbol{\kappa}'\boldsymbol{z}_{t-1}) \tag{3.8}$$

Both the constant λ and vector $\boldsymbol{\kappa}$ are parameters which are estimated [Soydemir (2005)] in addition to the two vectors of GARCH parameters, $\boldsymbol{a}$ and $\boldsymbol{b}$**,** from Eq. (3.5).

As per the methodology of Verma, et al. (2008) investor sentiment is decomposed into its rational and irrational components using Eqs. (3.9a), (3.9b), and (3.9c).

$$AAII_t = \gamma_0 + \sum_{j=1}^{J} \gamma_j Fund_{jt} + AAII\_IRR_t \tag{3.9a}$$

$$II_t = \gamma_0 + \sum_{j=1}^{J} \gamma_j Fund_{jt} + II\_IRR_t \tag{3.9b}$$

$$CALL\_PUT_t = \gamma_0 + \sum_{j=1}^{J} \gamma_j Fund_{jt} + CALL\_PUT\_IRR_t \tag{3.9c}$$

Where $AAII_t$ and II_t represent the investor sentiment expectations of individual and institutional investors respectively. $CALL\_PUT_t$, an indirect measure of informed investor sentiment is estimated using (Eq. 3.9c). $Fund_{jt}$ is a set of economic fundamentals which have been shown to carry non-redundant information in asset pricing literature. $AAII\_IRR_t$, II_IRR_t, and $CALL\_PUT\_IRR_t$ are the residuals which represent irrational components of investor sentiment. After estimating the parameters γ_0, and γ_j, and the residuals, $AAII\_IRR_t$, II_IRR_t, and $CALL\_PUT\_IRR_t$, the fitted values, $\widehat{\mathrm{AAII}}_t$, $\widehat{\mathrm{II}}_t$, and $\mathrm{CA}\widehat{\mathrm{LL\_P}}\mathrm{UT}_t$ are then calculated. These fitted values represent the rational components of investor sentiment, or the rational future expectations of the investor.

3.4 Empirical Results

3.4.1 Sentiment Decomposition

Tables (3.3), (3.4), and (3.5) display the results of the individual regressions which decompose the three total sentiment measures into their irrational and rational components. The institutional investor sentiment (Table 3.4) has higher adjusted R-squared values than individual investor sentiment (Table 3.3). As Perez (2011) discusses, this is to be expected because individual investors are considered to be noise traders in the literature, thus less of their sentiment will be explained by the macroeconomic fundamentals. The regression of the secondary measure of investor sentiment, the call-put ratio has the lowest adjusted R-squared (Table 3.5). The literature considers the call-put ratio to be a measure of informed investor sentiment because options traders are supposedly well-informed. For this reason this is an interesting finding because one would expect it to follow macroeconomic fundamentals more closely. The low adjusted R-squared value may be due to day-traders, who often follow charts instead of fundamentals. All three regressions have several variables which are highly significant. This is to be expected because total sentiment should have rational components which co-vary with the macroeconomic fundamentals

3.4.2 Asset Pricing Results and Diagnostics Tests of the Residuals

Table 3.6, Panel A, Model 1depicts the results using the following conditional information variables: (a) the total sentiment from the AAII, (b) the total sentiment from the II, and (c) an indirect investor sentiment measure, the call-put ratio. The parameter estimate κ_1 (AAII sentiment) is insignificant, indicating the total uniformed individual investor sentiment does not affect the market price of risk. κ_2 (II sentiment) is significant at the 5% level and positive, thus with all else equal, an increase in the bull-bear spread of informed investors increases the market price of risk. κ_3 (call-put ratio) is negative and significant at the 1% level, thus with all other variables equal, as informed investors become more bullish the market price of risk decreases. The multivariate GARCH (1,1) parameters, a_i and b_i, are within the expected range, with the persistence of the GARCH terms around 0.97 and the ARCH terms around 0.2. Stationarity conditions are met with all elements of $\boldsymbol{aa}' + \boldsymbol{bb}' < 1$ [Brougerol and Picard

(1992)]. The mean and total likelihood scores of this model are -21.6312 and -12437.94 respectively.

Table 3.6, Panel B, Model 2 shows the results from decomposing both AAII and II sentiment into their rational and irrational components. The indirect sentiment measure, call-put, was not included in this model due to convergence problems[7]. Both κ_1 (AAII rational sentiment) and κ_3 (AAII irrational sentiment) are positive and significant at the 5% level. This indicates that, holding all else equal, an increase in the bull-bear spread of both the irrational and rational components for the individual investor increases the market price of risk. κ_2 (II rational sentiment) is negative and significant at the 10% level. This provides evidence an increase in the rational component of the institutional investor decreases the market price of risk. While $\kappa 4$ (II irrational sentiment) is not significantly different than zero, indicating the irrational component of the informed investor does not affect the market price of risk. The GARCH parameters are very close to those in Table 3.6, Panel A, and also satisfy stationarity conditions. The mean log-likelihood is -21.6294 while the total Likelihood function is -12415.3, which is slightly higher than that of the model used in Table 2, Panel A.

Table 3.6) Panel C, Model 3 includes the results from using the thre irrational components of investor sentiment. The parameter estimate κ_1 (AAII irrational sentiment) is negative and significant, indicating the irrational component of the uninformed individual investor sentiment inversely affects the market price of risk. These results confirm those found in the literature, where bullish sentiment from noise traders cause lower future returns. The parameters κ_2 (II irrational sentiment) and κ_3 (call-put ratio irrational sentiment) are insignificant. Because they both represent informed investors, this is expected because their irrational

[7] Whenever more than five parameters (including the constant) were estimated in the price of covariance risk section of the model the iterative maximum likelihood program would not converge on a solution.

component should be small, in this case the parameter estimates do not statistically different from zero. The GARCH parameters are in Panel C are again all significant and reasonable in value.

Table 3.6, Panel D, Model 4 shows the results from the traditional macroeconomic fundamentals. All three parameter estimates, the term premium, default premium and change in dividends did not differ from zero. This result was surprising, but not the main focus of this dissertation. It was important to include this model for comparison via likelihood ratio tests, which will be discussed in Section 3.4.3.

Table 3.7, Panels A, B, C, and D shows the results for the diagnostics tests of the residuals. The standardized residuals are constructed by: $\varepsilon_t h_t^{-1/2}$. The first section includes the serial and partial autocorrelations for the residuals of each sector through the first six lags. The second section shows the Q-statistics. The null hypothesis for the Q-statistic [Ljung and Box (1978)] is: no autocorrelation up to the indicated lag order. The results show the null is only rejected three times at a 1% significance level, and twice at a 5% significance level out of sixty-four observations. This provides statistical evidence the inclusion of GARCH modeling of the second moments is appropriate. For the variance ratio tests [Cochrane (1988)] the null hypothesis is: series is a martingale (residuals are serially independent). The row labeled joint at max |z| is a joint test at the maximum absolute value of the z-score from lags 2 through 16, while rows at indicated lags 2 through 8 are individual variance ratio tests at indicated lags. None of the variance ratio tests reject the null hypothesis of serial independence.

3.4.3 Model Comparisons using the Vuong Closeness and Clarke Tests.

Information criteria such as the Akaike (AIC) (1974), (1976), the Bayesian (BIC) [Schwarz (1978)] and the QIC [Hannan and Quinn (1979)] can be used to compare non-nested models [Bierens (2004)], but they do not offer a statistical test as to determine if a model is significantly closer to the true data generating process. Likelihood ratio tests [Wilks (1938)] can be used to compare models when they are nested. The likelihood ratio test is simply twice the likelihood ratio, and is chi-squared distributed with the degrees of freedom equal to the difference in the number of parameters. Two statistical tests which are used to compare non-nested models based on the likelihood values of the competing models are the Vuong closeness test [Voung (1989) and Rivers and Vuong (2002)] and the Clarke test [Clarke (2001), (2007), (2011) and Clarke and Signorino (2010)]. The Vuong test statistic is normally distributed and can be calculated using:

$$z = \frac{\ell_1 - \ell_2 - \left[\frac{p_1}{2}\ln(N) - \frac{p_2}{2}\ln(N)\right]}{\sqrt{N}\widehat{\omega}_N} \tag{3.10}$$

where ℓ_1 and ℓ_2 are the total log-likelihood values of the two models to be compared; $\left[\frac{p_1}{2}\ln(N) - \frac{p_2}{2}\ln(N)\right]$ is a degrees of freedom adjustment which penalizes the model which is less parsimonious, while p_1 and p_2 are the number of parameters estimated in each model; N is the number of observations.

$\widehat{\omega}_N$ is calculated by:

$$\widehat{\omega}_N^2 = \frac{1}{N}\sum_{i=1}^{N} ln\left(\frac{\ell_{i,1}}{\ell_{i,2}}\right)^2 - \left[\frac{1}{N}\sum_{i=1}^{N} ln\left(\frac{\ell_{i,1}}{\ell_{i,2}}\right)\right]^2 \tag{3.11}$$

where $\ell_{i,1}$ and $\ell_{i,2}$ are the individual log-likelihood values for each observation. A positive (negative) value of z means model 1 (model 2) is closer than model 2 (model 1) to the true data generating process, while the magnitude of $|z|$ determines whether the difference is statistically significant.

The Clarke test is a non-parametric test and simpler to perform than the Vuong closeness test. The Clarke test also has more power than the Vuong closeness test. The Clarke test is performed by comparing the individual log-likelihood values, $\ell_{i,1}$ and $\ell_{i,2}$ and counting the number of times each one is greater. The null hypothesis is the two competing models are equal. The test statistic is simply a cumulative Binomial distribution with the probability of success of 0.50 in N trials, thus it is relatively simple to compute the number of successes required to reject the null hypothesis and conclude the competing models differ significantly[8].

Ranking the models by total likelihood scores: model 2 > model 1 > model 3 > model 4. Where model 1 includes the information variables: AAII total sentiment, II total sentiment, and call-put ratio; model 2 information variables: total sentiment decomposed into both the rational and irrational components of AAII and II; model 3 information variables are the irrational components of: AAII sentiment, II sentiment, and the call-put ratio; and last, model 4 information variables are the following economic fundamentals: CHDIV, DP, and CHTP. Table 3.4.3 displays the results from conducting both the Clarke and the Vuong closeness tests on the four competing models. The Clark tests revealed four significant differences while the Vuong test had one significant difference. This result is to be expected because the non-parametric Clarke test theoretically has more power.

The Clarke tests reveal first, model 1(total sentiment: AAII, II, Call-put ratio) is statistically closer to the "true" model than model 4 (macroeconomic fundamentals). This indicates total investor sentiment contains more information than the economic fundamentals. Since total investor sentiment contains both rational and irrational components, and rational

[8] De Boer, P., & Paap, R. (2009). Testing non-nested demand relations: linear expenditure system versus indirect addilog*. *Statistica Neerlandica*, *63*(3), 368-384. list GAUSS code in the appendix of their article which does both the Vuong and Clarke comparison tests. SAS also has programming which will perform both tests, see: http://support.sas.com/kb/42/514.html.

sentiment should be similar to the macroeconomic fundamentals, one could conclude irrational sentiment is priced. Second, model 1 is closer to the true model than model 3(Irrational sentiment: AAII, II, Call-put ratio). This is a reasonable result, since total investor sentiment logically contains more useful information than irrational investor sentiment alone. Third, Model 3 is closer to the true model than model 4. This is an interesting result because it shows the irrational components of investor sentiment contain more useful information than the traditional macroeconomic fundamentals model. Fourth, model 2 (irrational and rational sentiment: AAII and II) is closer than model 3. This result is also reasonable, one would logically think sentiment decomposed into it rational and irrational components will contain more useful information than irrational sentiment by itself. Finally, the remaining two Clarke tests found no statistical differences; model 2 did not differ from either model 1 or model 4.

The Vuong tests revealed model 1(total sentiment: AAII, II, Call-put ratio) is statistically closer to the "true" model than model 4 (macroeconomic fundamentals). This confirms the results from the Clarke test. The other Vuong comparisons show no statistical differences between models.

3.4.4 Time-varying Correlations

Figure 3.13 displays the time varying correlations between the S&P 500 Composite and each GICS sector from the time varying CAPM from Eq. (3.7).The gray shaded chart areas represent official U.S. recessionary periods as per the National Bureau of Economic Research (NBER) retrieved from www.nber.org/cycles.html June 2011. GICS sector correlations to the S&P 500 composite tend to group together during recessionary periods. This grouping of correlations will greatly reduce any benefits of diversification an investor might be counting on during recessionary periods. This confirms results from other research, where increased correlations are observed between markets in periods of economic crisis [Baig and Goldfajn (1999) , Loretan and English (2000), Forbes and Rigobon (2002), and Hartmann, Straetmans, and Vries (2004). In the non-recessionary periods the GICS sector correlations divide into two similar groups by response and magnitude. The two groups are (a) Information Technology, Finance, Industrials and Consumer Discretionary, and (b) Consumer Staples, Health Care and Energy. Group (a) tends to correlate higher in magnitude with the S&P 500, usually with Pearson Product-Moment correlation coefficients of 0.7 or higher, while group (b) tends to correlate much lower, except in recessionary periods.

Figure 3.14 depicts the mean time-varying correlation coefficients of groups (a) and (b) with the S&P 500 composite. The solid and double lines represent equally weighted mean portfolio correlations of the GICS sectors from group (a) while the solid line represents group (b).The dotted and dashed lines are the H-P filtered [Hodrick and Prescott (1997)] portfolio correlations with the S&P 500. The H-P filter isolates the cyclical component from the trend component (trend component shown). Equally weighed portfolio mean correlations were calculated using the Fisher's z transformation as recommended by Silver & Dunlap (1987). This figure shows more clearly how the two groups tend to be similar in response and in magnitude, while increasing to similar magnitude correlations with the S&P 500 in recessionary periods.

In Figure 3.15 the solid line represents the time varying mean correlation between an equally weighted portfolio composed of all seven GICS sector and the S&P 500 composite. The dotted line represents the H-P filtered data. This figure clearly shows the increased correlations of all GISC sectors with the S&P 500 before, during, and following recessionary periods.

3.4.5 Time-varying Market Price of Risk

Figure 3.16 shows the fitted values for the price of covariance risk from the solid line represent the H-P filtered MGARCH estimates of the price of covariance risk for the S&P 500 (see Table 3A). Rational and irrational investor sentiment for both informed and uniformed investors are used as information variables. The dotted line represents the H-P filtered covariance price of risk of the S&P 500, exponentiated and scaled for comparison by:

$$\frac{e^{-\delta_t}}{10} - 0.05 \tag{3.12}$$

and

$$\delta_t = \frac{R_{mt} - R_{ft}}{VAR(R_{mt})} \tag{3.13}$$

where $VAR(R_{mt})$ is the rolling variance in percent, using a 13 week window, of the continuous weekly return of the S&P 500 composite index.

The market price of risk from the two time series mostly co-vary, with peaks tending to be around similar times. Johnk and Soydemir (2012) found, using monthly observations, the peaks of the market price of risk from the investor sentiment MGARCH model mostly lead those of the market price of risk from Eq. (3.13). This phenomenon is not obvious in Figure 3.15. The different result may be due to the fact the data is weekly in frequency instead of monthly, this resulted more noise in the time series.

Table 3.1 Summary Statistics of Excess Returns – Seven Largest S&P 500 GICS Sectors

Panel A: summary statistics of excess returns

	Information Technology	Finance	Consumer Staples	Health Care	Industrials	Energy	Consumer Discretionary	S&P 500 Composite
Mean	-0.156	-0.073	0.064	0.003	0.008	0.143	-0.026	-0.039
Median	0.067	0.116	0.118	-0.055	0.078	0.415	0.082	0.118
Maximum	14.478	29.242	10.566	9.119	11.777	12.296	15.924	11.415
Minimum	-24.305	-27.007	-17.353	-20.310	-19.160	-28.819	-20.155	-20.021
Std. Dev.	4.230	4.500	2.179	2.579	3.191	3.536	3.376	2.753
Skewness	-0.542	0.006	-1.370	-0.943	-0.492	-1.292	-0.360	-0.835
Kurtosis	5.956	13.928	14.749	11.630	6.971	11.369	7.650	9.726
Jarque-Bera	237.088***	2856.323***	3480.681***	1866.247***	400.293***	1834.613***	529.508***	1148.655***
Lilliefors	0.082***	0.113***	0.091***	0.069***	0.084***	0.065***	0.070***	0.077***
Sum	-89.713	-41.990	36.833	1.986	4.575	82.213	-15.007	-22.526
Sum Sq. Dev.	10252.030	11602.350	2721.050	3809.941	5835.288	7163.920	6531.736	4341.855
Observations	574	574	574	574	574	574	574	574

Panel B: autocorrelations of excess returns

Lag	Information Technology	Finance	Consumer Staples	Health Care	Industrials	Energy	Consumer Discretionary	S&P 500 Composite
1	-0.047	-0.134***	-0.113***	-0.082**	-0.029	-0.067	-0.051	-0.064
2	0.018	0.061***	0.049**	-0.029	0.069	0.023	0.067	0.068*
3	0.002	-0.093***	-0.022**	-0.075*	-0.096**	-0.136***	-0.042	-0.087**
4	-0.043	0.041***	-0.060**	-0.004	0.031*	-0.014***	-0.013	-0.029**
5	0.058	0.025***	0.064**	0.033	0.021*	0.005**	0.043	0.054**
6	0.060	0.063***	-0.027**	0.011	0.057*	-0.004**	0.044	0.072**

Panel C: autocorrelations of excess returns squared

Lag	Information Technology	Finance	Consumer Staples	Health Care	Industrials	Energy	Consumer Discretionary	S&P 500 Composite
1	0.178***	0.412***	0.218***	0.192***	0.331***	0.242***	0.306***	0.275***
2	0.175***	0.167***	0.104***	0.087***	0.154***	0.024***	0.228***	0.129***
3	0.208***	0.210***	0.146***	0.051***	0.183***	0.141***	0.344***	0.203***
4	0.091***	0.146***	0.028***	0.002***	0.157***	0.059***	0.273***	0.109***
5	0.138***	0.137***	0.013***	0.031***	0.114***	0.077***	0.175***	0.106***
6	0.110***	0.216***	0.054***	0.119***	0.072***	0.017***	0.093***	0.130***

Panel D: unconditional cross-correlations of excess returns

	Information Technology	Finance	Health Care	Consumer Staples	Industrials	Energy	Consumer Discretionary	S&P 500 Composite
Inf. Tech.	1							
Finance	0.525***	1						
Health Care	0.261***	0.561***	1					
Cons. Staples	0.343***	0.562***	0.700***	1				
Industrials	0.663***	0.788***	0.620***	0.611***	1			
Energy	0.392***	0.514***	0.488***	0.532***	0.612***	1		
Cons. Discr.	0.710***	0.808***	0.613***	0.565***	0.862***	0.554***	1	
S&P 500 Comp.	0.805***	0.841***	0.639***	0.685***	0.905***	0.686***	0.916***	1

Significance levels of 0.01, 0.05 and 0.10 are denoted by ***, **, and * respectively. Excess returns (R_{it}^{e}) are calculated by subtracting the closest 3 month U.S. Treasury Bill weekly rate from the S&P 500 GICS sector continuously compounded weekly returns (US dollar denominated). Sample period: 2000:w1 through 2010:w52, 574 observations. The asymptotic standard errors for the contemporaneous cross-correlations under an i.d. null hypothesis are given by $1/\sqrt{n}$ = 0.042.

Table 3.2 Summary Statistics: Sentiment and Macroeconomic Variables

Panel A: summary statistics of sentiment and macroeconomic variables

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
AAII	9.253	8.570	62.860	-51.350	20.868	0.042	2.503	6.094	0.047
II	19.239	21.500	44.100	-32.200	14.422	-0.865	3.620	80.980	0.000
CALL_PUT	1.251	1.192	2.365	0.767	0.283	1.431	5.520	348.351	0.000
HML	0.149	0.140	9.820	-6.880	1.623	0.435	8.085	637.658	0.000
SMB	0.110	0.120	6.300	-9.430	1.446	-0.522	8.582	772.656	0.000
MKT_RF	0.024	0.170	13.030	-18.410	2.835	-0.613	8.786	838.195	0.000
MOM	0.013	0.050	2.422	-3.448	0.597	-1.118	9.057	998.787	0.000
D(RTBILL)	0.000	0.000	0.020	-0.038	0.004	-2.488	26.148	13407.790	0.000
D(ERP)	-0.001	0.000	0.058	-0.072	0.011	-1.313	15.622	3975.243	0.000
D(DY)	0.001	0.000	0.500	-0.360	0.057	0.718	19.405	6486.150	0.000
D(TP)	0.003	-0.011	0.711	-0.554	0.159	0.640	5.281	163.665	0.000
DP	1.120	0.950	3.470	0.520	0.526	2.634	10.215	1911.756	0.000
INFL	0.203	0.219	1.377	-1.811	0.334	-1.621	11.610	2028.169	0.000

Panel B: cross-correlations of sentiment and macroeconomic variables

	AAII	II	CALL_PUT	HML	SMB	MKT_RF	MOM	D(RTBILL)	D(ERP)	D(DY)	D(TP)	DP	INFL
AAII	1												
II	0.4911	1											
CALL_PUT	0.4767	0.1968	1										
HML	0.1012	0.0861	0.0683	1									
SMB	0.1061	0.0275	0.1070	-0.2463	1								
MKT_RF	0.1089	0.0018	0.2174	0.0156	0.2154	1							
MOM	-0.0409	0.0674	-0.0772	-0.3098	0.2021	-0.2997	1						
D(RTBILL)	0.0362	0.0767	-0.0134	0.0370	-0.0182	-0.0392	0.0019	1					
D(ERP)	0.1461	0.0850	0.1172	-0.0741	0.0554	0.1776	0.0305	-0.3224	1				
D(DY)	-0.0767	0.0159	-0.2082	-0.2132	-0.0974	-0.9219	0.4234	0.0218	-0.1494	1			
D(TP)	-0.0964	-0.0576	-0.0197	0.0614	0.0830	0.1286	-0.1575	-0.0310	-0.5323	-0.1425	1		
DP	-0.3531	-0.5945	-0.2568	-0.0802	0.0053	0.0008	-0.1461	-0.0467	-0.0266	-0.0413	0.0235	1	
INFL	-0.0270	0.2151	0.0411	0.0191	-0.0196	-0.0348	0.0932	0.0051	0.0610	0.0220	0.0536	-0.3931	1

Data is weekly in frequency, and ranges from 1999:W52 – 2010:W52

AAII - The AAII Investor Sentiment Survey bull-bear spread (%).

II – The Investors Intelligence Advisors’ Sentiment Report bull-bear spread(%).

CALL_PUT – The weekly average of the total volume of calls to puts (call-put ratio) from the Chicago Board Options Exchange (CBOE).

HML – A Fama and French (1996) factor; high minus low book-to-price ratio.

SMB - A Fama and French (1996) factor; small minus big market capitalization.

MKT_RF - A Fama and French (1996) factor; market risk premium.

MOM – Jegadeesh and Titman (1993) momentum factor.

D(RTBILL) - The first difference of the return on the 1-month Treasury Bill.

D(ERP) - The economic risk premia - measured by the difference between the return on the 3-month and 1-month Treasury Bills.

D(DY) - The dividend yield - measured as the first difference of the U.S. dividend yield.

D(TP) -The term premium - measured as the first difference of the yield of the 10-year U.S. Treasury Bond in excess of the 3-month U.S. Treasury Bill.

DP - The default premium – the difference in Baa and the risk free rate.

INFL - The inflation rate in percent is calculated using the U.S. Consumer Price Index (CPI), all urban, seasonally adjusted value from the U.S. Department of Commerce, Bureau of Economic Analysis. U.S. CPI data is interpolated form monthly to weekly using a cubic spline interpolation.

Table 3.3 Individual Investor Sentiment (AAII) Regression on Macroeconomic Variables

Independent Variables	Coefficient	Std. Error	t-Statistic	P-value
C	29.826	3.193	9.341	0.000
HML	1.524	0.612	2.491	0.013
SMB	1.814	0.613	2.958	0.003
MKT_RF	1.476	0.767	1.926	0.055
MOM	-3.627	1.458	-2.488	0.013
D(RTBILL)	343.435	208.087	1.650	0.099
D(ERP)	300.339	102.298	2.936	0.004
D(DY)	70.886	40.273	1.760	0.079
D(TP)	-3.272	6.527	-0.501	0.616
DP	-16.534	2.151	-7.685	0.000
INFL	-11.631	3.556	-3.271	0.001
Adjusted R-squared	0.202226			

$$AAII_t = \gamma_0 + \sum_{j=1}^{J} \gamma_j Fund_{jt} + AAII\_IRR_t$$

Data is weekly in frequency, and ranges from 1999:W52 – 2010:W52
AAII - The AAII Investor Sentiment Survey bull-bear spread (%).
HML – A Fama and French (1996) factor; high minus low book-to-price ratio.
SMB - A Fama and French (1996) factor; small minus big market capitalization.
MKT_RF - A Fama and French (1996) factor; market risk premium.
MOM – Jegadeesh and Titman (1993) momentum factor.
D(RTBILL) - The first difference of the return on the 1-month Treasury Bill.
D(ERP) - The economic risk premia - measured by the difference between the return on the 3-month and 1-month Treasury Bills.
D(DY) - The dividend yield - measured as the first difference of the U.S. dividend yield.
D(TP) -The term premium - measured as the first difference of the yield of the 10-year U.S. Treasury Bond in excess of the 3-month U.S. Treasury Bill.
DP - The default premium – the difference in Baa and the risk free rate.
INFL - The inflation rate in percent is calculated using the U.S. Consumer Price Index (CPI), all urban, seasonally adjusted value from the U.S. Department of Commerce, Bureau of Economic Analysis. U.S. CPI data is interpolated form monthly to weekly using a cubic spline interpolation.

Table 3.4 Institutional Investor Sentiment (II) Regression on Macroeconomic Variables

Independent Variables	Coefficient	Std. Error	t-Statistic	P-value
C	37.883	2.923	12.961	0.000
HML	0.441	0.410	1.076	0.282
SMB	0.484	0.445	1.086	0.278
MKT_RF	-0.135	0.503	-0.269	0.788
MOM	-0.619	1.056	-0.586	0.558
D(RTBILL)	293.125	130.449	2.247	0.025
D(ERP)	154.256	70.603	2.185	0.029
D(DY)	2.673	31.308	0.085	0.932
D(TP)	1.343	4.974	0.270	0.787
DP	-16.419	2.286	-7.183	0.000
INFL	-1.159	3.292	-0.352	0.725
Adjusted R-squared	0.357741			

$$II_t = \gamma_0 + \sum_{j=1}^{J} \gamma_j Fund_{jt} + II\_IRR_t$$

Data is weekly in frequency, and ranges from 1999:W52 – 2010:W52.
II – The Investors Intelligence Advisors' Sentiment Report bull-bear spread(%).
HML – A Fama and French (1996) factor; high minus low book-to-price ratio.
SMB - A Fama and French (1996) factor; small minus big market capitalization.
MKT_RF - A Fama and French (1996) factor; market risk premium.
MOM – Jegadeesh and Titman (1993) momentum factor.
D(RTBILL) - The first difference of the return on the 1-month Treasury Bill.
D(ERP) - The economic risk premia - measured by the difference between the return on the 3-month and 1-month Treasury Bills.
D(DY) - The dividend yield - measured as the first difference of the U.S. dividend yield.
D(TP) -The term premium - measured as the first difference of the yield of the 10-year U.S. Treasury Bond in excess of the 3-month U.S. Treasury Bill.
DP - The default premium – the difference in Baa and the risk free rate.
INFL - The inflation rate in percent is calculated using the U.S. Consumer Price Index (CPI), all urban, seasonally adjusted value from the U.S. Department of Commerce, Bureau of Economic Analysis. U.S. CPI data is interpolated form monthly to weekly using a cubic spline interpolation.

Table 3.5 CALL_PUT Ratio Regression on Macroeconomic Variables

Independent Variables	Coefficient	Std. Error	t-Statistic	P-value
C	1.436	0.066	21.757	0.000
HML	0.006	0.010	0.611	0.542
SMB	0.020	0.017	1.153	0.250
MKT_RF	0.007	0.014	0.462	0.644
MOM	-0.030	0.023	-1.285	0.199
D(RTBILL)	0.343	3.622	0.095	0.925
D(ERP)	2.173	1.694	1.283	0.200
D(DY)	-0.507	0.668	-0.759	0.448
D(TP)	-0.016	0.100	-0.161	0.872
DP	-0.156	0.042	-3.677	0.000
INFL	-0.056	0.058	-0.967	0.334
Adjusted R-squared	0.120355			

$$CALL\_PUT_t = \gamma_0 + \sum_{j=1}^{J} \gamma_j Fund_{jt} + CALL\_PUT\_IRR_t$$

Data is weekly in frequency, and ranges from 1999:W52 – 2010:W52.
CALL_PUT – The weekly average of the total volume of calls to puts (call-put ratio) from the Chicago Board Options Exchange (CBOE).
HML – A Fama and French (1996) factor; high minus low book-to-price ratio.
SMB - A Fama and French (1996) factor; small minus big market capitalization.
MKT_RF - A Fama and French (1996) factor; market risk premium.
MOM – Jegadeesh and Titman (1993) momentum factor.
D(RTBILL) - The first difference of the return on the 1-month Treasury Bill.
D(ERP) - The economic risk premia - measured by the difference between the return on the 3-month and 1-month Treasury Bills.
D(DY) - The dividend yield - measured as the first difference of the U.S. dividend yield.
D(TP) -The term premium - measured as the first difference of the yield of the 10-year U.S. Treasury Bond in excess of the 3-month U.S. Treasury Bill.
DP - The default premium – the difference in Baa and the risk free rate.
INFL - The inflation rate in percent is calculated using the U.S. Consumer Price Index (CPI), all urban, seasonally adjusted value from the U.S. Department of Commerce, Bureau of Economic Analysis. U.S. CPI data is interpolated form monthly to weekly using a cubic spline interpolation.

Table 3.6 Panel A Model 1 - Total Sentiment as Information Variables

ML parameter estimates of time varying CAPM for seven GICS sectors from S&P 500 and the S&P 500 composite

Price of covariance risk	parameter estimate (standard error)
κ_0 (constant)	11.024*** (3.328)
κ_1 (AAII sentiment)	0.007 (0.014)
κ_2 (II sentiment)	0.131** (0.062)
κ_3 (call-put ratio)	-5.398*** (1.770)

GARCH (1,1) process

	Information Technology	Finance	Consumer Staples	Health Care	Industrials	Energy	Consumer Discretionary	S&P 500 Composite
a_i	0.199***	0.241***	0.211***	0.202***	0.220***	0.201***	0.226***	0.212***
	(0.012)	(0.009)	(0.016)	(0.014)	(0.010)	(0.012)	(0.012)	(0.010)
b_i	0.973***	0.967***	0.974***	0.976***	0.972***	0.975***	0.969***	0.973***
	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)

Mean log-likelihood = -21.6405

Likelihood function = -12421.67

** and *** denote significance levels of 5% and 1% respectively. Parameter estimates are followed by the standard error in parentheses.

The MGARCH estimates are based on the time-varying version of the CAPM from Eq. (3.7): $R_{it} - R_{ft} = \delta_{t-1}\ \mathrm{COV}(R_{it}, R_{mt}|\Im_{t-1}) + \varepsilon_{it}\ \ \forall_i$, with δ_{t-1} restricted to be non-negative by Eq. (3.8): $\delta_{t-1} = \exp(\lambda + \boldsymbol{\kappa}'\boldsymbol{z}_{t-1})$.

The information variables in this model include:

- κ_1, AAII sentiment - is the bull-bear spread from the American Association of Individual Investors (AAII) Investor Sentiment.
- κ_2, II sentiment - is the bull-bear spread from the Investors Intelligence Advisors Sentiment (II) Investor Sentiment Survey.
- κ_3, call-put ratio – is the ratio of the total volume of call to total volume of puts from the Chicago Board of Options Exchange (http://www.cboe.com/data/PutCallRatio.aspx)

GARCH(1, 1) process:

- a_i, The persistence of the ARCH term for each portfolio, *i*.
- b_i, The persistence of the GARCH term for each portfolio, *i*.

Likelihood values are total and mean likelihood at convergence using the BHHH algorithm.

Table 3.6 Panel B Model 2 - Total Sentiment Decomposed into its Rational and Irrational Components as Information Variables

ML parameter estimates of time varying CAPM for seven GICS sectors and the S&P 500 composite

Price of covariance risk	parameter estimate (standard error)
κ_0 (constant)	11.413*** (4.040)
κ_1 (AAII rational sentiment)	0.304** (0.140)
κ_2 (II rational sentiment)	-0.398* (0.216)
κ_3 (AAII irrational sentiment)	0.130** (0.052)
κ_4 (II irrational sentiment)	-0.004 (0.041)

GARCH (1,1) process

	Information Technology	Finance	Consumer Staples	Health Care	Industrials	Energy	Consumer Discretionary	S&P 500 Composite
a_i	0.203***	0.248***	0.219***	0.205***	0.222***	0.206***	0.231***	0.216***
	(0.010)	(0.007)	(0.011)	(0.008)	(0.012)	(0.009)	(0.012)	(0.008)
b_i	0.972***	0.965***	0.972***	0.975***	0.971***	0.975***	0.968***	0.971***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.004)	(0.002)

Mean log-likelihood = -21.6294

Likelihood function = -12415.29

*, **, and *** denote significance levels of 10%, 5%, and 1% respectively, followed by the standard errors in parentheses.

The MGARCH estimates are based on the time-varying version of the CAPM from Eq. (5): $R_{it} - R_{ft} = \delta_{t-1}\,\mathrm{COV}(R_{it}, R_{mt}|\Im_{t-1}) + \varepsilon_{it}\ \ \forall_i$, with δ_{t-1} restricted to be non-negative by Eq. (6): $\delta_{t-1} = \exp(\lambda + \boldsymbol{\kappa}'\boldsymbol{z}_{t-1})$.

The information variables in this model include:

- κ_1, AAII rational sentiment, is the fitted values ($\widehat{Sent_{1t}}$), from decomposing the bull-bear spread from the American Association of Individual Investors (AAII) Investor Sentiment Survey using: $Sent_{1t} = \gamma_0 + \gamma_j \sum_{j=1}^{J} Fund_{jt} + \xi_{it}$, where $Sent1_{it}$ is AAII. The variables in $Fund_{jt}$ consist of several economic fundamentals including the first difference of the term premium, the default premium the (E.F. Fama & French, 1992) factors SMB, HML and Rm-Rf, the momentum factor (Jegadeesh & Titman, 1993), MOM, and the first difference of the dividend yield. This parameter represents the rational component of sentiment of the uninformed investors.
- κ_2, II rational sentiment, is the fitted values ($\widehat{Sent_{2t}}$), from decomposing the bull-bear spread from the Investors Intelligence Advisors Sentiment (II) Investor Sentiment Survey using: $Sent_{2t} = \gamma_0 + \gamma_j \sum_{j=1}^{J} Fund_{jt} + \xi_{it}$, where $Sent_{2t}$ is II. This parameter represents the rational component of sentiment from the informed investors.
- κ_3, AAII irrational sentiment – is the irrational measure (ξ_{it}) representing the uninformed investors.
- κ_4, II irrational sentiment – is the irrational measure (ξ_{it}) representing the informed investors.

GARCH(1, 1) process:

- a_i, The persistence of the ARCH term for each portfolio, *i*.
- b_i, The persistence of the GARCH term for each portfolio, *i*.

Likelihood values are total and mean likelihood at convergence using the BHHH algorithm.

Table 3.6 Panel C Model 3 - Irrational Sentiment including Call-put Ratio as Information Variables

ML parameter estimates of time varying CAPM for seven GICS sectors from S&P 500 and the S&P 500 composite

Price of covariance risk	parameter estimate (standard error)
κ_0 (constant)	35.891*** (11.593)
κ_1 (AAII irrational sentiment)	-0.316*** (0.093)
κ_2 (II irrational sentiment)	1.047*** (0.328)
κ_3 (Call-put irrational sentiment)	-1.877 (5.183)

GARCH (1,1) process

	Information Technology	Finance	Consumer Staples	Health Care	Industrials	Energy	Consumer Discretionary	S&P 500 Composite
a_i	0.200*** (0.010)	0.242*** (0.008)	0.214*** (0.015)	0.204*** (0.012)	0.220*** (0.016)	0.200*** (0.014)	0.228*** (0.012)	0.213*** (0.009)
b_i	0.972*** (0.003)	0.967*** (0.002)	0.973*** (0.005)	0.975*** (0.003)	0.972*** (0.004)	0.976*** (0.003)	0.968*** (0.003)	0.972*** (0.002)

Mean log-likelihood = -21.6649

Likelihood function = -12435.65

*** denotes significance levels of 1%. Parameter estimates are followed by the standard error in parentheses.

The MGARCH estimates are based on the time-varying version of the CAPM from Eq. (3.7): $R_{it} - R_{ft} = \delta_{t-1}\,\mathrm{COV}(R_{it}, R_{mt}|\Im_{t-1}) + \varepsilon_{it}\ \ \forall_i$, with δ_{t-1} restricted to be non-negative by Eq. (3.8): $\delta_{t-1} = \exp(\lambda + \boldsymbol{\kappa}'\boldsymbol{z}_{t-1})$.

The information variables in this model include:

- κ_1, AAII irrational sentiment, is the error term, ξ_{it}, from decomposing the bull-bear spread from the American Association of Individual Investors (AAII) Investor Sentiment Survey using: $Sent_{1t} = \gamma_0 + \gamma_j \sum_{j=1}^{J} Fund_{jt} + \xi_{it}$, where $Sent1_{it}$ is AAII. The variables in $Fund_{jt}$ consist of several economic fundamentals including the first difference of the term premium, the default premium the (E.F. Fama & French, 1992) factors SMB, HML and Rm-Rf, the momentum factor (Jegadeesh & Titman, 1993), MOM, and the first difference of the dividend yield. This parameter represents the irrational component of sentiment of the uninformed investors.
- κ_2, II irrational sentiment, is the error term, ξ_{it}, from decomposing the bull-bear spread from the Investors Intelligence Advisors Sentiment (II) Investor Sentiment Survey using: $Sent_{2t} = \gamma_0 + \gamma_j \sum_{j=1}^{J} Fund_{jt} + \xi_{it}$, where $Sent_{2t}$ is II. This parameter represents the irrational component of sentiment from the informed investors.
- κ_3, Call_put irrational sentiment , is the error term, ξ_{it}, from decomposing the bull-bear spread from the Investors Intelligence Advisors Sentiment (II) Investor Sentiment Survey using: $Sent_{3t} = \gamma_0 + \gamma_j \sum_{j=1}^{J} Fund_{jt} + \xi_{it}$, where $Sent_{3t}$ is Call_put. This parameter represents an indirect measure of the irrational component of sentiment from the informed investors.

GARCH(1, 1) process:

- a_i, The persistence of the ARCH term for each portfolio, *i*.
- b_i, The persistence of the GARCH term for each portfolio, *i*.

Likelihood values are total and mean likelihood at convergence using the BHHH algorithm.

Table 3.6 Panel D Model 4 - Economic Fundamentals as Information Variables

ML parameter estimates of time varying CAPM for seven GICS sectors from S&P 500 and the S&P 500 composite

Price of covariance risk	parameter estimate (standard error)
κ_0 (constant)	4.619** (2.065)
κ_1 (CHDIV)	-0.819 (0.922)
κ_2 (DP)	-0.549 (0.706)
κ_3 (CHTP)	0.658 (0.907)

GARCH (1,1) process

	Information Technology	Finance	Consumer Staples	Health Care	Industrials	Energy	Consumer Discretionary	S&P 500 Composite
a_i	0.201***	0.243***	0.212***	0.202***	0.220***	0.202***	0.228***	0.213***
	(0.012)	(0.009)	(0.015)	(0.014)	(0.010)	(0.012)	(0.012)	(0.010)
b_i	0.973***	0.967***	0.974***	0.976***	0.972***	0.975***	0.969***	0.972***
	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)

Mean log-likelihood = -21.665

Likelihood function = -12435.69

*, **, and *** denote significance levels of 10%, 5%, and 1% respectively. Parameter estimates are followed by the standard errors in parentheses.

The MGARCH estimates are based on the time-varying version of the CAPM from Eq. (3.7): $R_{it} - R_{ft} = \delta_{t-1}\, \mathrm{COV}(R_{it}, R_{mt}|\Im_{t-1}) + \varepsilon_{it}\ \ \forall_i$, with δ_{t-1} restricted to be non-negative by Eq. (3.8): $\delta_{t-1} = \exp(\lambda + \boldsymbol{\kappa}'\boldsymbol{z}_{t-1})$.

The information variables in model 4 include the following economic fundamentals:

- the default premium (DP), which is the difference between the U.S. corporate bond yield in Moody's seasoned issued Baa and Aaa bonds.
- the term premium (TP),which is the difference in Baa and the risk free rate
- the change in the U.S. market dividend yield in excess of the risk free rate (CHDIV).

Table 3.7 Panel A Model 1- Information variables include: AAII total sentiment, II total sentiment, and call-put ratio

Diagnostics tests of the residuals

lag	Information Technology	Finance	Consumer Staples	Health Care	Industrials	Energy	Consumer Discretionary	S&P 500 Composite
autocorrelation: serial | partial								
1	-0.030 | -0.030	-0.056 | -0.056	-0.055 | -0.055	-0.051 | -0.051	-0.020 | -0.020	0.006 | 0.006	-0.027 | -0.027	-0.022 | -0.022
2	0.028 | 0.027	0.035 | 0.032	0.041 | 0.038	-0.007 | -0.010	0.065 | 0.065	0.065 | 0.065	0.056 | 0.055	0.063 | 0.062
3	0.035 | 0.037	-0.038 | -0.034	0.015 | 0.019	-0.029 | -0.030	-0.034 | -0.031	-0.069 | -0.070	0.043 | 0.046	0.005 | 0.008
4	-0.001 | 0.000	0.029 | 0.025	-0.024 | -0.024	0.017 | 0.014	0.028 | 0.023	-0.003 | -0.006	0.001 | 0.001	-0.013 | -0.017
5	0.050 | 0.048	-0.006 | -0.001	0.032 | 0.028	0.033 | 0.035	0.017 | 0.022	-0.004 | 0.005	0.008 | 0.003	0.027 | 0.025
6	0.053 | 0.055	0.045 | 0.042	0.026 | 0.031	0.039 | 0.042	0.042 | 0.038	-0.036 | -0.041	0.046 | 0.044	0.048 | 0.051
Ljung-Box Q-statistic (p-value)								
1	0.536 (0.464)	1.827 (0.177)	1.731 (0.188)	1.497 (0.221)	0.237 (0.626)	0.021 (0.885)	0.417 (0.518)	0.284 (0.594)
2	0.987 (0.610)	2.528 (0.283)	2.704 (0.259)	1.529 (0.466)	2.707 (0.258)	2.440 (0.295)	2.201 (0.333)	2.549 (0.280)
3	1.702 (0.637)	3.347 (0.341)	2.830 (0.419)	2.007 (0.571)	3.362 (0.339)	5.160 (0.160)	3.266 (0.352)	2.566 (0.464)
4	1.703 (0.790)	3.851 (0.427)	3.160 (0.531)	2.169 (0.705)	3.810 (0.432)	5.165 (0.271)	3.267 (0.514)	2.667 (0.615)
5	3.134 (0.679)	3.874 (0.568)	3.748 (0.586)	2.817 (0.728)	3.976 (0.553)	5.175 (0.395)	3.301 (0.654)	3.077 (0.688)
6	4.790 (0.571)	5.075 (0.534)	4.135 (0.658)	3.714 (0.715)	4.981 (0.546)	5.941 (0.430)	4.530 (0.605)	4.421 (0.620)
Variance Ratio Tests: z-score (p-value)								
joint @ max |z|	1.732 (0.728)	0.823 (0.998)	0.780 (1.000)	0.391 (1.000)	1.598 (0.826)	0.876 (0.999)	1.581 (0.837)	1.907 (0.998)
2	0.132 (0.895)	-0.823 (0.411)	-0.359 (0.719)	-0.291 (0.771)	-0.141 (0.888)	0.174 (0.862)	-0.016 (0.988)	0.731 (0.465)
3	0.555 (0.579)	-0.205 (0.838)	0.222 (0.824)	-0.070 (0.944)	0.801 (0.423)	0.653 (0.514)	0.829 (0.407)	0.997 (0.319)
4	0.659 (0.510)	-0.221 (0.825)	0.519 (0.604)	-0.063 (0.950)	0.975 (0.330)	0.513 (0.608)	1.256 (0.209)	1.046 (0.296)
5	0.813 (0.416)	-0.113 (0.910)	0.549 (0.583)	-0.002 (0.999)	1.114 (0.265)	0.490 (0.624)	1.376 (0.169)	1.109 (0.267)
6	1.046 (0.296)	-0.082 (0.935)	0.602 (0.547)	0.126 (0.900)	1.174 (0.241)	0.458 (0.647)	1.413 (0.158)	1.283 (0.200)
7	1.169 (0.242)	0.084 (0.933)	0.719 (0.472)	0.299 (0.765)	1.321 (0.186)	0.376 (0.707)	1.557 (0.120)	1.362 (0.173)
8	1.169 (0.242)	0.152 (0.879)	0.751 (0.453)	0.373 (0.709)	1.383 (0.167)	0.331 (0.741)	1.581 (0.114)	1.362 (0.173)

*, **, and *** denote significance levels of 10%, 5%, and 1% respectively. Standardized residuals are constructed by: $\varepsilon_t h_t^{-1/2}$. Null hypothesis for the Q-statistic [Ljung and Box (1978)]: no autocorrelation up to the indicated lag order. For the variance ratio tests [Cochrane (1988)] null hypothesis: series is a martingale (residuals are serially independent). The row labeled joint at max |z| is a joint test at the maximum absolute value of the z-score from lags 2 through 16, while rows at indicated lags 2 through 8 are individual variance ratio tests at indicated lags.

The information variables in model 1 include:

- κ1, AAII sentiment - is the bull-bear spread from the American Association of Individual Investors (AAII) Investor Sentiment.
- κ2, II sentiment - is the bull-bear spread from the Investors Intelligence Advisors Sentiment (II) Investor Sentiment Survey.
- κ3, call-put ratio – is the ratio of the total volume of call to total volume of puts from the Chicago Board of Options Exchange (http://www.cboe.com/data/PutCallRatio.aspx)

Table 3.7 Panel B Model 2 - Information Variables include both Rational and Irrational Components of AAII and II

Diagnostics tests of the residuals

lag	Information Technology	Finance	Consumer Staples	Health Care	Industrials	Energy	Consumer Discretionary	S&P 500 Composite
autocorrelation: serial | partial								
1	0.005 | 0.005	-0.004 | -0.004	-0.025 | -0.025	-0.023 | -0.023	0.011 | 0.011	0.021 | 0.021	0.022 | 0.022	0.016 | 0.016
2	0.067 | 0.067	0.059 | 0.059	0.051 | 0.051	0.006 | 0.006	0.110 | 0.110	0.059 | 0.059	0.101 | 0.101	0.093 | 0.093
3	0.015 | 0.014	-0.033 | -0.033	0.023 | 0.026	-0.030 | -0.030	-0.034 | -0.037	-0.073 | -0.076	0.032 | 0.028	-0.001 | -0.004
4	-0.047 | -0.052	0.021 | 0.017	-0.038 | -0.040	-0.005 | -0.006	0.004 | -0.007	-0.013 | -0.013	-0.025 | -0.037	-0.040 | -0.049
5	0.031 | 0.030	0.025 | 0.029	0.020 | 0.015	0.025 | 0.025	0.020 | 0.028	-0.014 | -0.005	0.010 | 0.005	0.026 | 0.028
6	0.037 | 0.044	0.044 | 0.041	0.038 | 0.042	0.034 | 0.034	0.037 | 0.036	-0.041 | -0.045	0.047 | 0.053	0.038 | 0.046
Ljung-Box Q-statistic (p-value)								
1	0.012 (0.913)	0.011 (0.916)	0.357 (0.550)	0.301 (0.583)	0.067 (0.796)	0.248 (0.619)	0.273 (0.602)	0.150 (0.699)
2	2.627 (0.269)	2.048 (0.359)	1.882 (0.390)	0.325 (0.850)	7.054** (0.029)	2.273 (0.321)	6.230** (0.044)	5.177* (0.075)
3	2.755 (0.431)	2.695 (0.441)	2.199 (0.532)	0.858 (0.836)	7.736* (0.052)	5.355 (0.148)	6.826* (0.078)	5.178 (0.159)
4	4.038 (0.401)	2.949 (0.566)	3.057 (0.548)	0.870 (0.929)	7.746 (0.101)	5.454 (0.244)	7.201 (0.126)	6.115 (0.191)
5	4.597 (0.467)	3.302 (0.654)	3.281 (0.657)	1.229 (0.942)	7.983 (0.157)	5.571 (0.350)	7.260 (0.202)	6.506 (0.260)
6	5.401 (0.494)	4.449 (0.616)	4.111 (0.662)	1.894 (0.929)	8.803 (0.185)	6.560 (0.363)	8.570 (0.199)	7.355 (0.289)
Variance Ratio Tests: z-score (p-value)								
joint at max |z|	1.028 (0.996)	1.041 (0.995)	0.400 (1.000)	0.420 (1.000)	1.429 (0.917)	0.896 (0.999)	1.816 (0.660)	1.373 (0.939)
2	1.008 (0.875)	0.999 (0.985)	0.979 (0.717)	0.980 (0.737)	1.014 (0.795)	1.024 (0.679)	1.025 (0.631)	1.020 (0.722)
3	1.057 (0.438)	1.040 (0.613)	1.007 (0.933)	0.976 (0.779)	1.095 (0.222)	1.073 (0.370)	1.104 (0.170)	1.091 (0.251)
4	1.092 (0.313)	1.046 (0.637)	1.035 (0.736)	0.961 (0.698)	1.120 (0.207)	1.064 (0.518)	1.162* (0.084)	1.128 (0.185)
5	1.095 (0.366)	1.058 (0.603)	1.037 (0.755)	0.953 (0.674)	1.138 (0.204)	1.053 (0.630)	1.188* (0.083)	1.135 (0.222)
6	1.108 (0.359)	1.073 (0.552)	1.042 (0.750)	0.956 (0.721)	1.155 (0.198)	1.040 (0.740)	1.209* (0.084)	1.147 (0.231)
7	1.129 (0.312)	1.100 (0.455)	1.057 (0.689)	0.969 (0.815)	1.180 (0.167)	1.021 (0.876)	1.239* (0.069)	1.169 (0.202)
8	1.136 (0.322)	1.108 (0.448)	1.058 (0.704)	0.971 (0.838)	1.191 (0.171)	1.005 (0.971)	1.248* (0.079)	1.174 (0.219)

*, **, and *** denote significance levels of 10%, 5%, and 1% respectively. Standardized residuals are constructed by: $\varepsilon_t h_t^{-1/2}$. Null hypothesis for the Q-statistic [Ljung and Box (1978)]: no autocorrelation up to the indicated lag order. For the variance ratio tests [Cochrane (1988)] null hypothesis: series is a martingale (residuals are serially independent). The row labeled joint at max |z| is a joint test at the maximum absolute value of the z-score from lags 2 through 16, while rows at indicated lags 2 through 8 are individual variance ratio tests at indicated lags.

The information variables in model 2 include:

- AAII rational sentiment, is the fitted values ($\widehat{Sent_{1t}}$), from decomposing the bull-bear spread from the American Association of Individual Investors (AAII) Investor Sentiment Survey
- II rational sentiment, is the fitted values ($\widehat{Sent_{2t}}$), from decomposing the bull-bear spread from the Investors Intelligence Advisors Sentiment (II) Investor Sentiment Survey.
- AAII irrational sentiment, is the irrational measure (ξ_{it}) representing the uninformed investors.
- II irrational sentiment, is the irrational measure (ξ_{it}) representing the informed investors.

Table 3.7 Panel C Model 3 - Information Variables Include the Irrational Components of: AAII and II Sentiment, and the Call-put Ratio.

Diagnostics tests of the residuals

lag	Information Technology	Finance	Consumer Staples	Health Care	Industrials	Energy	Consumer Discretionary	S&P 500 Composite
autocorrelation: serial | partial								
1	-0.030 | -0.030	-0.056 | -0.056	-0.055 | -0.055	-0.051 | -0.051	-0.020 | -0.020	0.006 | 0.006	-0.027 | -0.027	-0.022 | -0.022
2	0.028 | 0.027	0.035 | 0.032	0.041 | 0.038	-0.007 | -0.010	0.065 | 0.065	0.065 | 0.065	0.056 | 0.055	0.063 | 0.062
3	0.035 | 0.037	-0.038 | -0.034	0.015 | 0.019	-0.029 | -0.030	-0.034 | -0.031	-0.069 | -0.070	0.043 | 0.046	0.005 | 0.008
4	-0.001 | 0.000	0.029 | 0.025	-0.024 | -0.024	0.017 | 0.014	0.028 | 0.023	-0.003 | -0.006	0.001 | 0.001	-0.013 | -0.017
5	0.050 | 0.048	-0.006 | -0.001	0.032 | 0.028	0.033 | 0.035	0.017 | 0.022	-0.004 | 0.005	0.008 | 0.003	0.027 | 0.025
6	0.053 | 0.055	0.045 | 0.042	0.026 | 0.031	0.039 | 0.042	0.042 | 0.038	-0.036 | -0.041	0.046 | 0.044	0.048 | 0.051
Ljung-Box Q-statistic (p-value)								
1	0.536 (0.464)	1.827 (0.177)	1.731 (0.188)	1.497 (0.221)	0.237 (0.626)	0.021 (0.885)	0.417 (0.518)	0.284 (0.594)
2	0.987 (0.610)	2.528 (0.283)	2.704 (0.259)	1.529 (0.466)	2.707 (0.258)	2.440 (0.295)	2.201 (0.333)	2.549 (0.280)
3	1.702 (0.637)	3.347 (0.341)	2.830 (0.419)	2.007 (0.571)	3.362 (0.339)	5.160 (0.160)	3.266 (0.352)	2.566 (0.464)
4	1.703 (0.790)	3.851 (0.427)	3.160 (0.531)	2.169 (0.705)	3.810 (0.432)	5.165 (0.271)	3.267 (0.514)	2.667 (0.615)
5	3.134 (0.679)	3.874 (0.568)	3.748 (0.586)	2.817 (0.728)	3.976 (0.553)	5.175 (0.395)	3.301 (0.654)	3.077 (0.688)
6	4.790 (0.571)	5.075 (0.534)	4.135 (0.658)	3.714 (0.715)	4.981 (0.546)	5.941 (0.430)	4.530 (0.605)	4.421 (0.620)
Variance Ratio Tests: z-score (p-value)								
joint @ max |z|	0.770 (0.660)	1.074 (0.660)	0.890 (0.660)	0.946 (0.660)	0.673 (0.660)	0.669 (0.660)	0.893 (0.660)	0.679 (0.660)
2	-0.533 (0.594)	-1.074 (0.283)	-0.890 (0.374)	-0.866 (0.387)	-0.356 (0.722)	0.150 (0.881)	-0.467 (0.641)	-0.347 (0.728)
3	-0.215 (0.830)	-0.612 (0.541)	-0.461 (0.645)	-0.864 (0.387)	0.323 (0.747)	0.669 (0.503)	0.101 (0.920)	0.232 (0.816)
4	0.100 (0.921)	-0.644 (0.520)	-0.238 (0.812)	-0.946 (0.344)	0.317 (0.752)	0.476 (0.634)	0.491 (0.623)	0.422 (0.673)
5	0.233 (0.816)	-0.543 (0.587)	-0.213 (0.831)	-0.885 (0.376)	0.409 (0.682)	0.365 (0.715)	0.650 (0.516)	0.441 (0.659)
6	0.434 (0.664)	-0.478 (0.633)	-0.134 (0.893)	-0.733 (0.464)	0.491 (0.623)	0.293 (0.770)	0.737 (0.461)	0.510 (0.610)
7	0.684 (0.494)	-0.322 (0.748)	-0.039 (0.969)	-0.544 (0.586)	0.642 (0.521)	0.175 (0.861)	0.893 (0.372)	0.668 (0.504)
8	0.770 (0.442)	-0.311 (0.756)	-0.046 (0.963)	-0.469 (0.639)	0.673 (0.501)	0.072 (0.942)	0.890 (0.374)	0.679 (0.497)

*, **, and *** denote significance levels of 10%, 5%, and 1% respectively. Standardized residuals are constructed by: $\varepsilon_t h_t^{-1/2}$. Null hypothesis for the Q-statistic [Ljung and Box (1978)]: no autocorrelation up to the indicated lag order. For the variance ratio tests [Cochrane (1988)] null hypothesis: series is a martingale (residuals are serially independent). The row labeled joint at max |z| is a joint test at the maximum absolute value of the z-score from lags 2 through 16, while rows at indicated lags 2 through 8 are individual variance ratio tests at indicated lags.

The information variables in model 3 include:

- AAII irrational sentiment component from decomposing the Association of Individual Investors (AAII) Investor Sentiment Survey,
- II irrational sentiment component from decomposing the Investors Intelligence Advisors Sentiment (II) Investor Sentiment Survey
- Call_put irrational sentiment from decomposing the ratio of the total volume of call to total volume of puts from the Chicago Board of Options Exchange (http://www.cboe.com/data/PutCallRatio.aspx).

Table 3.7 Panel D Model 4 - Economic Fundamentals - Information Variables include CHDIV, DP, and CHTP.

Diagnostics tests of the residuals

lag	Information Technology	Finance	Consumer Staples	Health Care	Industrials	Energy	Consumer Discretionary	S&P 500 Composite
autocorrelation: serial | partial								
1	-0.039 | -0.039	-0.061 | -0.061	-0.057 | -0.057	-0.045 | -0.037	-0.035 | -0.035	-0.015 | -0.015	-0.027 | -0.027	-0.026 | -0.026
2	0.029 | 0.028	0.030 | 0.027	0.039 | 0.036	-0.005 | -0.023	0.074 | 0.073	0.032 | 0.032	0.063 | 0.062	0.061 | 0.061
3	0.020 | 0.022	-0.061 | -0.057	0.022 | 0.026	-0.021 | -0.045	-0.038 | -0.033	-0.074 | -0.073	0.020 | 0.024	-0.011 | -0.008
4	-0.020 | -0.019	0.021 | 0.014	-0.033 | -0.031	0.009 | -0.007	0.015 | 0.008	0.007 | 0.004	-0.020 | -0.023	-0.025 | -0.030
5	0.043 | 0.041	0.001 | 0.006	0.029 | 0.024	0.034 | -0.022	0.013 | 0.019	0.003 | 0.008	0.006 | 0.002	0.033 | 0.033
6	0.048 | 0.052	0.059 | 0.055	0.039 | 0.044	0.042 | 0.007	0.041 | 0.040	-0.040 | -0.046	0.049 | 0.052	0.052 | 0.058
Ljung-Box Q-statistic (p-value)								
1	0.868 (0.351)	2.153 (0.142)	1.843 (0.175)	1.185 (0.276)	0.696 (0.404)	0.137 (0.711)	0.432 (0.511)	0.401 (0.527)
2	1.365 (0.505)	2.679 (0.262)	2.735 (0.255)	1.200 (0.549)	3.850 (0.146)	0.726 (0.695)	2.715 (0.257)	2.585 (0.275)
3	1.588 (0.662)	4.806 (0.187)	3.015 (0.389)	1.460 (0.691)	4.688 (0.196)	3.881 (0.275)	2.956 (0.398)	2.659 (0.447)
4	1.817 (0.769)	5.072 (0.280)	3.628 (0.459)	1.509 (0.825)	4.823 (0.306)	3.908 (0.419)	3.185 (0.527)	3.031 (0.553)
5	2.910 (0.714)	5.072 (0.407)	4.125 (0.532)	2.182 (0.823)	4.915 (0.426)	3.912 (0.562)	3.204 (0.669)	3.657 (0.600)
6	4.235 (0.645)	7.089 (0.313)	4.990 (0.545)	3.188 (0.785)	5.906 (0.434)	4.833 (0.565)	4.594 (0.597)	5.251 (0.512)
Variance Ratio Tests: z-score (p-value)								
joint @ max |z|	0.726 (1.000)	0.912 (0.999)	0.633 (1.000)	0.808 (1.000)	0.590 (1.000)	0.469 (1.000)	1.088 (0.992)	0.730 (1.000)
2	-0.726 (0.468)	-0.912 (0.362)	-0.464 (0.643)	-0.730 (0.465)	-0.590 (0.555)	-0.200 (0.842)	-1.088 (0.277)	-0.359 (0.720)
3	-0.369 (0.712)	-0.515 (0.607)	0.156 (0.876)	-0.746 (0.456)	0.121 (0.904)	0.077 (0.939)	-0.706 (0.480)	0.135 (0.893)
4	-0.109 (0.913)	-0.255 (0.799)	0.445 (0.656)	-0.808 (0.419)	0.132 (0.895)	-0.181 (0.856)	-0.868 (0.386)	0.236 (0.814)
5	-0.064 (0.949)	-0.244 (0.807)	0.485 (0.628)	-0.768 (0.443)	0.186 (0.853)	-0.272 (0.785)	-0.848 (0.397)	0.189 (0.850)
6	0.083 (0.934)	-0.174 (0.862)	0.507 (0.612)	-0.623 (0.533)	0.239 (0.811)	-0.304 (0.761)	-0.800 (0.424)	0.239 (0.811)
7	0.296 (0.767)	-0.057 (0.955)	0.633 (0.527)	-0.431 (0.666)	0.372 (0.710)	-0.397 (0.691)	-0.622 (0.534)	0.388 (0.698)
8	0.355 (0.723)	-0.044 (0.965)	0.616 (0.538)	-0.355 (0.723)	0.405 (0.686)	-0.469 (0.639)	-0.566 (0.571)	0.410 (0.682)

*, **, and *** denote significance levels of 10%, 5%, and 1% respectively. Standardized residuals are constructed by: $\varepsilon_t h_t^{-1/2}$. Null hypothesis for the Q-statistic [Ljung and Box (1978)]: no autocorrelation up to the indicated lag order. For the variance ratio tests [Cochrane (1988)] null hypothesis: series is a martingale (residuals are serially independent). The row labeled joint at max |z| is a joint test at the maximum absolute value of the z-score from lags 2 through 16, while rows at indicated lags 2 through 8 are individual variance ratio tests at indicated lags.

The information variables in model 4 include the following economic fundamentals:

- The default premium (DP), which is the difference between the U.S. corporate bond yield in Moody's seasoned issued Baa and Aaa bonds.
- The term premium (TP),which is the difference in Baa and the risk free rate
- The change in the U.S. market dividend yield in excess of the risk free rate (CHDIV).

Table 3.8 Likelihood Ratio Tests: Models 1through 4.

Null Hypothesis A: $\Theta_1 = \Theta_2$	ℓ_1 = -12421.67, ℓ_2 = -12415.29	
Research Hypotheses A:	Two Tailed: $\Theta_1 \neq \Theta_2$	One Tailed: $\Theta_1 < \Theta_2$
	Voung Test: z-score = -0.2590, p-value = 0.7956	Voung Test: p-value = 0.3978
	Clarke Test: p-value = 1.0000	Clarke Test: p-value = 0.7063
Null Hypothesis B: $\Theta_1 = \Theta_3$	ℓ_1 = -12421.67, ℓ_3 = -12435.65	
Research Hypotheses B:	Two Tailed: $\Theta_1 \neq \Theta_3$	One Tailed: $\Theta_1 > \Theta_3$
	Voung Test: z-score = 0.8812, p-value = 0.3782	Voung Test: p-value = 0.1891
	Clarke Test: p-value = 0.0000***	Clarke Test: p-value = 0.0000***
Null Hypothesis C: $\Theta_1 = \Theta_4$	ℓ_1 = -12421.67, ℓ_4 = -12435.69	
Research Hypotheses C:	Two Tailed: $\Theta_1 \neq \Theta_4$	One Tailed: $\Theta_1 > \Theta_4$
	Voung Test: z-score = 2.6217, p-value = 0.0087***	Voung Test: p-value = 0.0044***
	Clarke Test: p-value = 0.0000***	Clarke Test: p-value = 0.0000***
Null Hypothesis D: $\Theta_2 = \Theta_3$	ℓ_2 = -12415.29, ℓ_3 = -12435.65	
Research Hypotheses D:	Two Tailed: $\Theta_2 \neq \Theta_3$	One Tailed: $\Theta_2 > \Theta_3$
	Voung Test: z-score = 0.5675, p-value = 0.5704	Voung Test: p-value = 0.2852
	Clarke Test: p-value = 0.0001***	Clarke Test: p-value = 0.0000***
Null Hypothesis E: $\Theta_2 = \Theta_4$	ℓ_2 = -12415.29, ℓ_4 = -12435.69	
Research Hypotheses E:	Two Tailed: $\Theta_2 \neq \Theta_4$	One Tailed: $\Theta_2 > \Theta_4$
	Voung Test: z-score = 0.4696, p-value = 0.6386	Voung Test: p-value = 0.3193
	Clarke Test: p-value = 0.6462	Clarke Test: p-value = 0.3231
Null Hypothesis F: $\Theta_3 = \Theta_4$	ℓ_3 = -12435.65, ℓ_4 = -12435.69	
Research Hypotheses F:	Two Tailed: $\Theta_3 \neq \Theta_4$	One Tailed: $\Theta_3 > \Theta_4$
	Voung Test: z-score = -0.2585, p-value = 0.7960	Voung Test: p-value = 0.3980
	Clarke Test: p-value = 0.0000***	Clarke Test: p-value = 0.0000***

ℓ_1, ℓ_2, ℓ_3, and ℓ_4 represent the total log-likelihood scores for models 1 through 4 shown in tables 2 Panels A through D.
Model 1 information variables: AAII total sentiment, II total sentiment, and call-put ratio
Model 2 information variables: total sentiment decomposed into both the rational and irrational components of AAII and II
Model 3 information variables are the irrational components of: AAII sentiment, II sentiment, and the call-put ratio.
Model 4 information variables are the following economic fundamentals: CHDIV, DP, and CHTP.

The Vuong test statistic is normally distributed and is calculated using: $z = \frac{\ell_1 - \ell_2 - \left[\frac{p_1}{2}\ln(N) - \frac{p_2}{2}\ln(N)\right]}{\sqrt{N}\widehat{\omega}_N}$

Where $\ell_1$and ℓ_2 are the total log-likelihood values of the two models to be compared; $\left[\frac{p_1}{2}\ln(N) - \frac{p_2}{2}\ln(N)\right]$ is a degrees of freedom adjustment which penalizes the model which is less parsimonious, while $p_1$and p_2 are the number of parameters estimated in each model; N is the number of observations; and $\widehat{\omega}_N$ is calculated by:

$$\widehat{\omega}_N^2 = \frac{1}{N}\sum_{i=1}^{N} ln\left(\frac{\ell_{i,1}}{\ell_{i,2}}\right)^2 - \left[\frac{1}{N}\sum_{i=1}^{N} ln\left(\frac{\ell_{i,1}}{\ell_{i,2}}\right)\right]^2$$

The Clarke test is performed by comparing the individual log-likelihood values, $\ell_{i,1}$ and $\ell_{i,2}$ and counting the number of times each one is greater. The null hypothesis is the two competing models are equal. The test statistic is simply a cumulative Binomial distribution with the probability of success of 0.50 in N trials.

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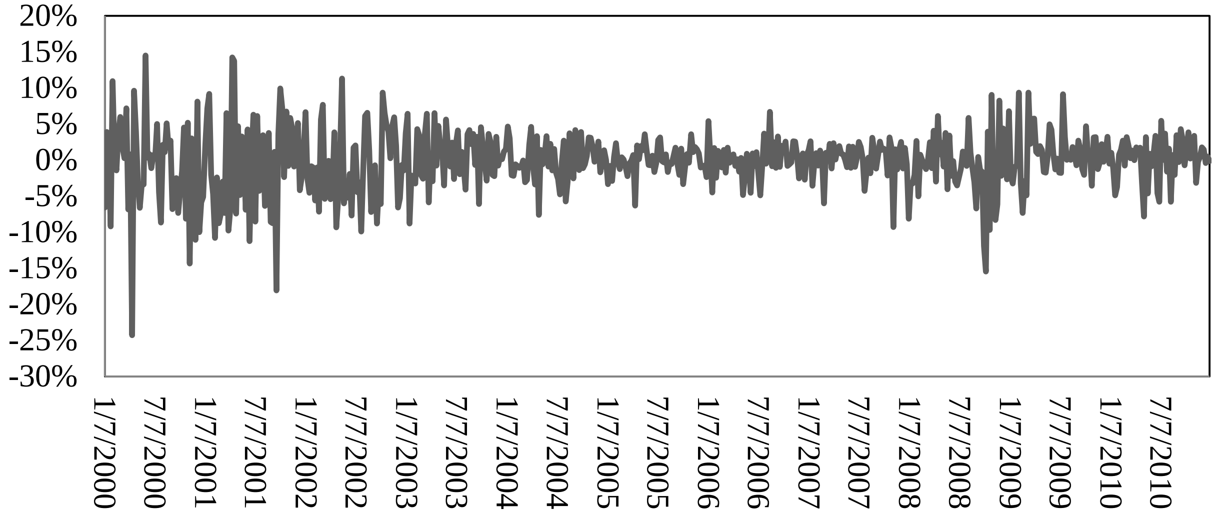
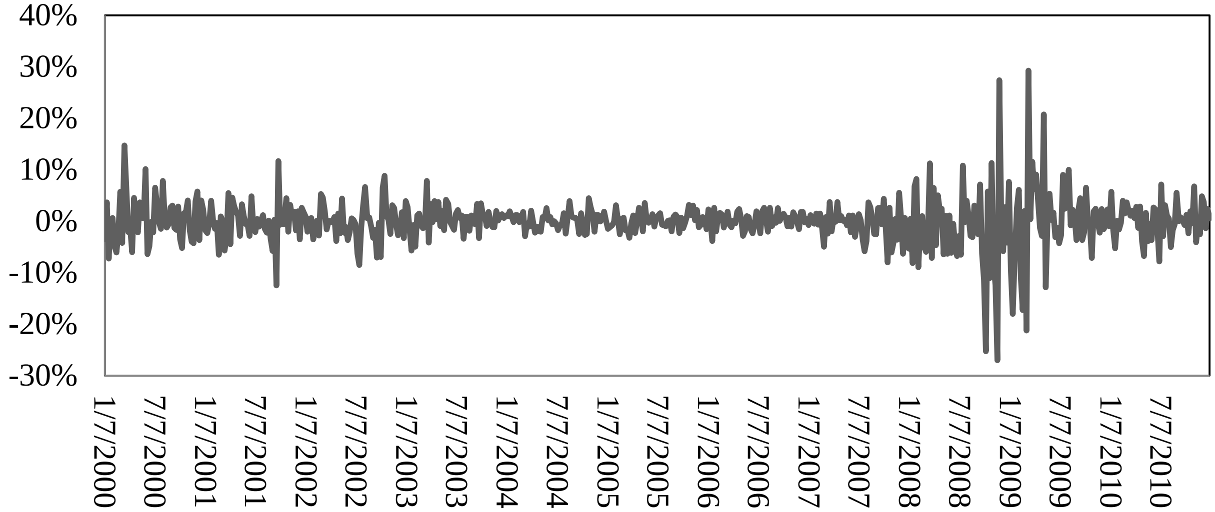
Figure 3.1 Excess Returns: Information Technology



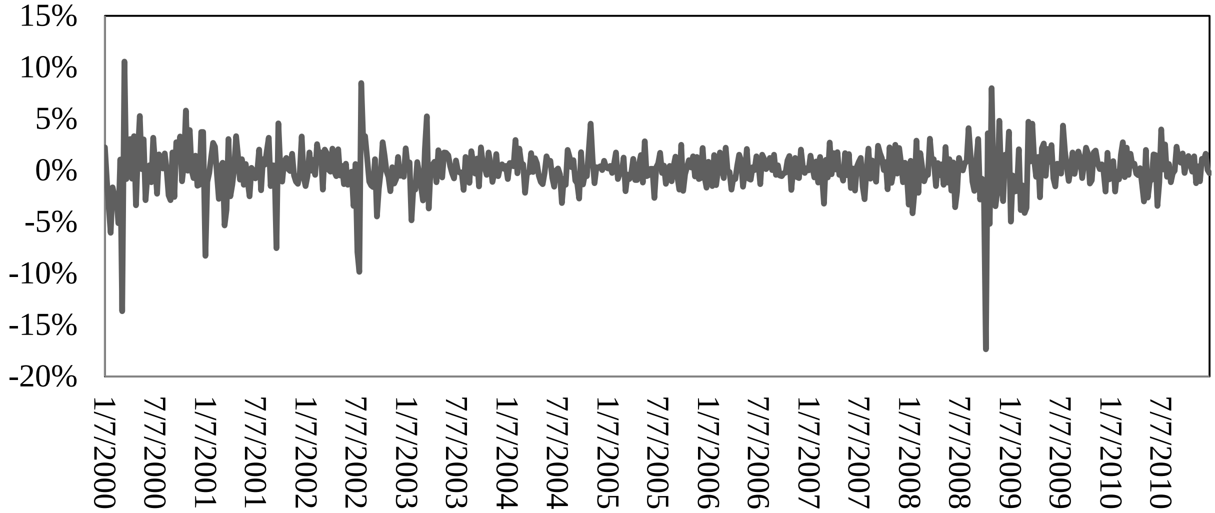
Weekly returns calculated from the price data from the Information Technology global industry classification standard (GICS) sector from the S&P 500. Data ranges from 2000:W1 through 2010:W52.

Figure 3.2 Excess Returns: Finance



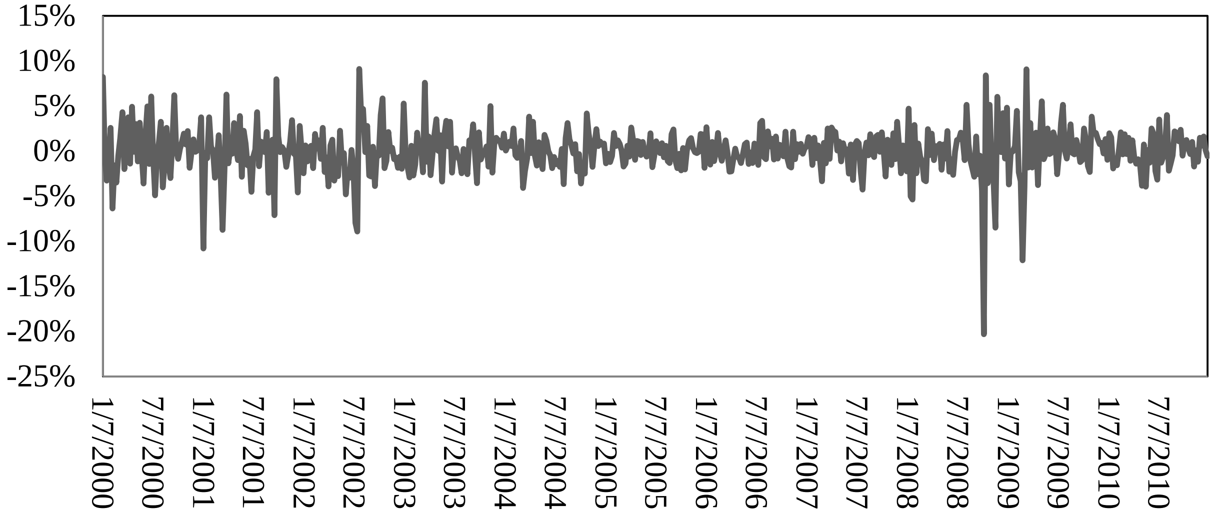
Weekly returns calculated from the price data from the Finance global industry classification standard (GICS) sector from the S&P 500. Data ranges from 2000:W1 through 2010:W52.

Figure 3.3 Excess Returns: Consumer Staples



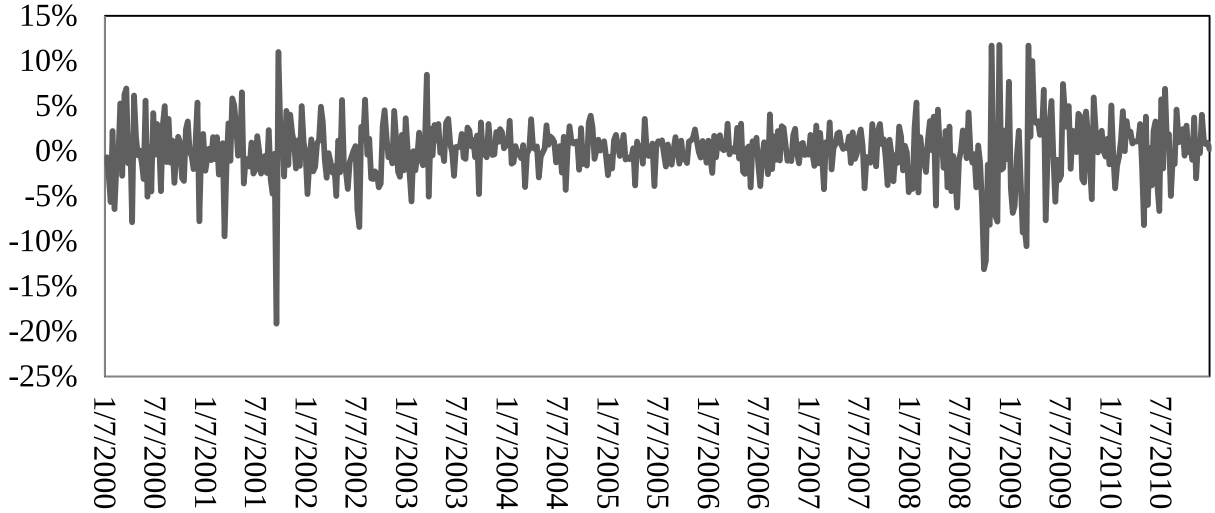
Weekly returns calculated from the price data from the Consumer Staples global industry classification standard (GICS) sector from the S&P 500. Data ranges from 2000:W1 through 2010:W52.

Figure 3.4 Excess Returns: Health



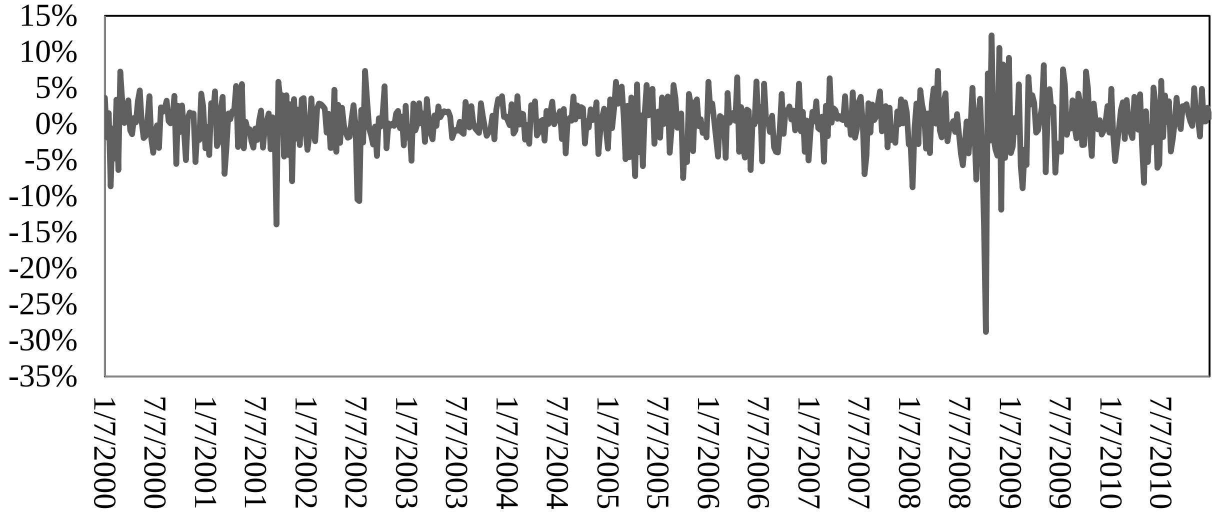
Weekly returns calculated from the price data from the Health global industry classification standard (GICS) sector from the S&P 500. Data ranges from 2000:W1 through 2010:W52.

Figure 3.5 Excess Returns: Industrials



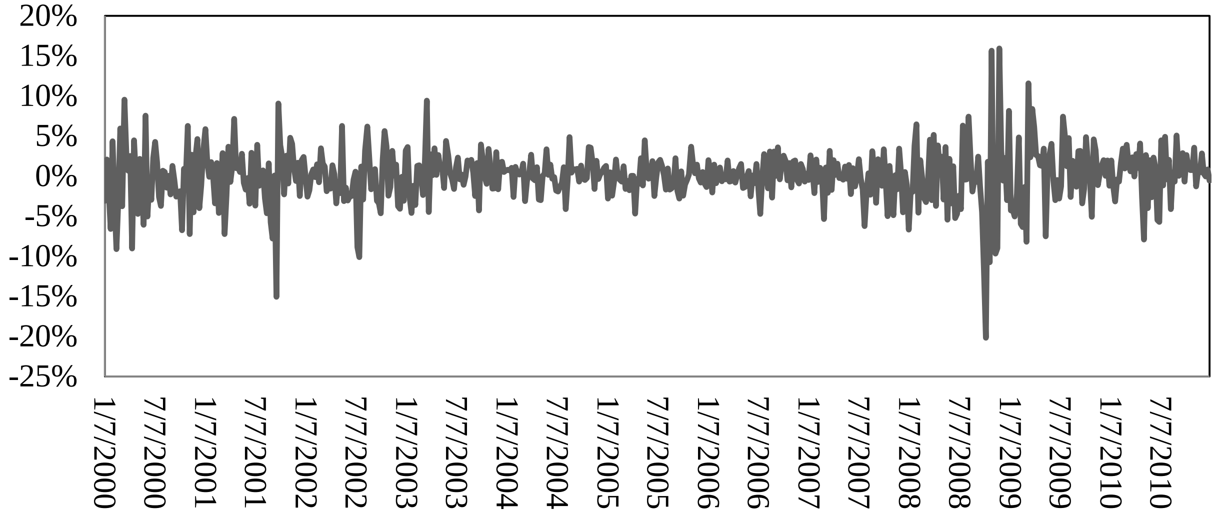
Weekly returns calculated from the price data from the Industrials global industry classification standard (GICS) sector from the S&P 500. Data ranges from 2000:W1 through 2010:W52.

Figure 3.6 Excess Returns: Energy



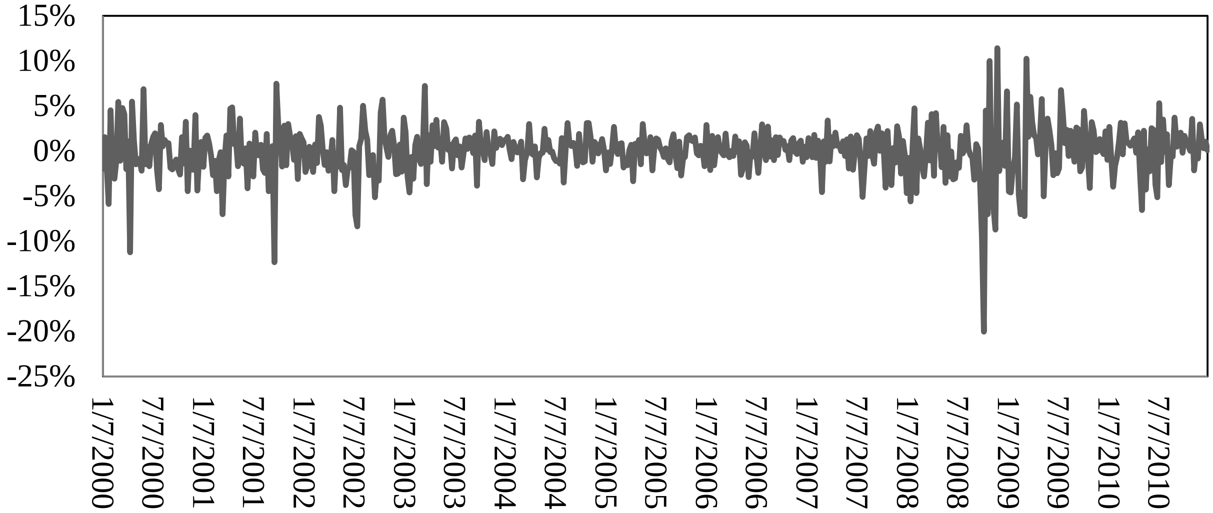
Weekly returns calculated from the price data from the Energy global industry classification standard (GICS) sector from the S&P 500. Data ranges from 2000:W1 through 2010:W52.

Figure 3.7 Excess Returns: Consumer Discretionary



Weekly returns calculated from the price data from the Consumer Discretionary global industry classification standard (GICS) sector from the S&P 500. Data ranges from 2000:W1 through 2010:W52.

Figure 3.8 Excess Returns: S&P 500 Composite



Weekly returns calculated from the price data from the S&P 500 Composite. Data ranges from 2000:W1 through 2010:W52.

Figure 3.9 Information Variables

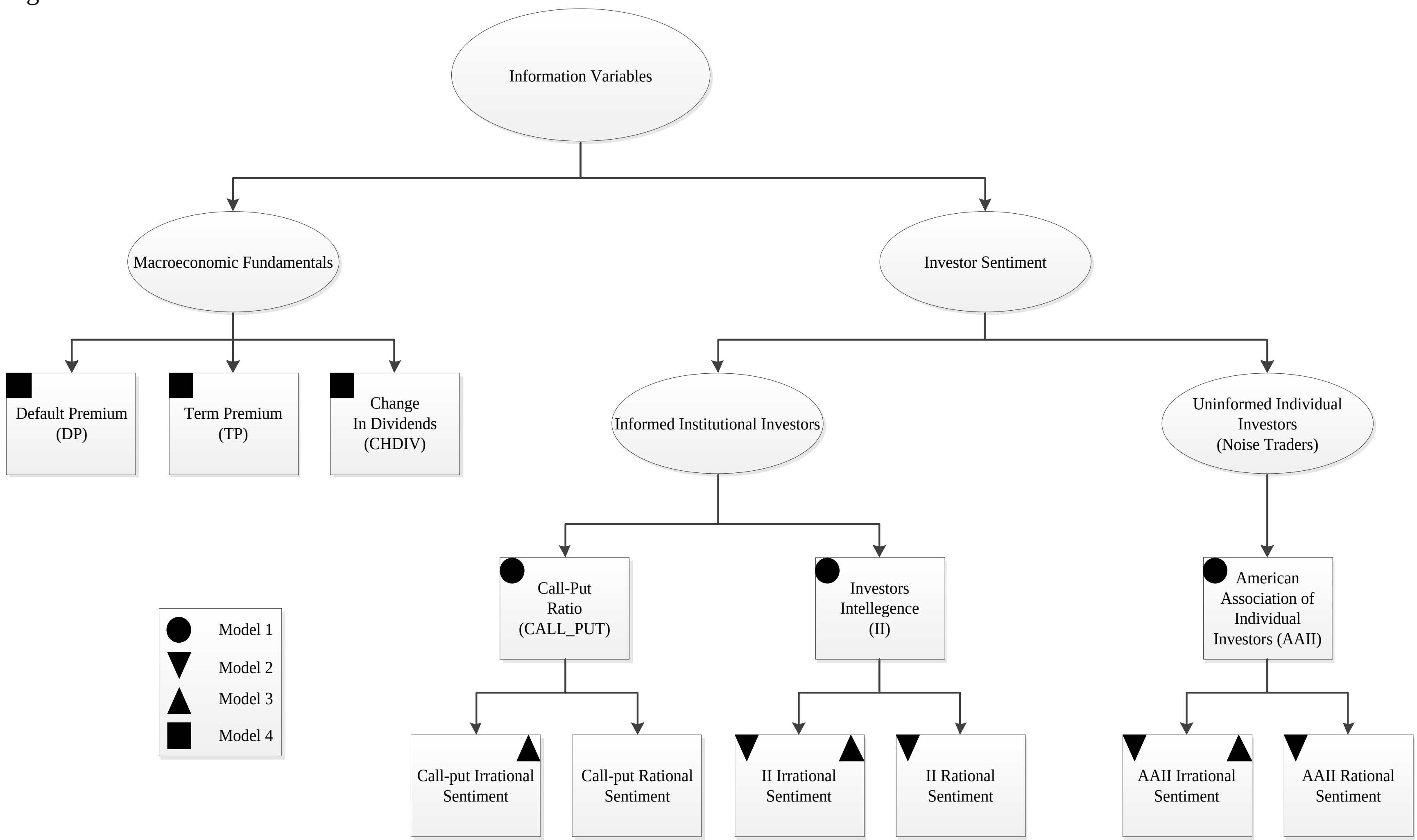
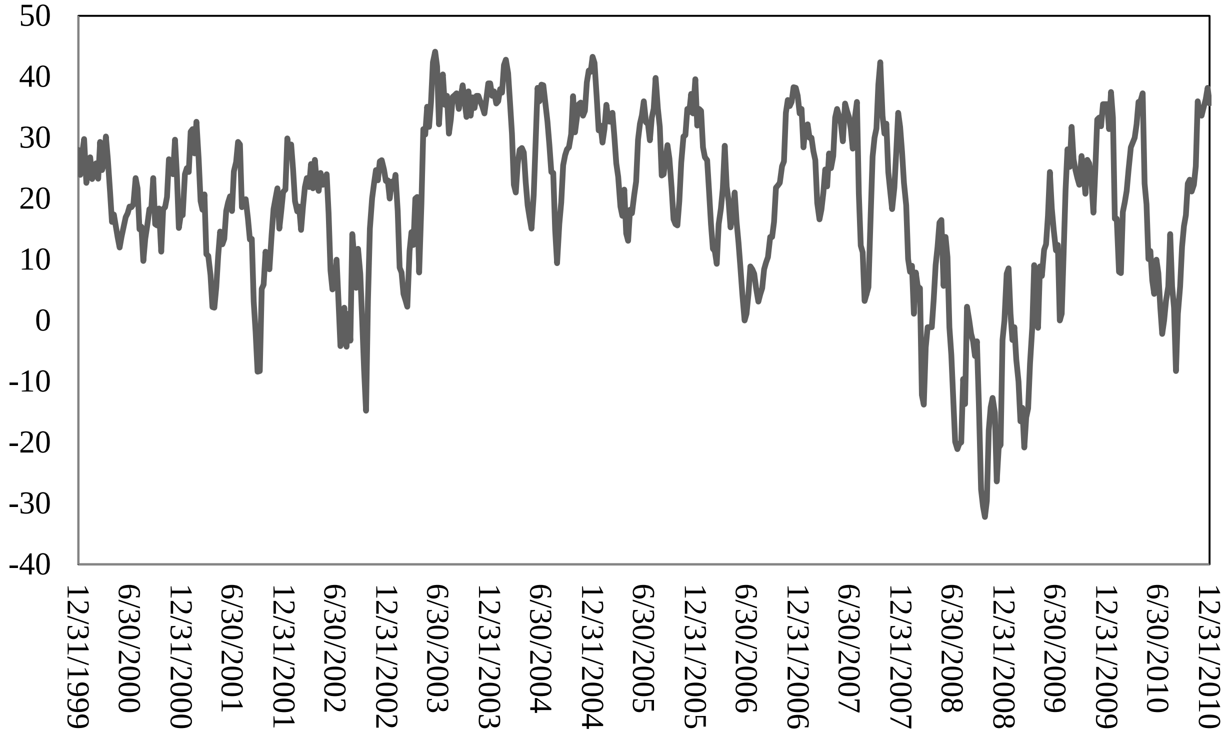
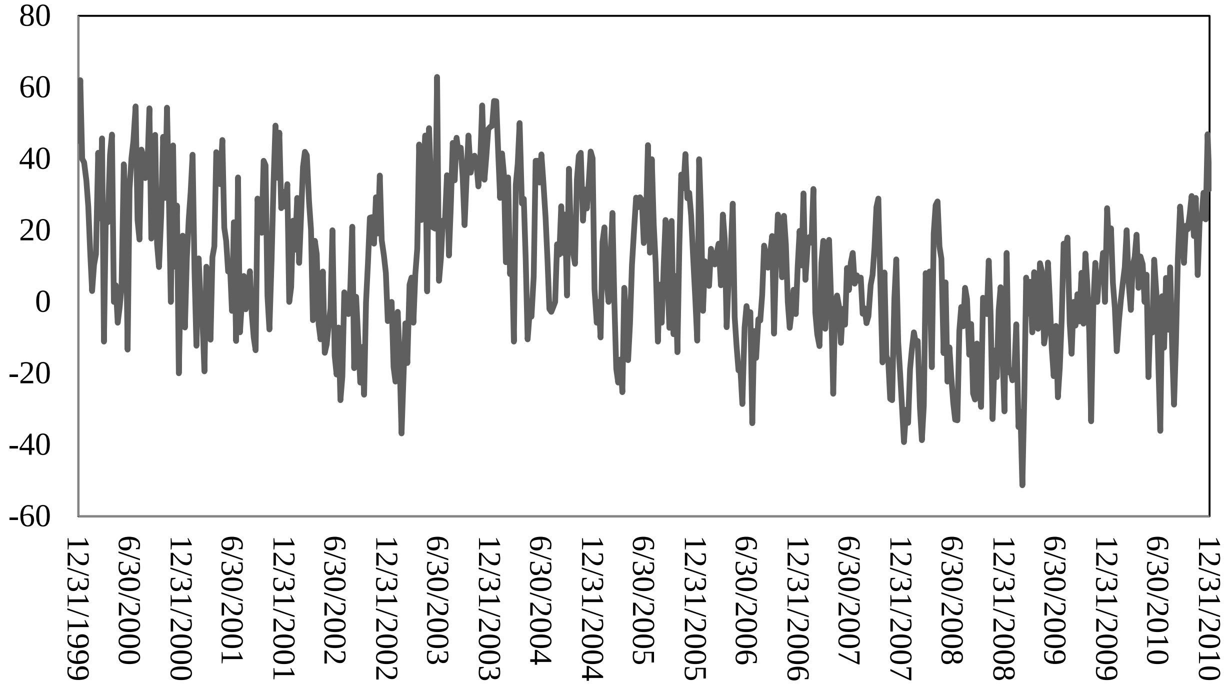


Figure 3.10 Institutional Investor (II) Sentiment Bull-Bear Spread



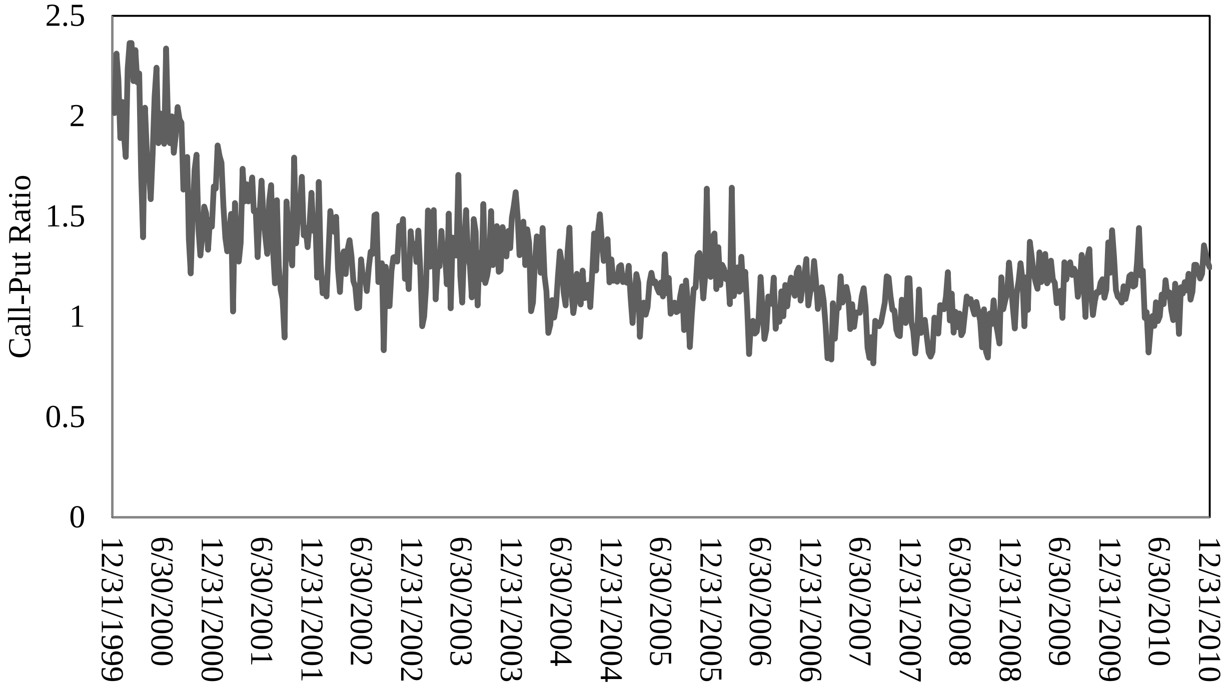
II Bull-Bear Spread (percent). This is calculated by subtracting the percent bearish from the percent bullish in the Investors Intelligence Advisors' Sentiment Report (II). Data is weekly in frequency ranging from 1999:W52 through 2010:W52.

Figure 3.11 Individual Investor Sentiment (AAII) Bull-Bear Spread



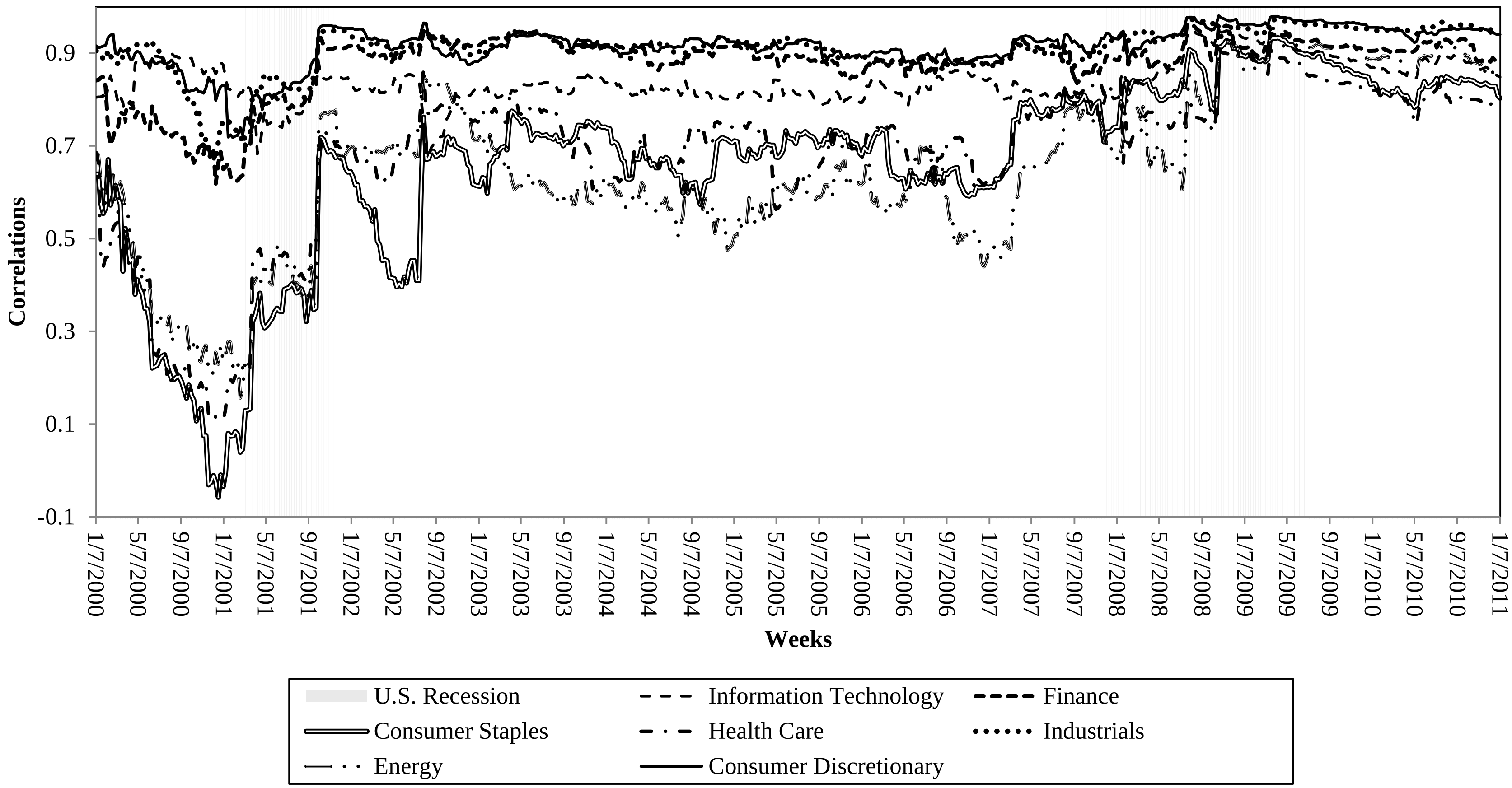
AAII Bull-Bear Spread (percent). This is calculated by subtracting the percent bearish from the percent bullish in the American Association of Individual Investors Sentiment Survey (AAII). Data is weekly in frequency ranging from 1999:W52 through 2010:W52.

Figure 3.12 Call-Put Ratio



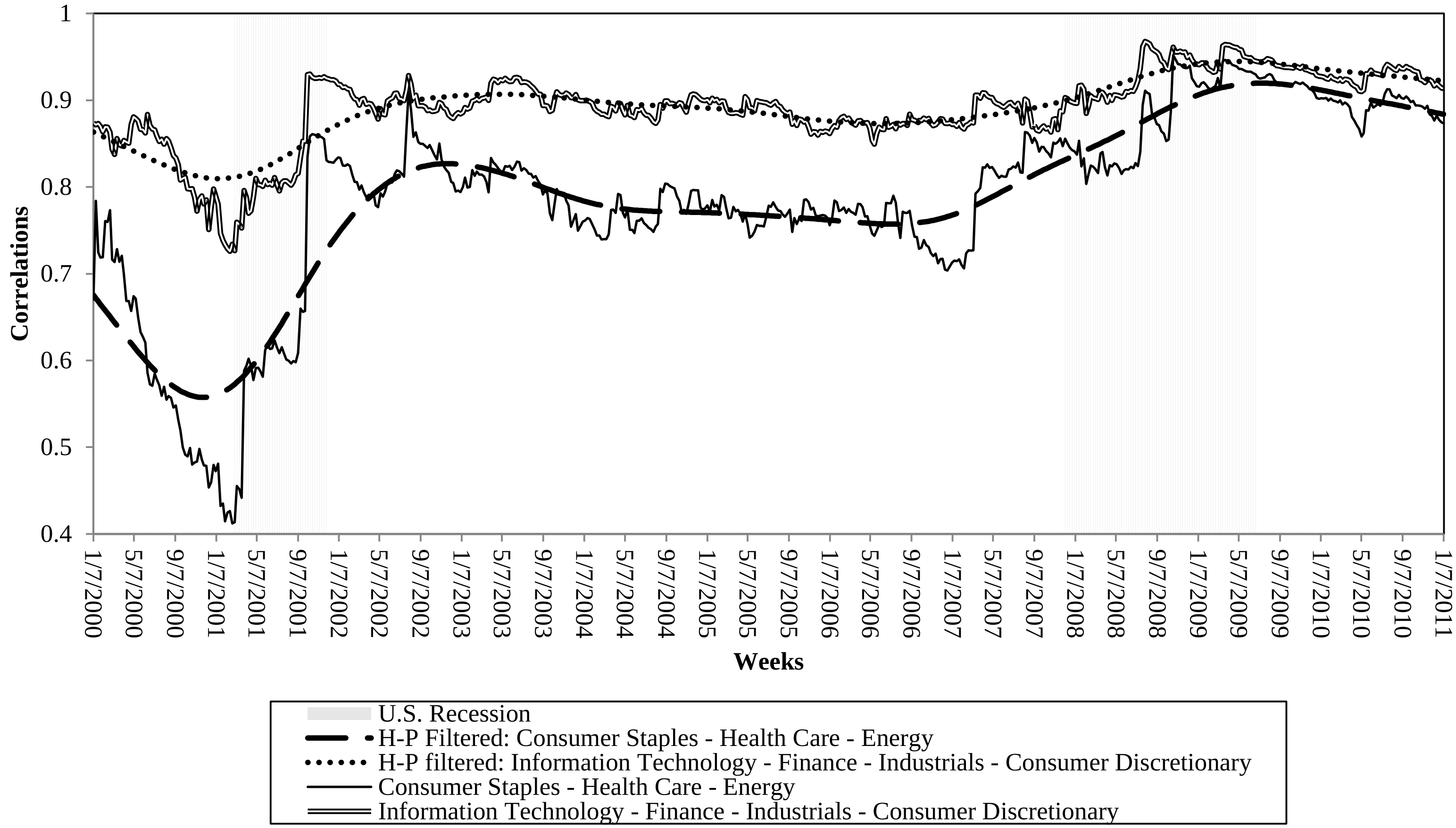
The weekly average of the total volume of calls to puts (call-put ratio) from the Chicago Board Options Exchange (CBOE). Data is weekly in frequency ranging from 1999:W52 through 2010:W52.

Figure 3.13 Mean correlations with the S&P 500 Composite



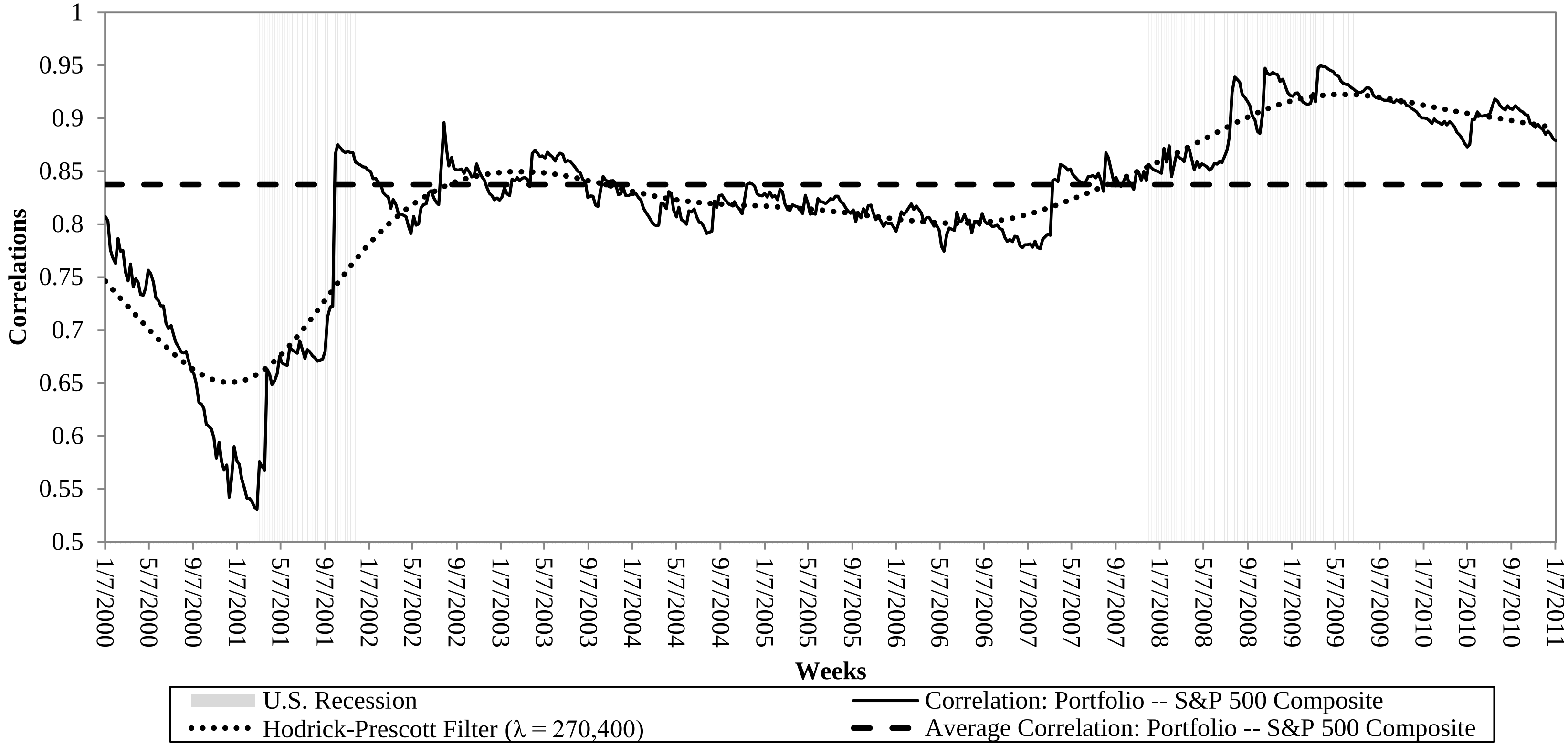
The lines represent the time varying correlations between the S&P 500 Composite and each GICS sector from the time varying CAPM from Eq. (3.7): $R_{it} - R_{ft} = \delta_{t-1}\,\mathrm{COV}(R_{it}, R_{mt}|\Im_{t-1}) + \varepsilon_{it}\ \ \forall_i$. The gray shaded chart areas represent official U.S. recessionary periods as per the National Bureau of Economic Research (NBER) retrieved from www.nber.org/cycles.html June 2011.

Figure 3.14 Grouped Mean Correlations with the S&P 500 Composite



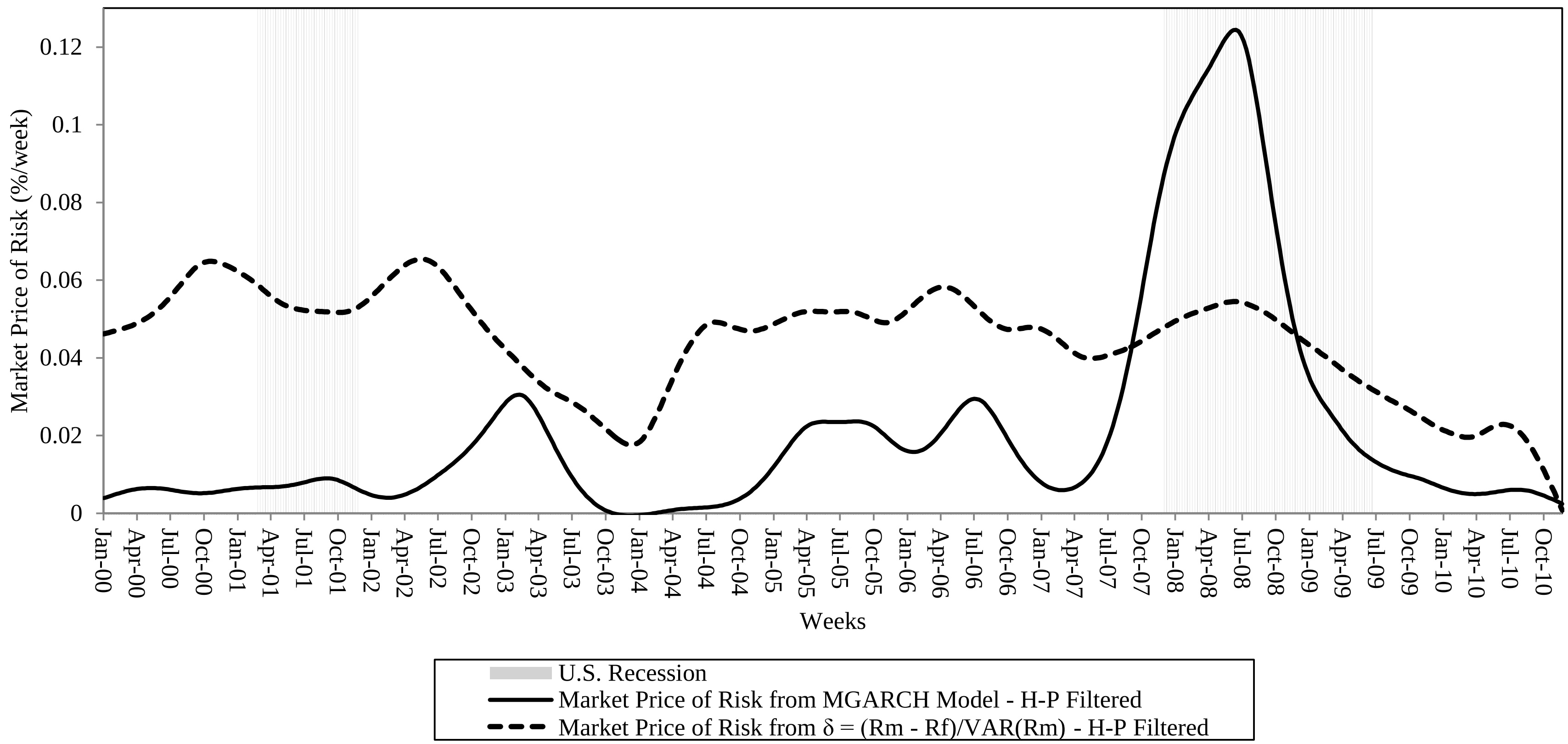
The solid and double lines represent equally weighted mean portfolio correlations (see legend) with the S&P 500 Composite from the time varying CAPM from Eq. (3.7): $R_{it} - R_{ft} = \delta_{t-1}\ \mathrm{COV}(R_{it}, R_{mt}|\Im_{t-1}) + \varepsilon_{it}\ \ \forall_i$. The groups are formed by similarity in response and magnitude (see Figure 2).The dotted and dashed lines represents the H-P filtered (Hodrick & Prescott, 1997) portfolio correlations with the S&P 500. The H-P filter isolates the cyclical component from the trend component (trend component shown). Equally weighed portfolio and mean correlations were calculated using the Fisher's z transformation as recommended by Silver & Dunlap (1987). The gray shaded chart areas represent official U.S. recessionary periods as per the National Bureau of Economic Research (NBER) retrieved from www.nber.org/cycles.html June 2011.

Figure 3.15 Entire Portfolio - Mean Correlation with the S&P 500 Composite.



The solid line represents the time varying mean correlation between the S&P 500 Composite and an equally weighted portfolio composed of all seven GICS sectors from the time varying CAPM from Eq. (3.7): $R_{it} - R_{ft} = \delta_{t-1}\,\mathrm{COV}(R_{it}, R_{mt}|\Im_{t-1}) + \varepsilon_{it}\ \ \forall_i$. The dotted line represents the H-P filtered (Hodrick & Prescott, 1997) portfolio correlation with the S&P 500. The H-P filter isolates the cyclical component from the trend component (trend component shown). The dashed line is the mean correlation of the portfolio and S&P 500 composite over the entire time period. Equally weighed portfolio and mean correlations were calculated using the Fisher's z transformation as recommended by Silver & Dunlap (1987). The gray shaded chart areas represent official U.S. recessionary periods as per the National Bureau of Economic Research (NBER) retrieved from www.nber.org/cycles.html June 2011.

Figure 3.16 Restricted Price of Covariance Risk – S&P 500 Composite Index



The solid line represents the H-P filtered MGARCH estimates of the price of covariance risk for the S&P 500 (see table 3A), rational and irrational investor sentiment for both informed and uniformed investors are used as information variables respectively. Model: $R_{it} - R_{ft} = \delta_{t-1}\,\mathrm{COV}(R_{it}, R_{mt}|\Im_{t-1}) + \varepsilon_{it}\ \ \forall_i$ Eq. (3.7) (price of risk is restricted to be non-negative). The dotted line represents the H-P filtered covariance price of risk of the S&P 500, exponentiated and scaled for comparison by: $\frac{e^{-\delta_t}}{10} - 0.05$, where $\delta_t = \frac{R_{mt} - R_{ft}}{VAR(R_{mt})}$, and $VAR(R_{mt})$ is the rolling variance in percent, using a 13 week window, of the continuous weekly return of the S&P 500 composite index. The H-P filter isolates the cyclical component from the trend component (trend component shown). The shaded areas indicate a U.S. recessions per the National Bureau of Economic Research (http://www.nber.org/cycles/cyclesmain.html).

CHAPTER IV

THE WORLD MARKET

4.1 Introduction

Over the last several years the U.S. financial markets experienced two major recessionary periods. The 2001 recession was the result of the dot-com market bubble and subsequent crash. The 2008 recession has been attributed to both the housing and energy price bubbles. During the year of 2008 the cost of a barrel of oil exceeded $100 for the first time in history. It then peaked in price at $147.30. This was followed by a collapse in price, ending below $35 per barrel. These two recent economic distresses were not isolated to the U.S. economy. When the housing bubble burst in the U.S. it affected global market prices.

The recent sovereign debt crises have recently become a major concern for our global economy. Waves of international concern are often blamed for falling security prices on the world markets. These recent global economic crises have increased research interest in time varying models of asset pricing, market efficiency, and irrational investor behavior. As the literature review in chapter II and evidence from chapter III has revealed, changes in investor sentiment measures are a contributing factor in asset pricing and contagion.

Instead of focusing on the U.S. equity market as chapter III does, this chapter examines the world market. We expand the discussion of the literature as it applies to the world market, including De Santis and Gerard (1997). The research questions in chapter IV are first, is U.S.

investor sentiment priced in the world market? And second, does U.S. investor sentiment contribute to international contagion?

We assume total investor sentiment is not entirely rational. Following the methodology of (Verma, et al., 2008), we decompose investor sentiment into its irrational and rational components. We decompose two measures of total investor sentiment; II to represent the informed investor and AAII the uninformed investor. This allows the testing of the following three null hypotheses:

1. U.S. total sentiment by both informed and uninformed investors is not priced internationally.
2. U.S. irrational sentiment by informed investors is not priced internationally.
3. U.S. irrational sentiment by uninformed investors is not priced internationally.

The extant literature shows U.S. investor sentiment is priced in the U.S. market. Chapter III also provides evidence. Therefore it is predicted null hypothesis (1) will be rejected in favor of the alterative. Null hypothesis (2) could have mixed results. Informed investors must have an irrational component, but it should be small in comparison to an uninformed investor. Chapter III reveals investor sentiment is priced in the U.S. market. Therefore it is predicted the null hypothesis will be rejected. Uniformed investors should by definition be noise traders, thus have a large irrational component. This component was not found to be priced in the U.S. market in chapter III. For this reason we predict null hypothesis (3) will not be rejected and the irrational component of uniformed U.S. investors will not be priced internationally.

This chapter contributes to the literature in the following distinct ways. First, two measures of U.S. total investor sentiment are tested internationally in a multivariate conditional CAPM. Second, U.S. investor sentiment is decomposed in order to test if irrational sentiment is priced in the international market. Finally, the predictive performance of the model is examined during the 2001 and 2008 U.S. recessions by plotting the time-varying market price of risk and correlations before, during and after the recessionary periods.

4.2 Review of the Literature

In the introduction in Section 4.1 it was mentioned there was increased interest in research areas such as market contagion, investor sentiment, bubbles, and herd-like behaviors following the two U.S. recessions in the last decade. Researchers also exhibited increased interest in these effects following earlier economic crises. Subsequent to the October 19, 1987 stock market crash there was increased research interest in how financial disturbances are transmitted between international markets. Researchers puzzled why macroeconomic fundamentals and market information did not adequately explain the nearly simultaneous extreme price drops across international markets.

King and Wadhwani (1990) discuss how international markets are not necessarily Walrasian efficient markets. For example, they are not open 24 hours nor have the same hours of operation. They hypothesize "*non-fully-revealing equilibrium implies the possibility of contagion effects*" (pg. 7). They develop a rational expectations model where contagion effects are the result of rational attempts of investors to use imperfect price information. After developing a theoretical framework and model they test their hypothesis using hourly data from July 1987 through February 1988 from the London, New York and Tokyo Stock Markets. They find their contagion coefficients increased during the 1987 crash. Increases in volatility increase the size of contagion effects. They also find increased correlations between the three markets immediately following the crash.

De Long and Shleifer (1991) calculate the difference in the net asset value of closed-end mutual funds and the actual stock market value of the portfolio making up the funds (an often-used measure of investor sentiment) during the 1920's. Using these price differences they study whether a bubble existed before the great crash of the U.S. stock market in 1929. They find evidence the S&P 500 was overpriced above fundamental values by 30 percent or more during the period right before the crash.

Frankel and Schmukler (1996) study the Mexican Peso crisis of 1994 using NAV values of Mexican held closed-end funds to proxy the investor sentiment of Mexican investors. They find Mexican nationals were the first to flee Mexico, and this instigated the crises. Their pessimistic signal in conjunction with the information asymmetry between the Mexican market and international investors were the main causes of the overreaction. They show Mexican NAV values Granger-cause the country fund prices.

Ang, Hodrick, Xing, and Zhang (2009) study high-idiosyncratic-volatility stocks and their relationship to low future returns both internationally and in the U.S. They measure idiosyncratic-volatility as the standard deviation of the error term from the standard Fama and French (1993) 3-factor model. They form portfolios by quintile and find the future returns of high-idiosyncratic-volatility stocks are 1.31 percent less than those of the lowest quintile. After controlling for size, value, and world market factors, they find this effect was significant for all of the G7 countries. They find high-idiosyncratic-volatility stocks directly co-move with future low returns. These findings suggest the benefits of international portfolio diversification are not as strong as investors might expect.

Siegel (1992) studies if there was a change of expectations in future profits or equity discount rates immediately before or following the 1987 U.S. stock market crash. He uses monthly analyst forecasts from the periodical *Blue chip Economic Indicators* to construct measures of expectations of future corporate profits and interest rates. He finds his measures cannot explain the abrupt price changes in the stock market crash of 1987. He suggests shift in investor sentiment perhaps were a factor.

Baur, Quintero, and Stevens (1998) test the hypothesis investor sentiment were a factor in the 1987 crash. They use weekly data consisting of the difference between the net asset value and the market value for 13 mutual funds during 1986 through 1988 as a measure of investor sentiment. They find no support for the hypothesis investor sentiment was a factor, and their investor sentiment measure does not significantly change during the crash. They find expectations about future interest rates and dividends did change significantly.

Schmeling (2009) uses a consumer confidence index as a proxy for individual investor sentiment to investigate the relationship between sentiment and asset returns in 18 industrialized countries. He finds when sentiment is bullish (bearish) stock returns tend to be lower (higher). This provides evidence a contrarian investment strategy might be effective even for international investing. He also finds the effect is present in value, growth, and small stocks. Different forecast horizons also are robust to the effect. Finally, he finds the impact of investor sentiment is larger for countries which are more prone to herd-like behavior or have less market integrity.

Zouaoui, Nouyrigat, and Beer (2011) employ logit modeling with a panel of 15 international stock markets and the United States to test the effect of investor sentiment on market crises. They decompose the consumer confidence index from the University of Michigan, and use the irrational sentiment component as their measure of investor sentiment. They find adding investor sentiment improves both the statistical quality (R-squared) and the crises prediction accuracy of the model. They find investor sentiment influence increases in countries are more prone to herd-like behavior due to cultural influences, have less institutional involvement, and are more likely to overreact.

Uygur and Taş (2012) study asymmetric volatility effects testing separate univariate GARCH, TARCH and EGARCH models on several international stock indexes. They use weekly and daily returns from the Nasdaq, Dow, S&P 500, Nikkei 225, HangSeng, FTSE100, CAC20, DAX, and ISE. Instead of using sentiment surveys or other traditionally used sentiment measures they form a sentiment index by calculating daily and weekly percent changes in trading volume for the indexes. They find strong evidence higher investor sentiment is related to lower returns, but higher volatility does not affect returns. They find during high sentiment periods returns decline for all the markets with the exception of the ISE, Nikkei225, and HangSeng. They also find there is asymmetric volatility in the market indexes, and when sentiment is high earning shocks have a larger influence on conditional volatility.

Gottesman, Jacoby, and Wang (2012) derive a new CAPM model which includes investor sentiment. They call the new model the SCAPM. It consists of beta terms as follows:

$$\begin{aligned} E\left[\tilde{R}_j\right] + E\left[\rho_j\right] = R_f + \lambda \frac{Cov(\tilde{R}_j, \tilde{R}_m)}{Var(\tilde{R}_m + \rho_m)} + \lambda \frac{Cov(\rho_j, \rho_m)}{Var(\tilde{R}_m + \rho_m)} \\ + \lambda \frac{Cov(\tilde{R}_j, \rho_m)}{Var(\tilde{R}_m + \rho_m)} + \lambda \frac{Cov(\rho_j, \tilde{R}_m)}{Var(\tilde{R}_m + \rho_m)}, \end{aligned} \tag{4.1}$$

where $\lambda = E\left[\tilde{R}_m + \rho_m - R_f\right]$ is the sentiment-adjusted market price of risk; ρ_j and ρ_m are investor sentiment misperception about the return on asset j and the return on the market respectively; $\tilde{R}_j$ and $\tilde{R}_m$ are the fundamental (sentiment-free) return on risky security j and the market respectively.

The first beta in Eq. (4.1) is similar to the traditional CAPM except for the additional sentiment term in the denominator. The second beta represents the amount of risk due to what the authors call the "*sentiment-contagion effect*." They further decompose this beta into several components including an "*investor-contagion effect*," which captures contagion effects or sentimental covariance between two investors. The third beta term is the amount of risk due to covariance between investors misperception on market returns overall and the fundamental return on security j. This term shows investors demand a premium for the risk the return of individual security j may be negatively affected by overall market misperceptions. The last beta term represents the covariance risk between sentiment misperceptions on the return of security j and the fundamental return of the market. The term implies investors require a premium for the risk sentiment mispricing on an individual security may affect the market return as a whole.

Lin, Engle, and Ito (1994) test whether stock returns and stock return volatility shocks are transmitted between the Tokyo and New York Stock markets. Their data consists of intraday and overnight returns in both markets. They use a model which incorporates GARCH parameterization in order to capture volatility clustering. Their study extends the model of King and Wadhwani (1990) and generally is consistent with their contagion-effect hypothesis. They find the daytime returns from the New York market are correlated with the overnight returns of Tokyo and the daytime returns of the Tokyo are also correlated with the overnight returns of New York. They find little evidence the lagged daytime-to-daytime spillovers are correlated between the two markets.

De Santis and Gerard (1997) test a multivariate time-varying conditional CAPM model with parsimonious GARCH-in-mean parameterization. They use macroeconomic fundamentals as the conditioning information available to the investor at time t-1. Their study uses monthly data from the G7 plus Switzerland from 1970 through 1994. They find allowing the market price of risk to vary through time significantly improves the performance of the static conditional CAPM model. They mention restricting the market price of risk to be non-negative causes some of the variation in the residual returns to be predicable. They find severe U.S. market declines are contagious internationally. They find although internationally diversified portfolios are not protected from severe U.S. declines, the overall benefits of international diversification have not declined over the two and one-half decades previous to their study.

Soydemir (2005) uses a methodology similar to De Santis and Gerard (1997) and a vector auto-regression model to examine the time-varying market price of risk in Asian markets. He rejects the static CAPM in favor of the time-varying CAPM. He finds evidence of partial market integration, and the time-varying cross-correlation between the Asian markets increase around the Asian crises of 1997. The VAR model estimations show shocks in the price of covariance risk can be contagious when originating from the U.S or emerging markets.

Bathia and Bredin (2012) study the relationship between investor sentiment and stock prices using monthly data on value stocks, growth stocks, and the aggregate country market in the G7. They use several international proxies for investor sentiment including the closed–end equity discount, the put-call ratio, the consumer confidence index, and equity fund flow. They use several separate fixed-effects panel regression models with various lags from 1 to 24months. Their findings are similar to those of Schmeling (2009), that is, when sentiment is bullish (bearish) stock returns tend to be lower (higher). These findings did not generally apply to the aggregate market, but were significant only for value and growth stocks.

This chapter extends study of De Santis and Gerard (1997) by introducing investor sentiment from AAII and II as an alternative to using the traditional macroeconomic fundamentals as the information available to investors in the previous period. The literature review could find no other studies which used an international conditional CAPM with parsimonious GARCH-in-mean parameterization in conjunction with investor sentiment as conditioning variables. As De Santis and Gerard (1997) and Soydemir (2005) have shown, the time varying model performs better than the static CAPM. It allows us to simultaneously capture the dynamics of the covariance structure, time-varying correlations, and time-varying market price of risk for all G7 countries and world market. We assume investor sentiment is not wholly irrational and decompose it into irrational and rational components. This model allows the testing of U.S. investor sentiment to see if it is priced internationally. The time-varying correlations and market price of risk for each G7 country are plotted over the last two recessions to visually look for international contagion effects. We employ both the Voung test and Clarke test to evaluate which model is closest to the true model.

4.3 Measurement and Data Sources

4.3.1 Portfolio Price and Return Data

The price data which is used to proxy the world market comes from the Morgan Stanley Capital International (MSCI) country and world indices. The countries consist of those in the G7. These economies are the largest in the world as measured by gross domestic product (GDP). The G7 accounts for 45.26 percent of the average GDP from 1995 through 2003 according to Jorgenson and Vu (2005). The International Monetary Fund world economic outlook database for April 2011 shows the portion of the G7's GDP to the world total is 49 percent[9]. The G7 consists of the following countries, listed in order from the largest to the smallest: 1) United States, 2) Japan, 3) Germany, 4) United Kingdom, 5) Italy, 6) France, and 7) Canada. Additional

[9]Data was retrieved from: http://bit.ly/fcv318 (on June 3, 2011)

countries were considered for this study, but not included in interest of model parsimony. Limiting the number of country portfolios to seven also avoids the two difficulties of computational expense and convergence problems in the estimation of the parameters using maximum likelihood. Data is retrieved from *Datastream.* The sample data spans from January 1990 to March 2010 for a total of 243 monthly observations. Investor sentiment data availability issues constrain the start date to January 1990.

Additionally, investor sentiment is used as an alternative to macroeconomic fundamentals as conditioning information available to the agent at time t-1. The primary investor sentiment survey data comes from two sources, Investors Intelligence (II) and The American Association of Individual Investors (AAII). The investor sentiment measures are further decomposed into their rational and irrational components following the methodology of Verma, Baklaci and Soydemir (2008). The total, rational, and irrational sentiment components, along with rational economic fundamentals are employed as information (conditioning) variables in various models in the conditional CAPM.

Returns are calculated as continuous in percent form using the following equation:

$$R_{it} = \ln\left(\frac{P_{it}}{P_{it-1}}\right) X100 \tag{4.1}$$

Where P_{it} is U.S. dollar-denominated and i represents each of G7 countries. The world market as a whole is the eighth portfolio, which is used as the market portfolio. The G7 and world market price data is in total return form, thus it reflects prices with dividends being reinvested. The calculation of excess returns using Eq. (4.1) yields 242 total return observations starting month 1, 1990 through month 3, 2010. Three remaining sectors, each about 3 percent of the total market capitalization were not included.

The excess returns, R_{it}^{e}, are calculated as:

$$R_{it}^{e} = R_{it} - R_{ft}, \tag{4.2}$$

where R_{ft} is the weekly return on the 3-month U.S. Treasury bill, secondary market, middle rate, at time t, and R_{it} are as defined in Eq. (4.1).

Table 4.1, Panel A shows the summary statistics for the excess returns of the G7country and world portfolios. All exhibit positive mean and median excess returns for the period studied, with the exception of Japan. It is interesting to note the two countries with the largest standard deviations (Japan and Italy) over the period also have the lowest mean and median excess returns. This risk-reward breakdown could at least be partially due to investor sentiment as Lee, et al. (2002) suggest. With the exception of Japan, all excess return distributions are negatively skewed with the mean excess return less than the median excess return. All of the distributions are leptokurtic in their fourth moments, with values greater than three, thus more peaked in shape than that of a normal distribution. With the exception of Japan, all reject the null hypothesis of normality ($p < 0.001$) using the Jarque-Bera (1980) test.

Table 4.1, Panel B reports the unconditional cross-sectional correlations for the excess returns. All correlations are significant at the 1% level. The countries which exhibit the highest correlation (with Pearson's product-moment coefficients 0.8 or higher) are Germany-France and U.K.-France. France-U.S., Canada-U.S., and France-Italy are the only country-to-country correlations between 0.7 and 0.8. U.S., U.K., France and Canada correlate highly with the World, all above a value of 0.8.

Table 4.1, Panel C depicts autocorrelation of excess returns. None of the autocorrelations of excess returns are significant at the 10 percent level. This suggests no autoregressive term is required in the mean equation. Analysis of the excess returns squared, shown in Table 4.1, Panel D, finds significant autocorrelation, thus multivariate

GARCH(1, 1) parameterization in the second moments is deemed appropriate.

Figures 4.1 through 4.8 depict the values of the excess returns of the G7 countries and the world market over time. As expected the most volatile periods generally occur during and around the dot-com bubble and the housing crises recessionary periods.

4.3.2 Information Variables

Two general sets of information variables (z_{t-1} in Eq. (4.8) in Section 4.4) are used in this study (see Figure 4.1). The first set is composed of the traditionally used economic fundamentals and the second set is investor sentiment. The macroeconomic fundamentals variables are: the default premium (DP), which is the difference between the U.S. corporate bond yield in Moody's seasoned issued Baa and Aaa bonds; the change in the term premium (CHTP), which is the change in the difference in Baa and the risk free rate, and the change in the U.S. market dividend yield in excess of the risk free rate (CHDIV). These variables have been used frequently in asset pricing literature; additionally they are often employed in technical and fundamental analysis by investors. They have also been shown to carry non-redundant information in several studies including Bekaert and Hodrick (1992), Bekaert and Harvey (1997), and De Santis and Gerard (1998).

The second general set of measures is composed of two investor sentiment survey measures. The first measure, $AAII_t$, is calculated as the monthly average from the weekly survey data from the Investor Sentiment Survey of the American Association of Individual Investor (AAII). The AAII Investor Sentiment Survey attempts to measure, by polling among their membership, the proportion that is bullish, bearish, or neutral on the stock market for the next six months. AAII members are only allowed one vote per week.

The second investor sentiment measure, II_t, is calculated from the Investors Intelligence Advisors' Sentiment Report (II). II is constructed by examination of over one hundred independent financial market newsletters. They examine at each article, and determine whether the author is bullish, bearish or neutral. II has historically used the same four editors when generating the report, and they claim this keeps their historical data consistent over time. Because the AAII Investor Sentiment Survey is polled from individual investors, literature generally considers it to be more irrational than the professional advisors in the II Advisors' Sentiment Report.

Both $AAII_t$ and II_t represent bull-bear spreads, which are calculated by subtracting the percent bearish from the percent bullish. Thus, a positive spread indicates more investors are more bullish. This measure is often employed in the literature, for example see Brown (1999), Brown and Cliff (2004), (2005), Schmeling (2007), Han (2008), Verma, et al. (2008), and Verma and Verma (2008). Figures 4.10 and 4.11 depict the AAII and II bull-bear spreads respectively. The investor sentiment variables are further decomposed into rational and irrational components as described later in Section (4.4), Eqs. (4.9a) and (4.9b).

There are ten macroeconomic fundamentals used as regressors in decomposing the investor sentiment measures ($AAII_t$ and II_t). These regressors ($Fund_{jt}$ in Eqs. (4.9a) and (4.9b)) consist of the three Fama and French (1996) factors; the high minus low book-to-price ratio (HML), the small minus big market capitalization (SMB) and market risk premium (MKT-RF); and the momentum factor (MOM) of Jegadeesh and Titman (1993) and Carhart (1997). Additional regressors include: (a) the first difference of the return on the 1-month Treasury Bill[10], (b) the economic risk premia [Campbell (1987); Ferson, Harvey, and Campbell (1991)]

[10] Weekly data on HML, SMB, MKT-RF, MOM and return on the one-month Treasury Bill are obtained from the Kenneth French data library located online at:

measured by the difference between the return on the 3-month and 1-month Treasury Bills, (c) the dividend yield [Harvey (1989); Litzenberger and Ramaswamy (1979)] measured as the first difference of the U.S. dividend yield, (d) the term premium [Fama (1990); Harvey (1989); Merton (1974)] measured as the first difference of the yield of the 10-year U.S. Treasury Bond in excess of the 3-month U.S. Treasury Bill, (e) the default premium as defined previously, and finally the inflation rate in percent [Asprem (1989)]. The inflation rate, expressed in percent form, is calculated using the U.S. Consumer Price Index (CPI), all urban, seasonally adjusted value from the U.S. Department of Commerce, Bureau of Economic Analysis. The irrational components of AAII and II are AAII_IRR and II_IRR respectively (see Eqs. (4.9a) and (4.9b). Similarly the rational components are henceforth labeled as AAII_RAT and II_RAT. These components are simply the fitted values, and can be considered to be the rational future expectations of the individual and institutional investors respectively.

Table 4.2, Panel A shows the descriptive statistics for the two groups of information variables. With the exception of The AAII Investor Sentiment Survey bull-bear spread and the first difference of the return on the 1-month Treasury Bill, the information variables reject the null hypothesis of normality at the 1 percent level or less. Table 4.2, Panel B shows the correlations to be particularly low, thus confirming the information variables carry mostly non-redundant information.

4.4 Model Specification and Econometric Methodology

The pricing is modeled utilizing the following, commonly used, conditional asset pricing CAPM benchmark model:

$$\mathrm{E}(R_{it}|\Im_{t-1}) - R_{ft} = \delta_{t-1}\,\mathrm{COV}(R_{it}, R_{mt}|\Im_{t-1})\ \forall_i \tag{4.3}$$

http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. Weekly MOM is calculated with a rolling sum of five daily observations, while the other variables are available as direct downloads in weekly form.

Where R_{it} is the return on the risky asset *i* (in this chapter, a G7 country portfolio of equity returns) between times t and $t-1$; R_{ft} is the risk free rate at time t; δ_{t-1} is the price of covariance risk (market price of risk); R_{mt} is the return on the market between times t and $t-1$; and $\Im_{t-1}$ is the information set available to the agents at time $t-1$. Equation (4.3) can be tested using:

$$\mathbf{R}_t - \mathrm{R}_{ft}\boldsymbol{\iota} = \delta_{t-1}\mathbf{h}_{Nt} + \boldsymbol{\epsilon}_t \qquad \boldsymbol{\epsilon}_t|\Im_{t-1} \sim \mathrm{N}(0, \mathbf{H}_t) \tag{4.4}$$

Where $\boldsymbol{R_t}$ is a (N X 1) vector (in this chapter N is 8, equal to the seven G7 countries plus one for the world market) of returns; $\boldsymbol{\iota}$ is a (N X 1) vector of ones; $\boldsymbol{H_t}$ is the (N X N) conditional covariance matrix; and $\boldsymbol{h_{Nt}}$ is the Nth column of $\boldsymbol{H_t}$ containing the covariance of each G7 country return with the world return variance at time t. The restrictions for the second moments are modeled by the following parsimonious multivariate generalized autoregressive conditional heteroscedasticity (GARCH) extension of a univariate GARCH (1, 1):

$$\boldsymbol{H}_t = \boldsymbol{H}_0 * (\boldsymbol{\iota\iota}' - \boldsymbol{aa}' - \boldsymbol{bb}') + \boldsymbol{aa}' * \boldsymbol{\epsilon}_{t-1}\boldsymbol{\epsilon}'_{t-1} + \boldsymbol{bb}' * \boldsymbol{H}_{t-1} \tag{4.5}$$

In the Eq. (4.5), for the first iteration $\boldsymbol{H}_0$ is an (N X N) unconditional covariance matrix (sample covariance matrix). It is updated to the covariance matrix of the residuals from the mean equation each iteration thereafter. The "*" symbol denotes the Hadamard matrix product (an element-by-element multiplication). The $\boldsymbol{a}$ and $\boldsymbol{b}$ are each (N X 1) vectors of parameter estimations. The log-likelihood function to be maximized is:

$$\ln L(\theta) = -\frac{TN}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T} ln|H_t(\theta)| - \frac{1}{2}\sum_{t=1}^{T} \boldsymbol{\epsilon}_t(\theta)' H_t(\theta)^{-1}\, \boldsymbol{\epsilon}_t(\theta), \tag{4.6}$$

where θ is the vector of unknown model parameter estimates. The model is tested using quasi-maximum likelihood (QML) due to non-normality (see Bollerslev and Wooldridge (1992)). The optimization algorithm is that of Berndt, Hall, Hall and Hausmann (1974), (BHHH).

In conditional asset pricing models the price of covariance risk (δ_{t-1}, Eqs. (4.7) and (4.8)) can be allowed to vary through time as a linear function of a set of instruments (vector $\boldsymbol{z}_{t-1}$ in Eq. (4.8)). However, as Merton (1980) discusses, the price of covariance risk is often negative using this methodology, which is against theoretical predictions. He shows a non-negativity restriction can be added to the model to achieve unbiased estimates of the market price of risk. In this study δ_{t-1} is constrained to be non-negative by employing an exponential function [Bekaert and Harvey (1995), De Santis and Gerard (1998), and Soydemir (2005)]:

$$R_{it} - R_{ft} = \delta_{t-1}\,\mathrm{COV}(R_{it}, R_{mt}|\Im_{t-1}) + \varepsilon_{it} \;\; \forall_i \tag{4.7}$$

$$\delta_{t-1} = \exp(\lambda + \boldsymbol{\kappa}'\boldsymbol{z}_{t-1}) \tag{4.8}$$

Both the constant λ and vector $\boldsymbol{\kappa}$ are parameters which are estimated [Soydemir (2005)] in addition to the two vectors of GARCH parameters, $\boldsymbol{a}$ and $\boldsymbol{b}$, which are estimated in Eq. (4.5).

As per the methodology in Verma, et al. (2008) investor sentiment is decomposed into its rational and irrational components using Eqs. (4.9a) and (4.9b).

$$AAII_t = \gamma_0 + \sum_{j=1}^{J} \gamma_j Fund_{jt} + AAII\_IRR_t \tag{4.9a}$$

$$II_t = \gamma_0 + \sum_{j=1}^{J} \gamma_j Fund_{jt} + II\_IRR_t \tag{4.9b}$$

Where $AAII_t$ and II_t represent the investor sentiment expectations of individual and institutional investors respectively. $Fund_{jt}$ is a set of economic fundamentals which have been shown to carry non-redundant information in asset pricing literature. $AAII\_IRR_t$ and II_IRR_t are the residuals which represent irrational components of investor sentiment. After estimating the parameters γ_0, and γ_j, and the residuals, $AAII\_IRR_t$ and II_IRR_t the fitted values, $\widehat{\mathrm{AAII}_t}$ and $\widehat{\mathrm{II}_t}$

are then calculated. These fitted values represent the rational components of investor sentiment, or the rational future expectations of the investor.

4.5 Empirical Results

4.5.1 Sentiment Decomposition

Tables (4.3) and (4.4) display the results of the individual regressions which decompose the three total sentiment measures into their irrational and rational components. Similarly to the results chapter III, the institutional investor sentiment (Table 4.4) has a higher adjusted R-squared value, 0.317, than that of the individual investor sentiment, 0.273 (Table 4.3). As Perez (2011) discusses, this is to be expected because individual investors are considered to be noise traders in the literature, thus less of their sentiment will be explained by the macroeconomic fundamentals. Both regressions have several variables which are highly significant. This is to be expected because total sentiment should have rational components which co-vary with macroeconomic fundamentals.

4.5.2 Asset Pricing Results and Diagnostics tests of the Residuals

Table 4.5, Panel A, Model 1 shows the results from the traditional macroeconomic fundamentals. Of the three parameter estimates, only the change in dividends κ_1 (CHDIV) differs from zero. The term premium, default premium and did not significantly differ from zero. All GARCH parameters are reasonable and are consistent with those of a univariate GARCH(1, 1). Stationarity conditions are met with all elements of $\boldsymbol{aa}' + \boldsymbol{bb}' < 1$ [Brougerol and Picard (1992)]. The mean and total likelihood scores of model 1 are -21.1647 and -6573.86 respectively.

Table 4.5, Panel B, Model 2 shows the results from decomposing both AAII and II sentiment into their irrational components. Neither κ_1 (AAII_IRR irrational individual sentiment) or κ_2 (II_IRR irrational institutional sentiment) significantly differ from zero. This indicates the bull-bear spread of both the irrational components of U.S. investor sentiment do not affect the world market price of risk. The multivariate GARCH (1, 1) parameters a_i and b_i are within the expected range, with the persistence of the GARCH and ARCH around 0.97 and 0.2 respectively. Stationarity conditions are again met. The mean and total likelihood scores of this model are -27.1669 and -6574.39.

Table 4.5, Panel C, Model 3 depicts the results using the following conditional information variables: (a) the total sentiment from the AAII and (b) the total sentiment from the II. Both the parameter estimates κ_1 (AAII sentiment) and κ_2 (II sentiment) do not significantly differ from zero. This indicates the total uniformed individual and institutional U.S. investor sentiment does not affect the world market price of risk. The GARCH parameters are also all significant very close to those in Table 4.5, Panels A and B, and satisfy stationarity conditions. The mean log-likelihood is -27.1731 while the total likelihood function score is -6576.89, which is lower than that of the two competing models.

Table 4.6, Panels A, B, and C show the results for the diagnostics tests of the residuals. The standardized residuals are constructed by: $\varepsilon_t h_t^{-1/2}$. The first section includes the serial and partial autocorrelations for the residuals of each sector through the first six lags. The second section shows the Q-statistics. The null hypothesis for the Q-statistic [Ljung and Box (1978)] is: no autocorrelation up to the indicated lag order. The results in all three tables show statistically most residuals do not show autocorrelation, with the exception of Canada. This provides statistical evidence the inclusion of GARCH modeling of the second moments is appropriate. For the variance ratio tests (Cochrane, 1988) the null hypothesis is: series is a martingale (residuals are serially independent). The row labeled joint at max |z| is a joint test at the maximum absolute value of the z-score from lags 2 through 16, while rows at indicated lags 2 through 8 are individual variance ratio tests at indicated lags. Again, with the exception of Canada, most variance ratio tests reject the null hypothesis of serial independence.

Vuong and Clarke competing model likelihood tests and plots of time-varying market price of risk were not performed in this chapter due to the insignificant results in the investor sentiment models

4.5.3 Time-varying Correlations

Figure 4.12 displays the time varying correlations between the world market portfolio and each G7 sector from the time varying CAPM from Eq. (4.7). The gray shaded chart areas represent official U.S. recessionary periods as per the National Bureau of Economic Research (NBER) retrieved from www.nber.org/cycles.html June 2011. Similarly to Chaper III, The G7 sector correlations to the world market tend to group together during recessionary periods, especially the latest recession following the U.S. housing crises. This grouping of correlations will greatly reduce any benefits of international diversification an investor might be counting on during recessionary periods. This confirms results from other research, where increased correlations are observed between markets in periods of economic crisis [Baig and Goldfajn (1999) , Loretan and English (2000), Forbes and Rigobon (2002), and Hartmann, Straetmans, and Vries (2004).

In the non-recessionary periods the G7 sector correlations divide into two similar groups by response and magnitude. The two groups are (a) Canada, Italy, and Japan, and (b) France Germany, United States, and the United Kingdom. Group (b) tends to correlate higher in magnitude with the S&P 500, usually with Pearson Product-Moment correlation coefficients higher than 0.80, while group (a) tends to correlate much lower, except during recessionary periods. Japan tends to have the lowest correlation with the world market following the 2001 recession. Prior to that Italy-world is the lowest country-world correlation. Throughout the decade, U.S. has the highest correlation with the world market.

Figure 4.13 depicts the mean time-varying correlation coefficients of groups (a) and (b) with the world market. The solid line represents equally weighted mean portfolio correlations of the country portfolios from group (a). The double line represents group (b). The dotted and dashed lines are the H-P filtered (Hodrick & Prescott, 1997) country portfolio correlations with the world market. The H-P filter isolates the cyclical component from the trend component (trend component shown). Equally weighed portfolio mean correlations were calculated using the Fisher's z transformation as recommended by Silver & Dunlap (1987). This figure shows more clearly the how the two groups tend to be similar in response and in magnitude, while increasing to similar magnitude correlations with the S&P 500 in recessionary periods, especially the recession following the housing crises in 2008.

In Figure 4.14 the solid line represents the time-varying mean correlation between an equally weighted portfolio composed of all seven GICS sector and the S&P 500 composite. The dotted line represents the H-P filtered. This figure clearly shows the increased correlations of all G7 countries with the world market portfolio during recessionary periods.

In addition to increased correlations during the two recessionary periods, one can clearly see in Figures 4.13 and 4.14 the correlations of the G7 country portfolios to the world market are sloping upward, or increasing through the entire sample period. This increased country correlation with the world market indicates continued international market integration as found by De Santis and Gerard (1997). This implies decreased benefits of international diversification and an increased risk of international contagion effects.

Table 4.1 Summary Statistics of Excess Returns – G7 Countries

Panel A: summary statistics – monthly excess returns

	U.S.	Japan	Germany	U.K.	Italy	France	Canada	World
Mean	0.366	-0.467	0.239	0.279	0.068	0.296	0.456	0.168
Median	1.035	-0.578	1.315	0.682	0.302	1.164	0.972	0.750
Maximum	11.864	21.116	16.772	13.319	24.953	12.232	16.696	13.568
Minimum	-27.647	-22.216	-26.670	-26.737	-24.605	-25.767	-35.766	-26.157
Std. Dev.	4.612	6.864	6.484	5.109	7.168	5.779	5.780	4.683
Skewness	-1.321	0.002	-0.912	-0.824	-0.229	-0.816	-1.426	-1.084
Kurtosis	8.274	3.324	5.056	5.734	4.307	4.575	9.858	6.758
Jarque-Bera	350.8***	1.1	76.1***	102.8***	19.3***	51.9***	556.2***	189.7***
Probability	0.000	0.589	0.000	0.000	0.000	0.000	0.000	0.000
Sum	88.5	-113.0	57.9	67.6	16.4	71.6	110.2	40.7
Sum Sq. Dev.	5127.0	11355.3	10132.6	6290.1	12383.2	8049.3	8050.8	5285.8

Panel B: unconditional cross-correlations of excess returns

	U.S.	Japan	Germany	U.K.	Italy	France	Canada	World
U.S.	1							
Japan	0.467***	1						
Germany	0.676***	0.462***	1					
U.K.	0.755***	0.533***	0.744***	1				
Italy	0.533***	0.465***	0.696***	0.594***	1			
France	0.718***	0.518***	0.857***	0.806***	0.706***	1		
Canada	0.786***	0.497***	0.649***	0.667***	0.563***	0.669***	1	
World	0.898***	0.734***	0.794***	0.866***	0.679***	0.844***	0.804***	1

Panel C: autocorrelations of excess returns

lag	U.S.	Japan	Germany	U.K.	Italy	France	Canada	World
1	0.006	0.000	0.017	0.050	-0.060	0.036	0.160	0.059
2	0.020	-0.040	0.033	-0.011	0.021	-0.046	0.082	0.004
3	0.108	0.093	0.031	0.055	0.042	0.107	0.084	0.087
4	-0.010	0.028	0.068	0.088	0.098	0.028	-0.028	0.022
5	0.090	0.042	0.022	0.088	-0.012	0.005	0.004	0.091
6	-0.079	-0.088	0.018	-0.091	-0.021	-0.019	-0.084	-0.082

Panel D: autocorrelations of excess returns squared

lag	U.S.	Japan	Germany	U.K.	Italy	France	Canada	World
1	0.060	0.147*	0.170**	0.248**	0.253**	0.144*	0.036	0.118
2	0.026	0.116*	0.003*	0.030**	-0.033**	-0.005	0.046	-0.011
3	0.115	-0.051*	0.010	0.108**	0.004**	0.081	0.006	0.075
4	-0.022	-0.015	-0.050	0.080**	0.031**	0.007	-0.028	0.016
5	0.081	0.105*	0.061	0.238**	0.196**	0.098	0.063	0.132
6	0.137	0.102*	0.231**	0.166**	0.252**	0.182**	0.159	0.206**

*, **, and *** denote significance levels of 10%, 5%, and 1% respectively

Monthly excess returns are calculated by subtracting the closest 3 month U.S. Treasury Bill monthly rate from the Morgan Stanley Capital International (MCSI) country and world total return Indices (U.S. dollar denominated). Sample period: 1990:2 to 2010:3, 242 observations. The asymptotic standard errors for the contemporaneous cross-correlations under an i.d. null hypothesis are given by $1/\sqrt{n}$ = 0.064.

Table 4.2 Summary Statistics: Sentiment and Macroeconomic Variables

Panel A: Summary statistics of sentiment and macroeconomic variables

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
AAII	9.858	10.945	56.180	-39.250	19.492	-0.221	2.670	3.159	0.206
II	13.944	16.000	42.400	-30.500	15.869	-0.586	2.952	14.331	0.001
HML	0.407	0.310	13.870	-9.890	3.297	0.422	5.405	67.711	0.000
SMB	-0.021	-0.065	13.800	-21.990	3.488	-1.055	10.959	706.168	0.000
MKT_RF	0.494	1.030	11.050	-18.550	4.450	-0.773	4.494	48.140	0.000
MOM	0.651	0.915	18.350	-34.690	5.288	-1.610	13.065	1163.148	0.000
D(RTBILL)	0.000	0.034	0.419	-0.321	0.174	-0.040	2.431	3.438	0.179
D(ERP)	0.002	-0.001	0.108	-0.081	0.032	0.439	3.611	11.934	0.003
D(DY)	2.060	1.820	3.930	0.950	0.706	0.606	2.368	19.446	0.000
D(TP)	0.148	0.138	0.318	-0.056	0.101	0.017	1.739	16.565	0.000
DP	0.079	0.071	0.282	0.046	0.036	3.232	15.565	2079.905	0.000
INFL	0.227	0.200	1.400	-1.800	0.274	-1.641	16.830	2104.776	0.000

Panel B: corss-correlations of sentiment and macroeonomic variables

	AAII	II	HML	SMB	MKT_RF	MOM	D(RTBILL)	D(ERP)	D(DY)	D(TP)	DP	INFL
AAII	1											
II	0.5430	1										
HML	0.1429	0.1868	1									
SMB	0.1182	0.1050	-0.3394	1								
MKT_RF	0.1689	0.0746	-0.2675	0.1954	1							
MOM	0.0398	0.0003	-0.0532	-0.1289	-0.2620	1						
D(RTBILL)	0.0229	-0.1603	-0.0343	-0.1911	-0.0013	0.1300	1					
D(ERP)	-0.1943	-0.0533	-0.0801	-0.0349	-0.0470	-0.0576	0.2384	1				
D(DY)	-0.3633	-0.5272	-0.1536	-0.0095	-0.0092	-0.0392	0.2694	0.0460	1			
D(TP)	-0.0855	-0.1457	0.0265	0.1610	-0.0030	-0.0508	-0.6868	-0.1169	0.2629	1		
DP	-0.3042	-0.2032	-0.1314	0.0990	-0.1038	-0.2188	-0.4444	0.1474	0.2199	0.2774	1	
INFL	-0.0472	0.0696	0.0630	-0.0235	-0.0355	0.0608	0.1945	-0.0615	0.0660	-0.1255	-0.2669	1

Data is montly in frequency, and ranges from 1990:M1 – 2010:M3
AAII - The AAII Investor Sentiment Survey bull-bear spread (%).
II – The Investors Intelligence Advisors' Sentiment Report bull-bear spread(%).
CALL_PUT – The weekly average of the total volume of calls to puts (call-put ratio) from the Chicago Board Options Exchange (CBOE).
HML – A Fama and French (1996) factor; high minus low book-to-price ratio.
SMB - A Fama and French (1996) factor; small minus big market capitalization.
MKT_RF - A Fama and French (1996) factor; market risk premium.
MOM – Jegadeesh and Titman (1993) momentum factor.
D(RTBILL) - The first difference of the return on the 1-month Treasury Bill.
D(ERP) - The economic risk premia - measured by the difference between the return on the 3-month and 1-month Treasury Bills.
D(DY) - The dividend yield - measured as the first difference of the U.S. dividend yield.
D(TP) -The term premium - measured as the first difference of the yield of the 10-year U.S. Treasury Bond in excess of the 3-month U.S. Treasury Bill.
DP - The default premium – the difference in Baa and the risk free rate.
INFL - The inflation rate in percent is calculated using the U.S. Consumer Price Index (CPI), all urban, seasonally adjusted value from the U.S. Department of Commerce, Bureau of Economic Analysis. U.S. CPI data is interpolated form monthly to weekly using a cubic spline interpolation.

Table 4.3 Individual Investor Sentiment (AAII) Regression on Macroeconomic Variables

Independent Variables	Coefficient	Std. Error	t-Statistic	P-value
C	32.628	4.171	7.823	0.000
HML	0.942	0.371	2.540	0.012
SMB	0.957	0.335	2.860	0.005
MKT_RF	0.733	0.266	2.761	0.006
MOM	0.128	0.220	0.581	0.562
D(RTBILL)	52.911	15.395	3.437	0.001
D(ERP)	-132.270	37.436	-3.533	0.001
D(DY)	-14.431	2.602	-5.546	0.000
D(TP)	61.613	21.882	2.816	0.005
DP	-16.372	44.566	-0.367	0.714
INFL	-6.273	4.065	-1.543	0.124
Adjusted R-squared	0.273			

$$AAII_t = \gamma_0 + \sum_{j=1}^{J} \gamma_j Fund_{jt} + AAII\_IRR_t$$

Data is monthly in frequency, and ranges from 1990:M1 – 2010:M3.
AAII - The AAII Investor Sentiment Survey bull-bear spread (%).
Variables in $Fund_{jt}$:
HML – A Fama and French (1996) factor; high minus low book-to-price ratio.
SMB - A Fama and French (1996) factor; small minus big market capitalization.
MKT_RF - A Fama and French (1996) factor; market risk premium.
MOM – Jegadeesh and Titman (1993) momentum factor.
D(RTBILL) - The first difference of the return on the 1-month Treasury Bill.
D(ERP) - The economic risk premia - measured by the difference between the return on the 3-month and 1-month Treasury Bills.
D(DY) - The dividend yield - measured as the first difference of the U.S. dividend yield.
D(TP) -The term premium - measured as the first difference of the yield of the 10-year U.S. Treasury Bond in excess of the 3-month U.S. Treasury Bill.
DP - The default premium – the difference in Baa and the risk free rate.
INFL - The inflation rate in percent is calculated using the U.S. Consumer Price Index (CPI), all urban, seasonally adjusted value from the U.S. Department of Commerce, Bureau of Economic Analysis.

Table 4.4 Institutional Investor Sentiment (II) Regression on Macroeconomic Variables

Independent Variables	Coefficient	Std. Error	t-Statistic	P-value
C	38.566	3.284	11.743	0.000
HML	0.909	0.292	3.113	0.002
SMB	0.695	0.263	2.636	0.009
MKT_RF	0.311	0.209	1.487	0.138
MOM	0.093	0.173	0.536	0.592
D(RTBILL)	-28.959	12.123	-2.389	0.018
D(ERP)	31.797	29.479	1.079	0.282
D(DY)	-7.083	2.049	-3.457	0.001
D(TP)	-38.496	17.231	-2.234	0.026
DP	-75.178	35.093	-2.142	0.033
INFL	4.192	3.201	1.310	0.192
Adjusted R-squared	0.319			

$$II_t = \gamma_0 + \sum_{j=1}^{J} \gamma_j Fund_{jt} + II\_IRR_t$$

Data is weekly in frequency, and ranges from 1999:W52 – 2010:W52.
II – The Investors Intelligence Advisors' Sentiment Report bull-bear spread(%).
Variables in $Fund_{jt}$:
HML – A Fama and French (1996) factor; high minus low book-to-price ratio.
SMB - A Fama and French (1996) factor; small minus big market capitalization.
MKT_RF - A Fama and French (1996) factor; market risk premium.
MOM – Jegadeesh and Titman (1993) momentum factor.
D(RTBILL) - The first difference of the return on the 1-month Treasury Bill.
D(ERP) - The economic risk premia - measured by the difference between the return on the 3-month and 1-month Treasury Bills.
D(DY) - The dividend yield - measured as the first difference of the U.S. dividend yield.
D(TP) -The term premium - measured as the first difference of the yield of the 10-year U.S. Treasury Bond in excess of the 3-month U.S. Treasury Bill.
DP - The default premium – the difference in Baa and the risk free rate.
INFL - The inflation rate in percent is calculated using the U.S. Consumer Price Index (CPI), all urban, seasonally adjusted value from the U.S. Department of Commerce, Bureau of Economic Analysis.

Table 4.5 Panel A Model 1- Economic fundamentals as information variables

ML parameter estimates of time varying CAPM for the G7 and world market

Price of covariance risk	parameter estimate (standard error)
κ_0 (constant)	4.884*** (1.479)
κ_1 (CHDIV)	-1.819** (0.898)
κ_2 (DP)	-0.539 (0.822)
κ_3 (CHTP)	-1.448 (1.472)

GARCH (1,1) process

	Canada	France	Germany	Italy	Japan	United Kingdom	United States	World
a_i	0.206*** (0.023)	0.214*** (0.017)	0.199*** (0.014)	0.274*** (0.041)	0.216*** (0.019)	0.226*** (0.021)	0.245*** (0.019)	0.230*** (0.015)
b_i	0.968*** (0.007)	0.968*** (0.006)	0.972*** (0.004)	0.953*** (0.015)	0.970*** (0.005)	0.967*** (0.007)	0.966*** (0.006)	0.968*** (0.005)

Mean log-likelihood = -27.1647

Likelihood function = -6573.86

** and *** denote significance levels of 5% and 1% respectively, parameter estimates are followed by the standard errors in parentheses.
The MGARCH estimates are based on the time-varying version of the conditional CAPM from Eq. (5): $R_{it} - R_{ft} = \delta_{t-1}\,\mathrm{COV}(R_{it}, R_{mt}|\Im_{t-1}) + \varepsilon_{it}\ \ \forall_i$, with δ_{t-1} restricted to be non-negative by Eq. (4.8): $\delta_{t-1} = \exp(\lambda + \boldsymbol{\kappa}'\mathbf{z}_{t-1})$.
The information variables in this model include the following economic fundamentals:

- κ_1, the change in dividends (CHDIV), the change in the U.S. market dividend yield in excess of the risk free rate.
- κ_2, the default premium (DP), which is the difference between the U.S. corporate bond yield in Moody's seasoned issued Baa and Aaa bonds.
- κ_3, the change in the term premium (CHTP), which is the difference in Baa and the risk-free rate.

GARCH(1, 1) process:

- a_i, The persistence of the ARCH term for each portfolio, *i*.
- b_i, The persistence of the GARCH term for each portfolio, *i*.

Likelihood values are total and mean likelihood at convergence using the BHHH algorithm.

Table 4.5 Panel B Model 2 - Irrational Sentiment as information variables.

ML parameter estimates of time varying CAPM for the G7 countries and the world market

Price of covariance risk	parameter estimate (standard error)
κ_0 (constant)	9.073 (8.501)
κ_1 (AAII_IRR)	-0.011 (0.023)
κ_2 (II_IRR)	0.210 (0.194)

GARCH (1,1) process

	Canada	France	Germany	Italy	Japan	United Kingdom	United States	World
a_i	0.213*** (0.036)	0.219*** (0.016)	0.203*** (0.018)	0.254*** (0.023)	0.218*** (0.019)	0.228*** (0.023)	0.252*** (0.021)	0.235*** (0.013)
b_i	0.966*** (0.011)	0.967*** (0.006)	0.970*** (0.006)	0.958*** (0.010)	0.970*** (0.005)	0.966*** (0.008)	0.965*** (0.007)	0.967*** (0.005)

Mean log-likelihood = -27.1669
Likelihood function = -6574.39

*** denotes a significance levels of 1%. Parameter estimates are followed by the standard error in parentheses.

The MGARCH estimates are based on the time-varying version of the CAPM from Eq. (4.7): $R_{it} - R_{ft} = \delta_{t-1}\,\mathrm{COV}(R_{it}, R_{mt}|\Im_{t-1}) + \varepsilon_{it}\ \ \forall_i$, with δ_{t-1} restricted to be non-negative by Eq. (4.8): $\delta_{t-1} = \exp(\lambda + \boldsymbol{\kappa}'\boldsymbol{z}_{t-1})$.

The information variables in this model include:

- κ_1, AAII_IRR, is the error term from decomposing the bull-bear spread from the American Association of Individual Investors (AAII) Investor Sentiment Survey using: $\mathrm{AAII_t} = \gamma_0 + \sum_{j=1}^{J}\gamma_j \mathrm{Fund_{jt}} + \mathrm{AAII\_IRR_t}$. The variables in $Fund_{jt}$ consist of several economic fundamentals including the first difference of the term premium, the default premium the (E.F. Fama & French, 1992) factors SMB, HML and Rm-Rf, the momentum factor (Jegadeesh & Titman, 1993), MOM, and the first difference of the dividend yield. This parameter represents the irrational component of sentiment of the uninformed investors.
- κ_2, II_IRR, is the error term from decomposing the bull-bear spread from the Investors Intelligence Advisors Sentiment (II) Investor Sentiment Survey using: $\mathrm{II_t} = \gamma_0 + \sum_{j=1}^{J}\gamma_j \mathrm{Fund_{jt}} + \mathrm{II\_IRR_t}$. This parameter represents the irrational component of sentiment from the informed investors.

GARCH(1, 1) process:

- a_i, The persistence of the ARCH term for each portfolio, *i*.
- b_i, The persistence of the GARCH term for each portfolio, *i*.

Likelihood values are total and mean likelihood at convergence using the BHHH algorithm.

Table 4.5 Panel C Model 3 – Total sentiment as information variables.

ML parameter estimates of time varying CAPM for seven GICS sectors from S&P 500 and the S&P 500 composite

Price of covariance risk	parameter estimate (standard error)
κ_0 (constant)	4.031** (1.874)
κ_1 (AAII)	-0.033 (0.051)
κ_2 (II)	0.035 (0.052)

GARCH (1,1) process

	Canada	France	Germany	Italy	Japan	United Kingdom	United States	World
a_i	0.213*** (0.036)	0.219*** (0.016)	0.203*** (0.018)	0.254*** (0.023)	0.218*** (0.019)	0.228*** (0.023)	0.252*** (0.021)	0.235*** (0.013)
b_i	0.966*** (0.011)	0.967*** (0.006)	0.970*** (0.006)	0.958*** (0.010)	0.970*** (0.005)	0.966*** (0.008)	0.965*** (0.007)	0.967*** (0.005)

Mean log-likelihood = -27.1731

Likelihood function = -6575.89

** and *** denote significance levels of 5% and 1% respectively. Parameter estimates are followed by the standard error in parentheses.

The MGARCH estimates are based on the time-varying version of the CAPM from Eq. (4.7): $R_{it} - R_{ft} = \delta_{t-1}\ \mathrm{COV}(R_{it}, R_{mt}|\Im_{t-1}) + \varepsilon_{it}\ \ \forall_i$, with δ_{t-1} restricted to be non-negative by Eq. (4.8): $\delta_{t-1} = \exp(\lambda + \boldsymbol{\kappa}'\mathbf{z}_{t-1})$.

The information variables in this model include:

- κ_1, AAII sentiment - is the bull-bear spread from the American Association of Individual Investors (AAII) Investor Sentiment.
- κ_2, II sentiment - is the bull-bear spread from the Investors Intelligence Advisors Sentiment (II) Investor Sentiment Survey.

GARCH(1, 1) process:

- a_i, The persistence of the ARCH term for each portfolio, *i*.
- b_i, The persistence of the GARCH term for each portfolio, *i*.

Likelihood values are total and mean likelihood at convergence using the BHHH algorithm.

Table 4.6 Panel A Model 1 – Economic fundamentals as information variables.

Diagnostics tests of the residuals

lag	Canada	France	Germany	Italy	Japan	United Kingdom	United States	World
autocorrelation: serial | partial								
1	0.128 | 0.128	0.027 | 0.027	0.018 | 0.018	-0.034 | -0.034	0.041 | 0.041	0.040 | 0.040	-0.018 | -0.018	0.034 | 0.034
2	0.090 | 0.075	-0.039 | -0.039	0.065 | 0.065	0.067 | 0.066	-0.021 | -0.023	-0.003 | -0.005	0.034 | 0.034	0.015 | 0.014
3	0.079 | 0.060	0.131 | 0.133	0.043 | 0.041	0.073 | 0.077	0.114 | 0.116	0.095 | 0.095	0.125 | 0.127	0.089 | 0.088
4	-0.061 | -0.086	0.002 | -0.008	0.070 | 0.064	0.070 | 0.072	0.036 | 0.026	0.057 | 0.050	-0.046 | -0.043	-0.027 | -0.034
5	-0.007 | 0.000	0.016 | 0.028	0.023 | 0.016	0.050 | 0.046	0.048 | 0.052	0.109 | 0.107	0.123 | 0.115	0.107 | 0.108
6	-0.045 | -0.039	0.042 | 0.023	0.068 | 0.058	0.060 | 0.050	-0.086 | -0.104	-0.012 | -0.028	-0.028 | -0.039	-0.027 | -0.043
Ljung-Box Q-statistic (p-value)								
1	4.028** (0.045)	0.177 (0.674)	0.077 (0.781)	0.278 (0.598)	0.409 (0.523)	0.396 (0.529)	0.076 (0.782)	0.291 (0.590)
2	6.032** (0.049)	0.545 (0.762)	1.132 (0.568)	1.385 (0.500)	0.520 (0.771)	0.399 (0.819)	0.365 (0.833)	0.344 (0.842)
3	7.587* (0.055)	4.776 (0.189)	1.588 (0.662)	2.685 (0.443)	3.718 (0.294)	2.606 (0.456)	4.242 (0.236)	2.306 (0.511)
4	8.505* (0.075)	4.777 (0.311)	2.787 (0.594)	3.906 (0.419)	4.044 (0.400)	3.416 (0.491)	4.757 (0.313)	2.491 (0.646)
5	8.516 (0.130)	4.842 (0.436)	2.921 (0.712)	4.531 (0.476)	4.628 (0.463)	6.369 (0.272)	8.550 (0.128)	5.330 (0.377)
6	9.019 (0.173)	5.276 (0.509)	4.062 (0.668)	5.417 (0.492)	6.495 (0.370)	6.405 (0.379)	8.751 (0.188)	5.515 (0.480)
Variance Ratio Tests: z-score (p-value)								
joint @ max |z|	2.528 (0.159)	1.881 (0.604)	2.157 (0.377)	2.574 (0.141)	0.673 (0.992)	2.992** (0.041)	2.886* (0.057)	2.295 (0.281)
2	1.875* (0.061)	0.442 (0.659)	0.322 (0.747)	-0.375 (0.708)	-0.356 (0.722)	0.631 (0.528)	-0.259 (0.796)	0.567 (0.571)
3	2.253** (0.024)	0.186 (0.852)	0.765 (0.444)	0.133 (0.894)	0.323 (0.747)	0.613 (0.540)	0.077 (0.938)	0.632 (0.528)
4	2.528** (0.012)	0.684 (0.494)	1.036 (0.300)	0.610 (0.542)	0.317 (0.752)	0.952 (0.341)	0.694 (0.488)	0.924 (0.355)
5	2.395** (0.017)	0.898 (0.369)	1.341 (0.180)	1.008 (0.313)	0.409 (0.682)	1.195 (0.232)	0.797 (0.426)	0.936 (0.349)
6	2.311** (0.021)	1.036 (0.300)	1.537 (0.124)	1.307 (0.191)	0.491 (0.623)	1.565 (0.118)	1.109 (0.267)	1.207 (0.227)
7	2.164** (0.030)	1.187 (0.235)	1.756* (0.079)	1.578 (0.115)	0.642 (0.521)	1.756* (0.079)	1.240 (0.215)	1.309 (0.190)
8	2.070** (0.038)	1.345 (0.179)	1.921* (0.055)	1.697* (0.090)	0.673 (0.501)	1.887* (0.059)	1.427 (0.154)	1.420 (0.156)

*, **, and *** denote significance levels of 10%, 5%, and 1% respectively. Standardized residuals are constructed by: $\varepsilon_t h_t^{-1/2}$. Null hypothesis for the Q-statistic [Ljung and Box (1978)]: no autocorrelation up to the indicated lag order. For the variance ratio tests [Cochrane (1988)] null hypothesis: series is a martingale (residuals are serially independent). The row labeled joint at max |z| is a joint test at the maximum absolute value of the z-score from lags 2 through 16, while rows at indicated lags 2 through 8 are individual variance ratio tests at indicated lags.

The information variables in this model include the following economic fundamentals:

- κ_1, the change in dividends (chdiv), the change in the U.S. market dividend yield in excess of the risk free rate.
- κ_2, the default premium (DP), which is the difference between the U.S. corporate bond yield in Moody's seasoned issued Baa and Aaa bonds.
- $\kappa 3$, the change in the term premium (CHTP), which is the difference in Baa and the risk-free rate

Table 4.6 Panel B Model 2 – Irrational Sentiment as information variables.

Diagnostics tests of the residuals

lag	Canada	France	Germany	Italy	Japan	United Kingdom	United States	World
autocorrelation: serial | partial								
1	0.131 | 0.131	0.023 | 0.023	0.010 | 0.010	-0.044 | -0.044	0.044 | 0.044	0.031 | 0.031	-0.025 | -0.025	0.027 | 0.027
2	0.054 | 0.037	-0.054 | -0.055	0.041 | 0.041	0.040 | 0.038	-0.045 | -0.047	-0.028 | -0.029	0.016 | 0.015	-0.010 | -0.010
3	0.091 | 0.081	0.119 | 0.122	0.037 | 0.037	0.058 | 0.061	0.109 | 0.114	0.091 | 0.093	0.108 | 0.109	0.078 | 0.079
4	-0.063 | -0.088	0.001 | -0.009	0.073 | 0.071	0.074 | 0.078	0.046 | 0.034	0.054 | 0.048	-0.039 | -0.034	-0.024 | -0.028
5	-0.010 | 0.002	0.012 | 0.027	0.018 | 0.014	0.040 | 0.043	0.040 | 0.047	0.092 | 0.096	0.114 | 0.110	0.098 | 0.102
6	-0.051 | -0.054	0.043 | 0.028	0.066 | 0.059	0.048 | 0.043	-0.077 | -0.091	-0.007 | -0.019	-0.029 | -0.035	-0.021 | -0.035
Ljung-Box Q-statistic (p-value)								
1	4.224** (0.040)	0.133 (0.716)	0.025 (0.876)	0.466 (0.495)	0.471 (0.492)	0.239 (0.625)	0.156 (0.693)	0.174 (0.676)
2	4.931* (0.085)	0.859 (0.651)	0.443 (0.801)	0.866 (0.648)	0.978 (0.613)	0.429 (0.807)	0.216 (0.898)	0.197 (0.906)
3	6.989* (0.072)	4.370 (0.224)	0.786 (0.853)	1.684 (0.641)	3.908 (0.272)	2.495 (0.476)	3.106 (0.376)	1.704 (0.636)
4	7.967* (0.093)	4.371 (0.358)	2.100 (0.717)	3.046 (0.550)	4.430 (0.351)	3.221 (0.522)	3.477 (0.481)	1.843 (0.765)
5	7.991 (0.157)	4.408 (0.492)	2.180 (0.824)	3.442 (0.632)	4.822 (0.438)	5.340 (0.376)	6.698 (0.244)	4.244 (0.515)
6	8.651 (0.194)	4.877 (0.560)	3.268 (0.774)	4.007 (0.676)	6.290 (0.392)	5.354 (0.499)	6.901 (0.330)	4.353 (0.629)
Variance Ratio Tests: z-score (p-value)								
joint @ max								
|z|	2.398 (0.221)	1.342 (0.949)	1.681 (0.768)	1.739 (0.723)	1.154 (0.986)	2.207 (0.340)	2.185 (0.356)	1.587 (0.833)
2	1.940* (0.052)	0.412 (0.680)	0.233 (0.816)	-0.510 (0.610)	0.747 (0.455)	0.544 (0.586)	-0.420 (0.674)	0.494 (0.621)
3	2.145** (0.032)	0.035 (0.972)	0.540 (0.590)	-0.178 (0.859)	0.344 (0.731)	0.366 (0.715)	-0.173 (0.863)	0.383 (0.702)
4	2.398** (0.017)	0.477 (0.633)	0.762 (0.446)	0.206 (0.837)	0.481 (0.631)	0.665 (0.506)	0.406 (0.685)	0.602 (0.547)
5	2.216** (0.027)	0.666 (0.506)	1.060 (0.289)	0.590 (0.555)	0.684 (0.494)	0.883 (0.377)	0.501 (0.616)	0.593 (0.553)
6	2.104** (0.035)	0.786 (0.432)	1.245 (0.213)	0.871 (0.384)	0.950 (0.342)	1.214 (0.225)	0.801 (0.423)	0.846 (0.397)
7	1.936* (0.053)	0.931 (0.352)	1.457 (0.145)	1.117 (0.264)	0.959 (0.337)	1.392 (0.164)	0.925 (0.355)	0.952 (0.341)
8	1.841* (0.066)	1.089 (0.276)	1.612 (0.107)	1.218 (0.223)	0.968 (0.333)	1.518 (0.129)	1.107 (0.268)	1.073 (0.283)

*, **, and *** denote significance levels of 10%, 5%, and 1% respectively. Standardized residuals are constructed by: $\varepsilon_t h_t^{-1/2}$. Null hypothesis for the Q-statistic [Ljung and Box (1978)]: no autocorrelation up to the indicated lag order. For the variance ratio tests [Cochrane (1988)] null hypothesis: series is a martingale (residuals are serially independent). The row labeled joint at max |z| is a joint test at the maximum absolute value of the z-score from lags 2 through 16, while rows at indicated lags 2 through 8 are individual variance ratio tests at indicated lags.

The information variables in this model include:

- AAII_IRR, is the error term, ξ_{it}, from decomposing the bull-bear spread from the American Association of Individual Investors (AAII) Investor Sentiment Survey using: $Sent_{1t} = \gamma_0 + \gamma_j \sum_{j=1}^{J} Fund_{jt} + \xi_{it}$, where $Sent1_{it}$ is AAII. The variables in $Fund_{jt}$ consist of several economic fundamentals including the first difference of the term premium, the default premium the (E.F. Fama & French, 1992) factors SMB, HML and Rm-Rf, the momentum factor (Jegadeesh & Titman, 1993), MOM, and the first difference of the dividend yield. This parameter represents the irrational component of sentiment of the uninformed investors.
- II_IRR, is the error term, ξ_{it}, from decomposing the bull-bear spread from the Investors Intelligence Advisors Sentiment (II) Investor Sentiment Survey using: $Sent_{2t} = \gamma_0 + \gamma_j \sum_{j=1}^{J} Fund_{jt} + \xi_{it}$, where $Sent_{2t}$ is II. This parameter represents the irrational component of sentiment from the informed investors.

Table 4.6 Panel C Model 3 - Total sentiment as information variables.

Diagnostics tests of the residuals

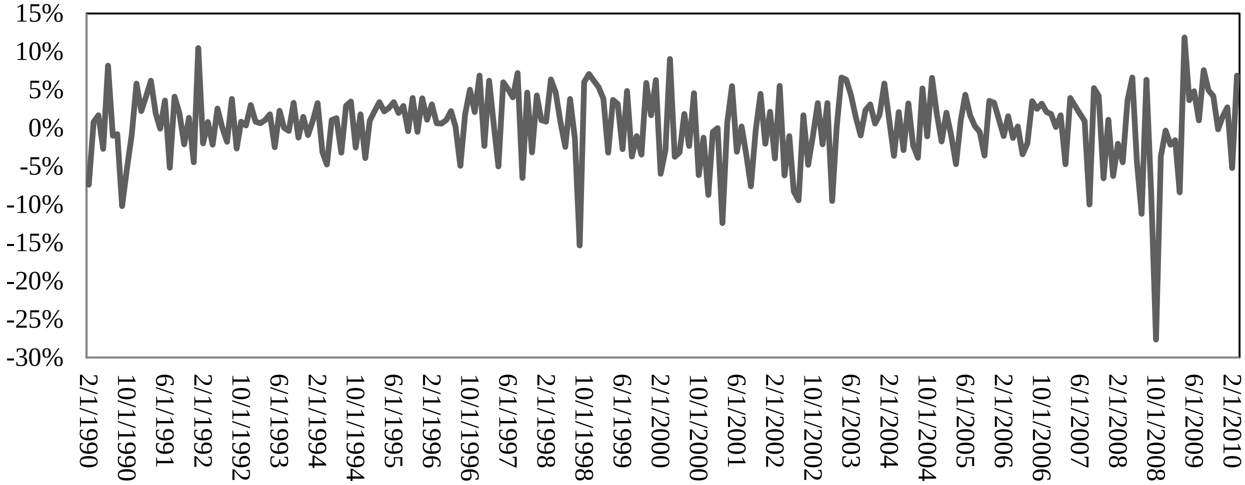
lag	Canada	France	Germany	Italy	Japan	United Kingdom	United States	World
autocorrelation: serial | partial								
1	0.131 | 0.131	0.023 | 0.023	0.011 | 0.011	-0.043 | -0.043	0.038 | 0.038	0.032 | 0.032	-0.026 | -0.026	0.029 | 0.029
2	0.073 | 0.057	-0.053 | -0.054	0.048 | 0.048	0.045 | 0.043	-0.035 | -0.036	-0.022 | -0.023	0.015 | 0.014	-0.002 | -0.003
3	0.065 | 0.049	0.113 | 0.116	0.024 | 0.023	0.055 | 0.059	0.106 | 0.109	0.075 | 0.077	0.101 | 0.102	0.068 | 0.068
4	-0.061 | -0.080	0.006 | -0.003	0.071 | 0.069	0.077 | 0.080	0.042 | 0.032	0.058 | 0.053	-0.045 | -0.040	-0.026 | -0.030
5	-0.016 | -0.005	0.006 | 0.019	0.010 | 0.006	0.035 | 0.037	0.044 | 0.050	0.099 | 0.100	0.112 | 0.108	0.096 | 0.099
6	-0.061 | -0.055	0.021 | 0.007	0.049 | 0.042	0.034 | 0.028	-0.098 | -0.112	-0.035 | -0.044	-0.053 | -0.059	-0.050 | -0.062
Ljung-Box Q-statistic (p-value)								
1	4.213** (0.040)	0.128 (0.721)	0.032 (0.859)	0.446 (0.504)	0.361 (0.548)	0.246 (0.620)	0.161 (0.689)	0.202 (0.654)
2	5.540* (0.063)	0.828 (0.661)	0.603 (0.740)	0.948 (0.623)	0.656 (0.720)	0.366 (0.833)	0.216 (0.897)	0.203 (0.903)
3	6.570* (0.087)	3.962 (0.266)	0.751 (0.861)	1.698 (0.637)	3.426 (0.330)	1.759 (0.624)	2.751 (0.432)	1.353 (0.717)
4	7.483 (0.112)	3.971 (0.410)	2.018 (0.733)	3.167 (0.530)	3.862 (0.425)	2.601 (0.627)	3.243 (0.518)	1.517 (0.824)
5	7.543 (0.183)	3.981 (0.552)	2.041 (0.843)	3.472 (0.628)	4.352 (0.500)	5.036 (0.412)	6.349 (0.274)	3.815 (0.576)
6	8.483 (0.205)	4.087 (0.665)	2.633 (0.853)	3.765 (0.708)	6.739 (0.346)	5.342 (0.501)	7.050 (0.316)	4.432 (0.618)
Variance Ratio Tests: z-score (p-value)								
joint @ max |z|	2.472 (0.184)	1.201 (0.980)	1.560 (0.850)	2.574 (0.705	1.048 (0.994)	2.145 (0.386	2.062 (0.451)	1.483 (0.892)
2	1.900* (0.057)	0.034 (0.973)	0.240 (0.811)	-0.375 (0.708)	0.658 (0.511)	0.517 (0.605)	-0.381 (0.703)	0.486 (0.627)
3	2.235** (0.025)	0.444 (0.657)	0.579 (0.562)	0.133 (0.894)	0.342 (0.733)	0.390 (0.697)	-0.166 (0.868)	0.443 (0.658)
4	2.472** (0.013)	0.647 (0.518)	0.767 (0.443)	0.610 (0.542)	0.487 (0.626)	0.640 (0.522)	0.358 (0.720)	0.642 (0.521)
5	2.312** (0.021)	0.765 (0.444)	1.054 (0.292)	1.008 (0.313)	0.683 (0.495)	0.862 (0.389)	0.438 (0.661)	0.627 (0.530)
6	2.195** (0.028)	0.874 (0.382)	1.222 (0.222)	1.307 (0.191)	0.957 (0.339)	1.217 (0.224)	0.733 (0.463)	0.879 (0.379)
7	1.994** (0.046)	0.993 (0.321)	1.398 (0.162)	1.578 (0.115)	0.932 (0.351)	1.367 (0.172)	0.818 (0.414)	0.935 (0.350)
8	1.858* (0.063)	0.993 (0.321)	1.524 (0.127)	1.697* (0.090)	0.903 (0.367)	1.456 (0.145)	0.969 (0.333)	1.005 (0.315)

*, **, and *** denote significance levels of 10%, 5%, and 1% respectively. Standardized residuals are constructed by: $\varepsilon_t h_t^{-1/2}$. Null hypothesis for the Q-statistic [Ljung and Box (1978)]: no autocorrelation up to the indicated lag order. For the variance ratio tests [Cochrane (1988)] null hypothesis: series is a martingale (residuals are serially independent). The row labeled joint at max |z| is a joint test at the maximum absolute value of the z-score from lags 2 through 16, while rows at indicated lags 2 through 8 are individual variance ratio tests at indicated lags.

The information variables in model 1 include:

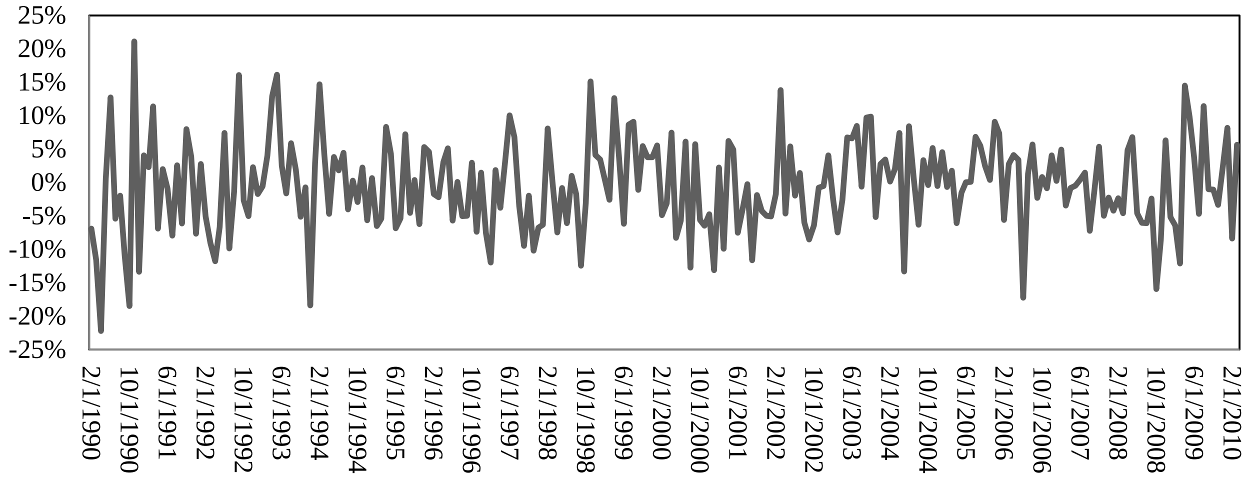
- AAII sentiment - is the bull-bear spread from the American Association of Individual Investors (AAII) Investor Sentiment.
- II sentiment - is the bull-bear spread from the Investors Intelligence Advisors Sentiment (II) Investor Sentiment Survey.

Figure 4.1 Excess Returns: U.S.



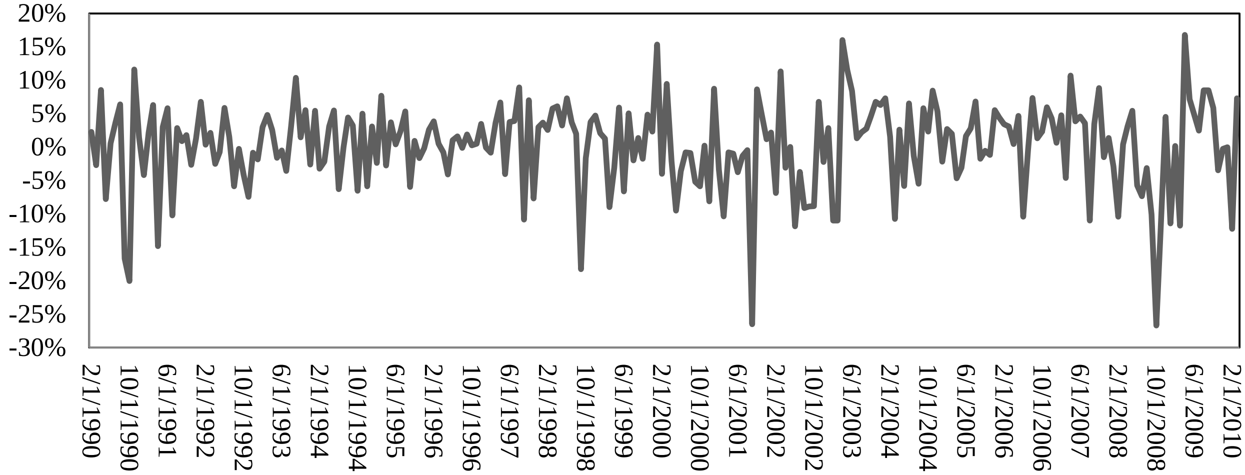
Weekly returns calculated from the price data from MSCI. Data ranges from 1990:M2 through 2010:M3.

Figure 4.2 Excess Returns: Japan



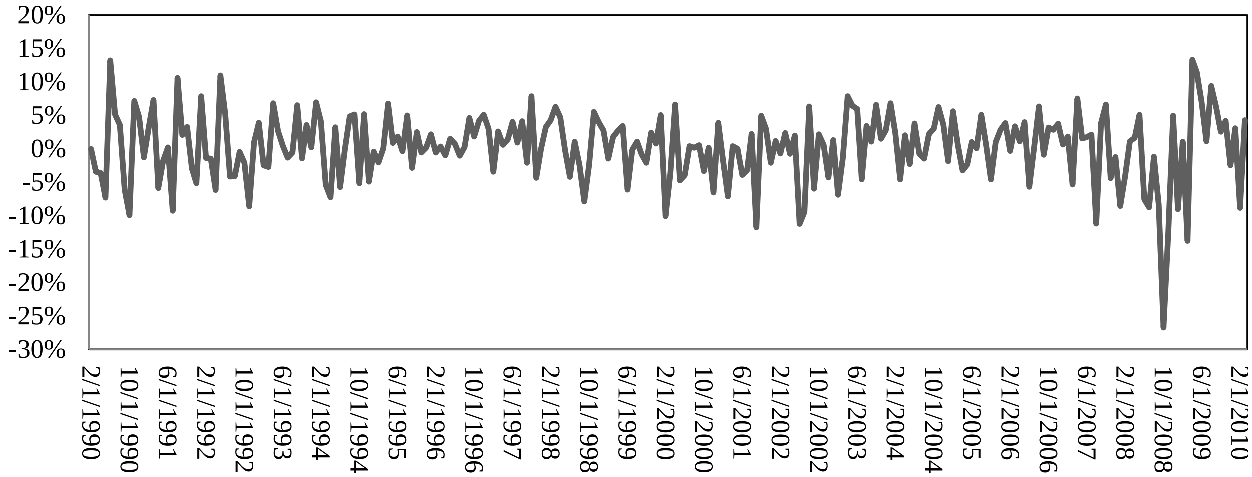
Weekly returns calculated from the price data from MSCI. Data ranges from 1990:M2 through 2010:M3.

Figure 4.3 Excess Returns: Germany



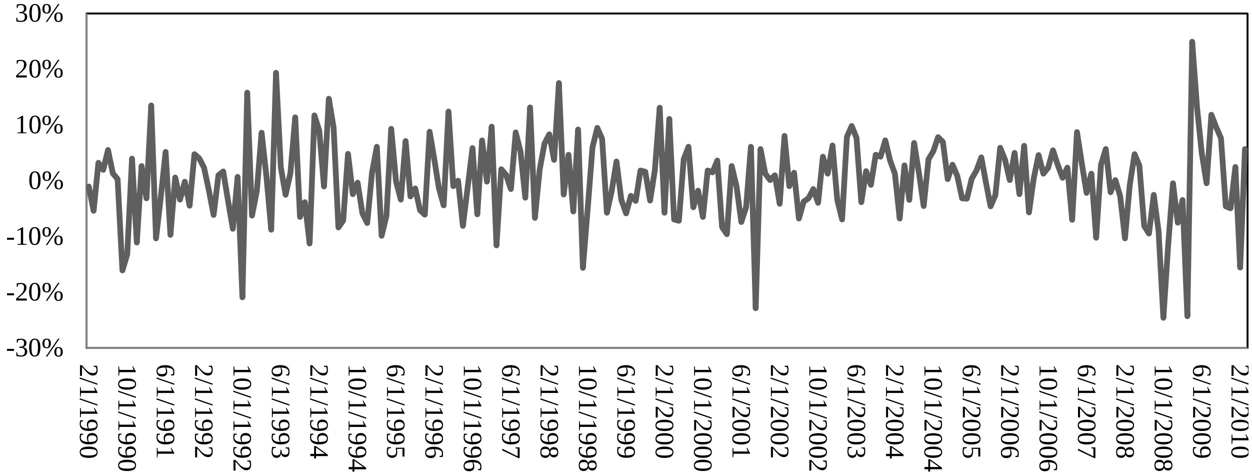
Weekly returns calculated from the price data from MSCI. Data ranges from 1990:M2 through 2010:M3.

Figure 4.4 Excess Returns: U.K.



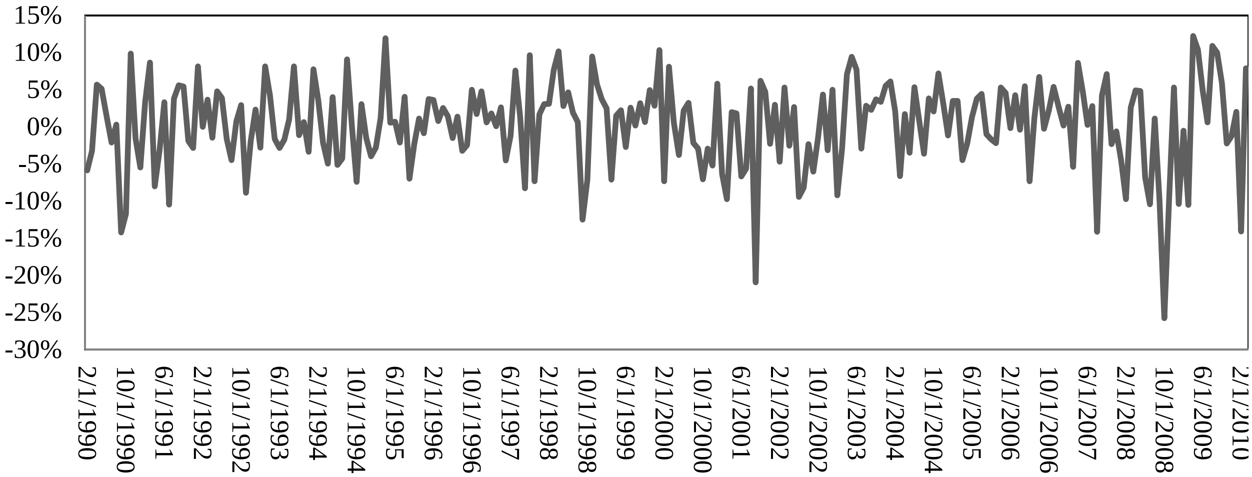
Weekly returns calculated from the price data from MSCI. Data ranges from 1990:M2 through 2010:M3.

Figure 4.5 Excess Returns: Italy



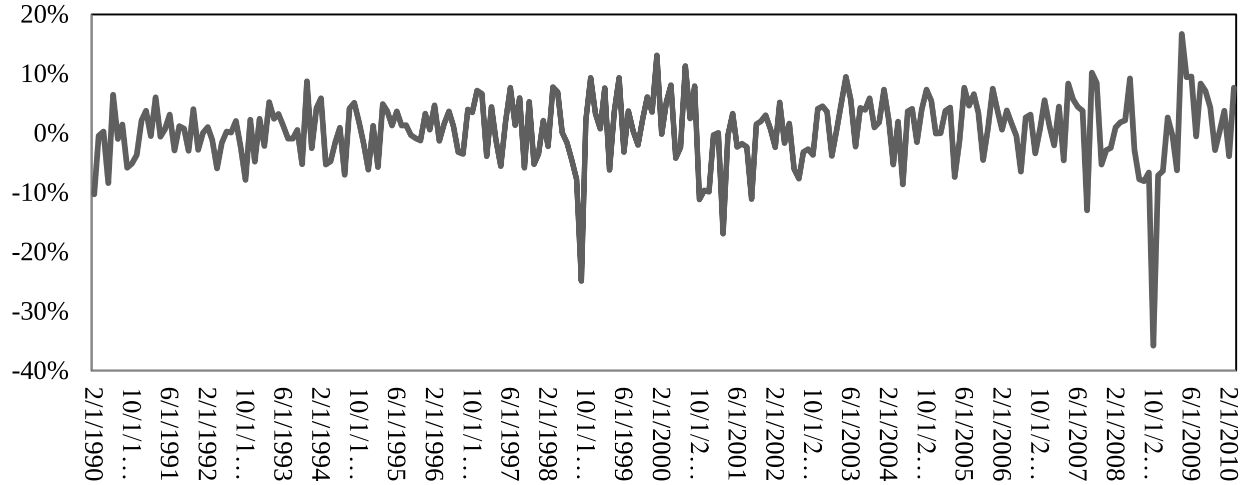
Weekly returns calculated from the price data from MSCI. Data ranges from 1990:M2 through 2010:M3.

Figure 4.6 Excess Returns: France



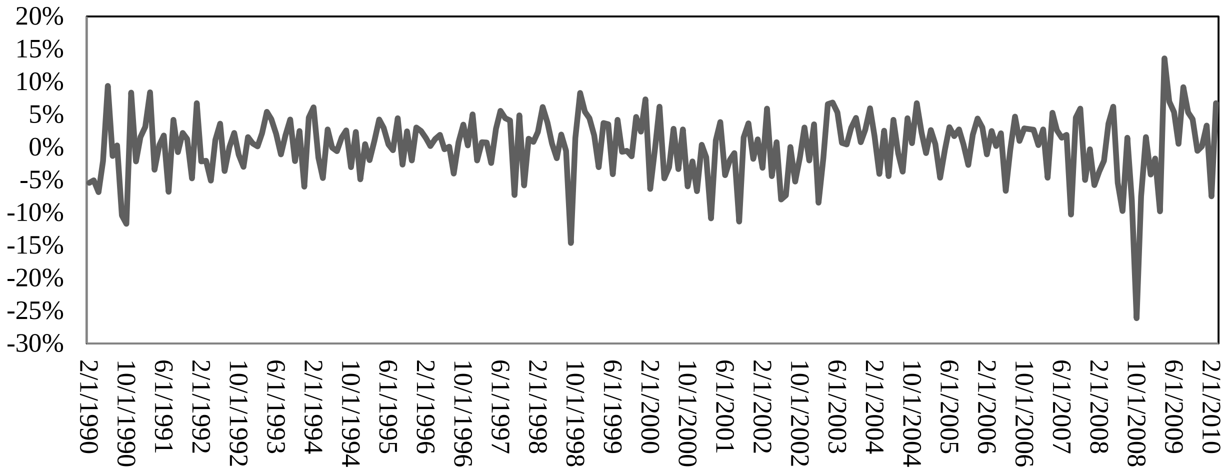
Weekly returns calculated from the price data from MSCI. Data ranges from 1990:M2 through 2010:M3.

Figure 4.7 Excess Returns: Canada



Weekly returns calculated from the price data from MSCI. Data ranges from 1990:M2 through 2010:M3.

Figure 4.8 Excess Returns: World



Weekly returns calculated from the price data from MSCI. Data ranges from 1990:M2 through 2010:M3.

Figure 4.9 Information Variables

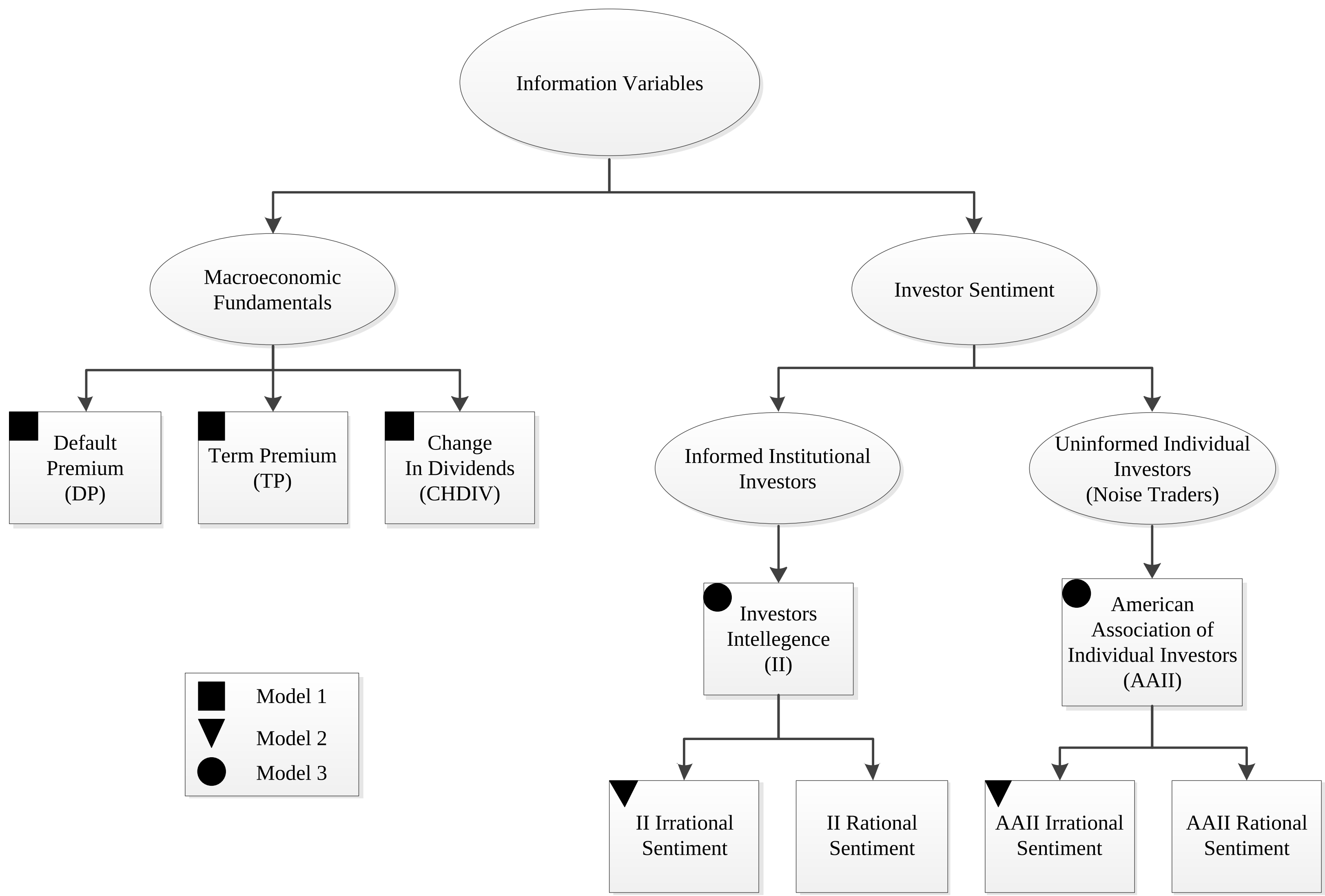
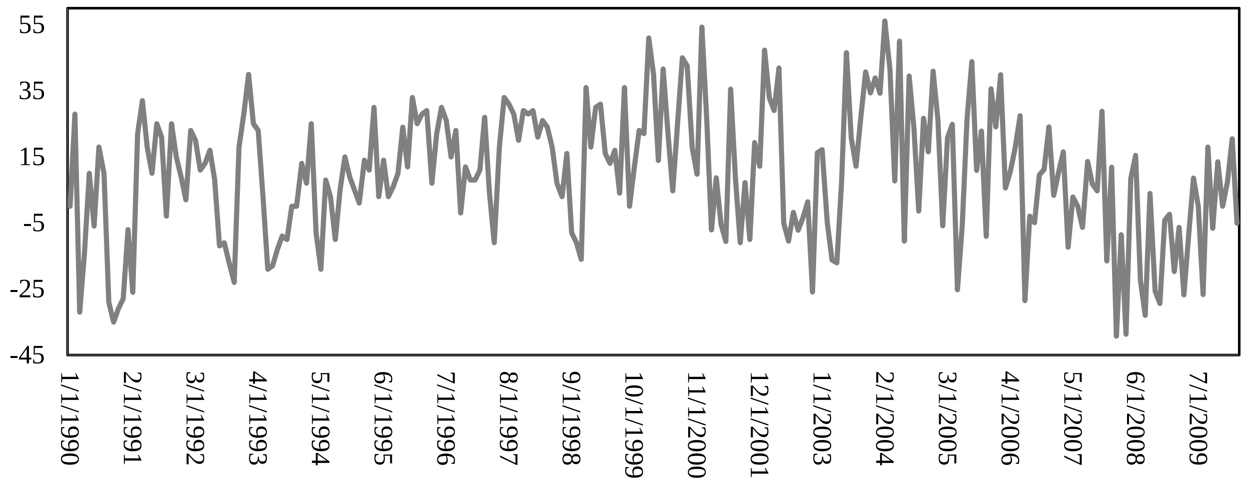
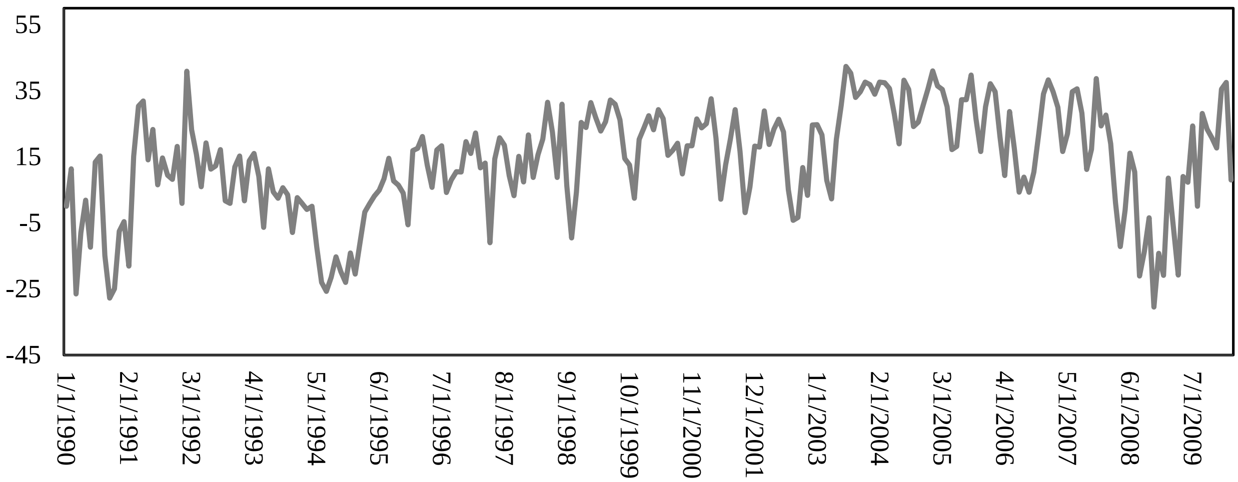


Figure 4.10 Individual Investor Sentiment (AAII) Bull-Bear Spread



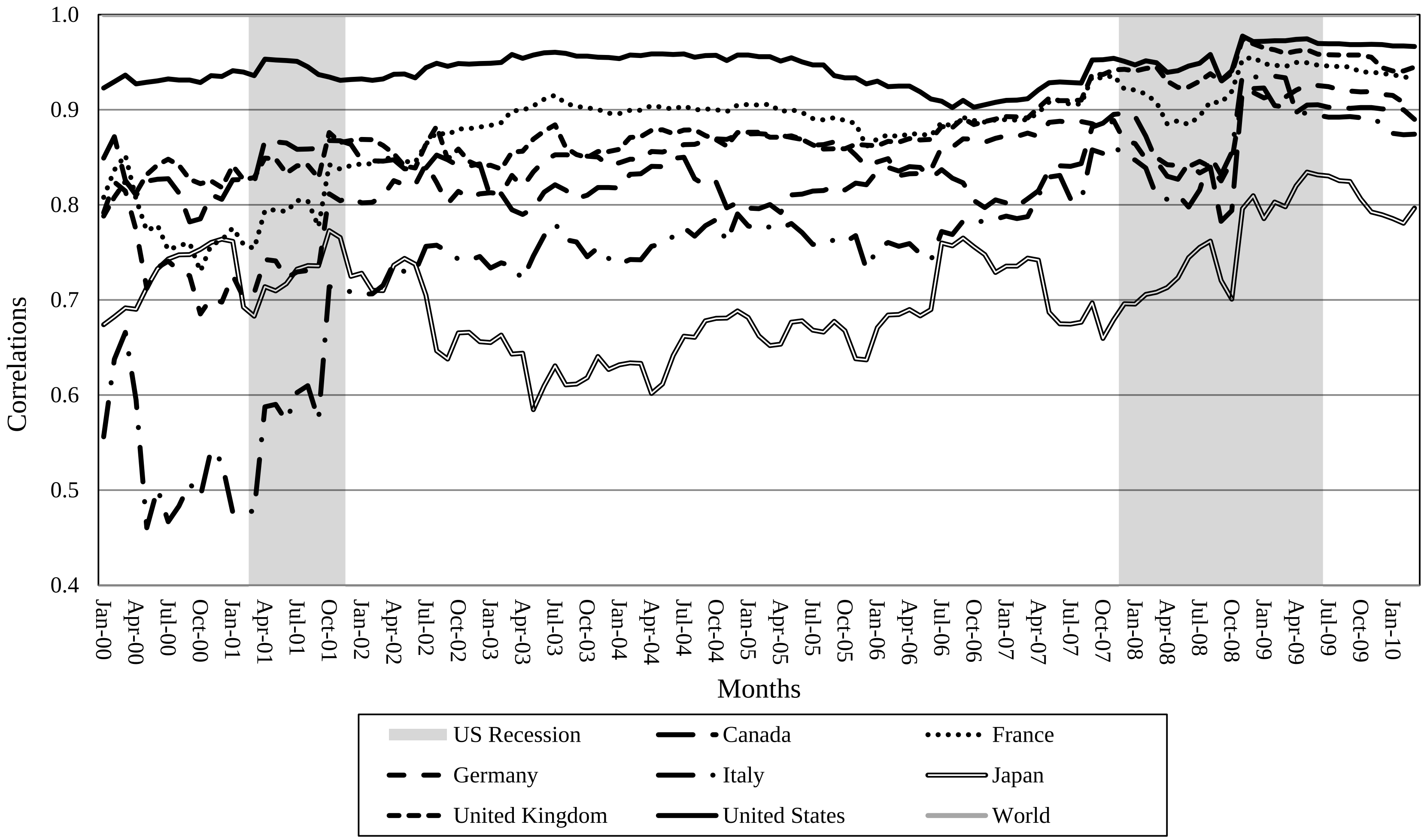
AAII Bull-Bear Spread (percent). This is calculated by subtracting the percent bearish from the percent bullish in the American Association of Individual Investors Sentiment Survey (AAII). Data is monthly in frequency ranging from 1990:M1 through 2010:M3.

Figure 4.11 Institutional Investor (II) Sentiment Bull-Bear Spread



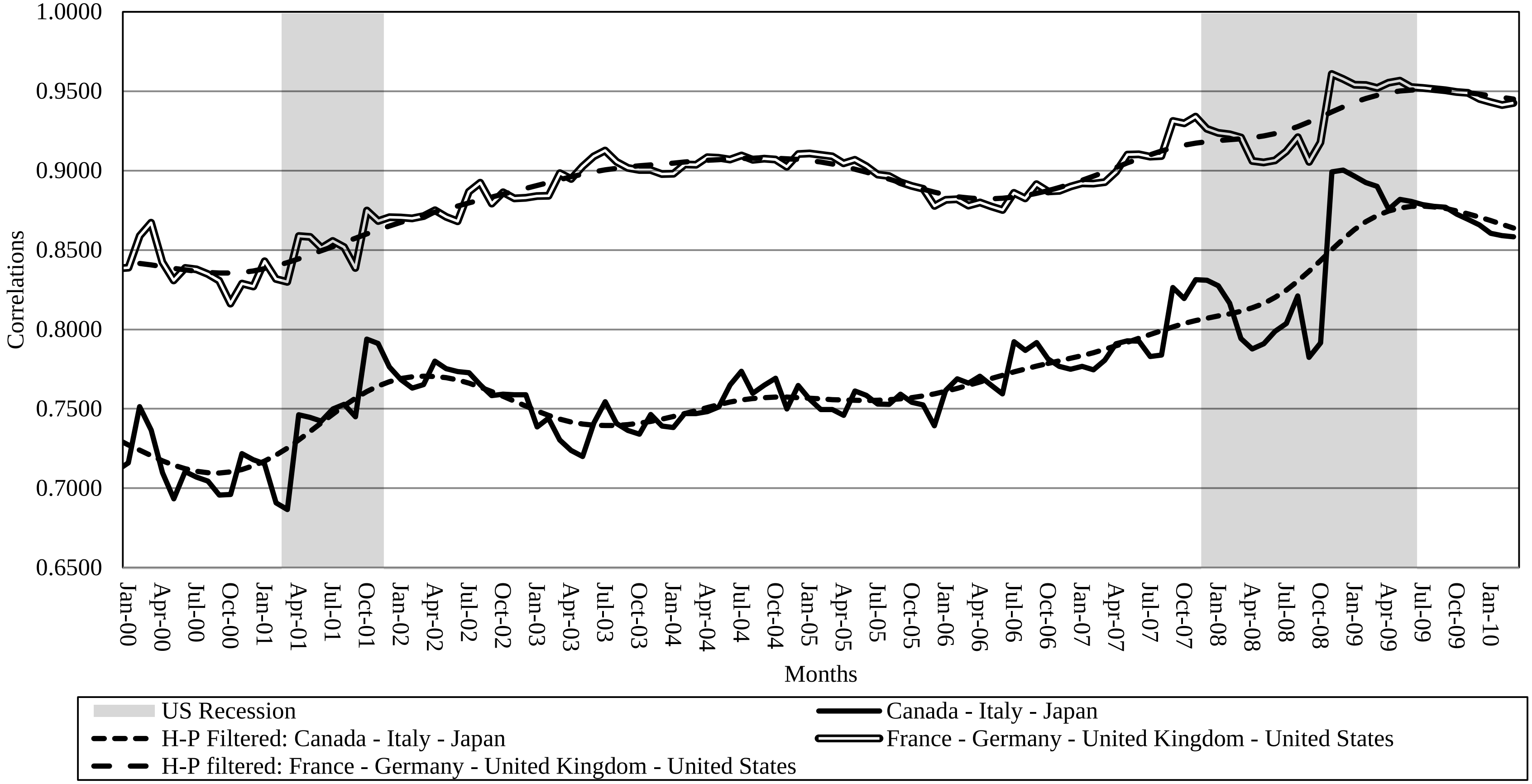
II Bull-Bear Spread (percent). This is calculated by subtracting the percent bearish from the percent bullish in the Investors Intelligence Advisors' Sentiment Report (II). Data is monthly in frequency ranging from 1990:M1 through 2010:M3.

Figure 4.12 Mean correlations with the world market.



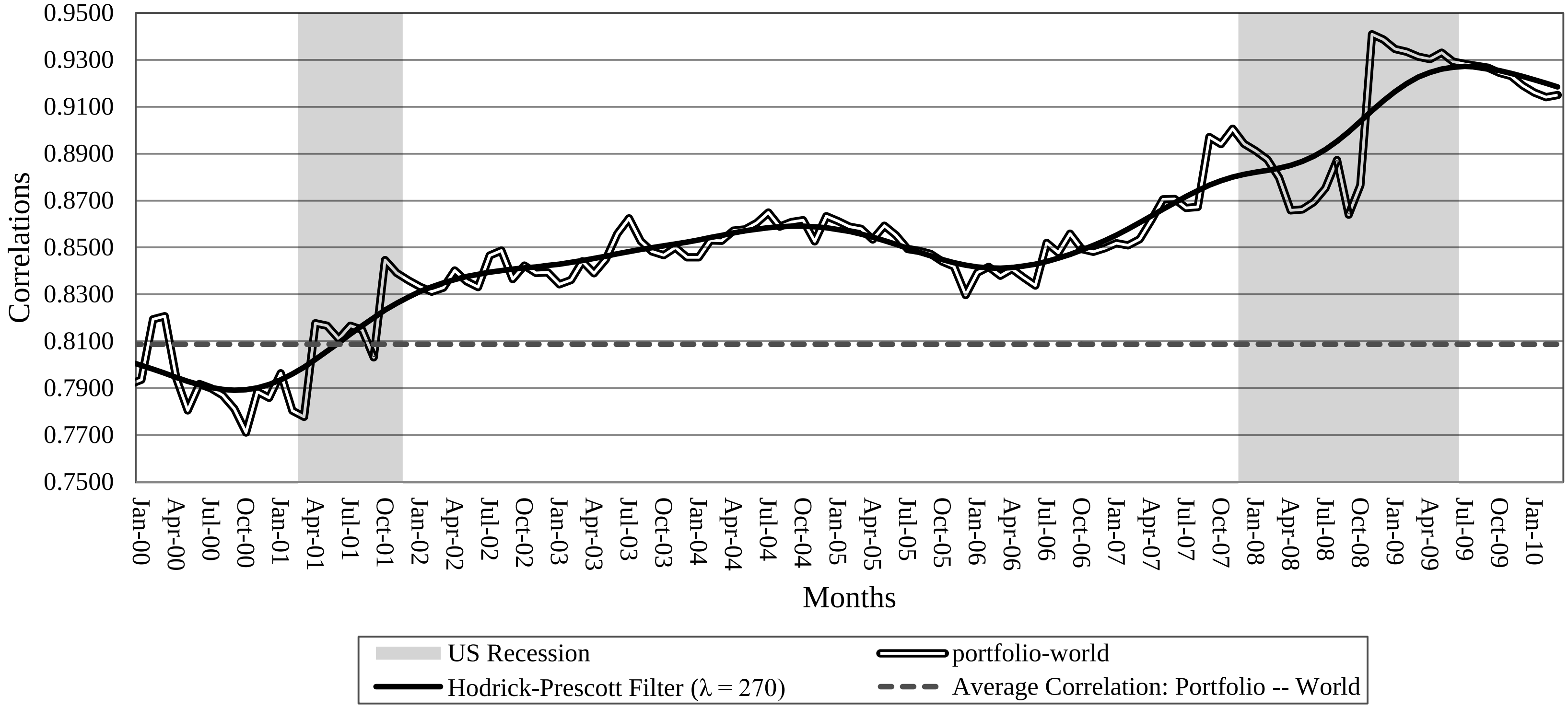
The lines represent the time varying correlations between the world and each MSCI country from the time varying CAPM from Eq. (5): $R_{it} - R_{ft} = \delta_{t-1}\,\mathrm{COV}(R_{it}, R_{mt}|\Im_{t-1}) + \varepsilon_{it}\ \forall_i$. The gray shaded chart areas represent official U.S. recessionary periods as per the National Bureau of Economic Research (NBER) retrieved from www.nber.org/cycles.html June 2011.

Figure 4.13 Grouped mean correlations with the world market



The solid and double lines represent equally weighted mean portfolio correlations (see legend) with the with the World from the time varying CAPM from Eq. (5): $R_{it} - R_{ft} = \delta_{t-1}\ \mathrm{COV}(R_{it}, R_{mt}|\Im_{t-1}) + \varepsilon_{it}\ \ \forall_i$. The groups are formed by similarity in response and magnitude (see Figure 6).The dotted and dashed lines represents the H-P filtered (Hodrick & Prescott, 1997) portfolio correlations with the world. The H-P filter isolates the cyclical component from the trend component (trend component shown). Equally weighed portfolio and mean correlations were calculated using the Fisher's z transformation as recommended by Silver & Dunlap (1987). The gray shaded chart areas represent official U.S. recessionary periods as per the National Bureau of Economic Research (NBER) retrieved from www.nber.org/cycles.html June 2011.

Figure 4.14 Entire Portfolio - Mean Correlation with the World Market



The solid line represents the time varying mean correlation between the world and an equally weighted portfolio composed of the G7 countries from the time varying CAPM from Eq. (5): $R_{it} - R_{ft} = \delta_{t-1}\,\mathrm{COV}(R_{it}, R_{mt}|\Im_{t-1}) + \varepsilon_{it} \;\; \forall_i$. The dotted line represents the H-P filtered (Hodrick & Prescott, 1997) portfolio correlation with the world. The H-P filter isolates the cyclical component from the trend component (trend component shown). The dashed line is the mean correlation of the portfolio and world over the entire time period. Equally weighed portfolio and mean correlations were calculated using the Fisher's z transformation as recommended by Silver & Dunlap (1987). The gray shaded chart areas represent official U.S. recessionary periods as per the National Bureau of Economic Research (NBER) retrieved from www.nber.org/cycles.html June 2011.

CHAPTER V

SUMMARY AND CONCLUSIONS

In chapter III of this dissertation we examine whether U.S. investor sentiment is priced in the U.S. Market using one indirect and two direct and measures of U.S. investor sentiment. For the direct investor sentiment measures we construct weekly bull-bear spreads from two investor sentiment surveys. The two surveys are the American Association of Individual Investors (AAII) sentiment survey and the Investors' Intelligence (II) institutional investor sentiment survey. The AAII survey represents sentiment from uniformed investors, often called "noise traders." The II survey is usually considered informed investor sentiment. The indirect investor sentiment measure used is the call-put ratio, which is considered to be an informed investor sentiment measure.

Furthermore, we assume the total investor sentiment measures are not entirely irrational and decompose each into their irrational and rational components by regressing a vector of macroeconomic fundamentals against the total U.S. investor sentiment measures. We use these nine measures of U.S. investor sentiment (three total, three rational and three irrational) in four models as conditioning information variables which are available to the investors at time t-1. We test a multivariate conditional CAPM with parsimonious GARCH parameterization in which correlations, betas, and the market price of risk are allowed to vary through time. The seven largest GICS sectors from the S&P 500 are used as portfolios with the entire S&P 500 a proxy for the U.S. Equity market.

In model 1 the total sentiment from the bull-bear spreads of the AAII and II surveys and the call-put ratio are used as conditional information variables. We find AAII is not related to the asset returns and the parameter estimate for II is positive and significant at a 5% level. Thus with all else equal, an increase in the bull-bear spread of informed investors increases the market price of risk. The parameter estimate for the indirect measure of informed U.S. investor sentiment, the call-put ratio is negative and significant at the 1% level. This result is opposite of the finding for that of II. This difference may be due to the fact the call-put ratio may be less “noisy” than the II measure.

In model 2 we employ the irrational and rational components of the bull-bear spreads from the AAII and II surveys as conditioning information variables. Both sentiment measures from the AAII survey are (irrational and rational) are positive and significant at the 5% level. The rational component of the informed investors (II) is negative and significant at the 10% level, while the irrational component is insignificant. This finding is important because it shows the irrational sentiment of the more informed investors does not influence asset prices while the rational component does. This makes logical sense because one would expect the irrational component of the informed investor to be small in comparison to that of their rational component and the irrational component of the uniformed investors. Both the irrational and rational components of the noise traders are priced which follows theory.

Decomposing the total investor sentiment and using only the irrational components as informational conditioning variables (Model 3) reveals irrational sentiment of both the informed and uninformed investor is priced. The irrational component of the secondary measure of informed investor sentiment is not priced.

Surprisingly, both the Clarke and the Vuong likelihood ratio tests reveal the total investor sentiment model (Model 1) is significantly closer to the “true model” than the traditional model (Model 4) which uses economic fundamentals as information variables

We observe markedly increased correlation of all GICS sector portfolios during the 2001 and 2008 U.S. recessions, while between the recessions, correlations remained relatively flat. Correlations remaining relatively flat during non-recessionary periods are reasonable. While the international markets have experienced increased market integration over the last several decades as legal barriers for international investing are reduced, the U.S. markets have few such barriers. The increased correlation during crisis periods confirms results previously found in market contagion literature. This is result is particularly important for investors who wish to diversify their investments between U.S. GICS industry sectors. The observed increased correlations, a sign of market contagion during crisis periods, would greatly decrease the expected benefits of diversification in the U.S. market.

Chapter IV explores the influence of U.S investor sentiment on international equity prices. This chapter uses basically the same econometric model as chapter III, but uses equity indices from the G7 countries and World index from MSCI. It is found U.S sentiment is not priced. We do not find U.S. investor sentiment is priced in the world market using several models.

Plotting the portfolio correlations of the G7 countries with the world market shows visual evidence of increased correlations during the two recessionary periods. Additionally, correlations of the G7 country portfolios to the world market are sloping upward, or increasing throughout the entire sample period. This increased country correlation with the world market indicates continued international market integration, due to financial liberalization and the reduction of legal barriers for international investing, as found by De Santis and Gerard (1997). This implies continued decreased benefits of international diversification over the last decade, and an increased risk of international contagion effects.

Some future extension to this research would be: a) include exchange rate risk in the international model, b) include a term for asymmetric volatility to study leverage effects by adding a $\boldsymbol{cc}' * \boldsymbol{\nu_{t-1}\nu'_{t-1}}$ term to Eqs. (3.5) and (4.5) as follows:

$$\boldsymbol{H}_t = \boldsymbol{H}_0 * (\boldsymbol{\iota\iota}' - \boldsymbol{aa}' - \boldsymbol{bb}') + \boldsymbol{aa}' * \boldsymbol{\epsilon}_{t-1}\boldsymbol{\epsilon}'_{t-1} + \boldsymbol{bb}' * \boldsymbol{H}_{t-1} + \boldsymbol{cc}' * \boldsymbol{\nu_{t-1}\nu'_{t-1}} \tag{5.1}$$

$$\boldsymbol{\nu_{t-1}} = \text{Max}[\boldsymbol{0}, -\boldsymbol{\epsilon}_{t-1}] \tag{5.2}$$

c) test if investor sentiment Granger-causes asset prices, d) include China in the international model if data is available, e) develop an international investor sentiment index using principle component analysis and decompose it into its irrational and rational components to test if international measures of investor sentiment are priced in the world market, and e) use the full sample estimates of the market price of risk to estimate a VAR model similar to Soydemir (2005). The VAR would be used to study contagion effects and how shocks to the market price transmit to other markets.

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BIOGRAPHICAL SKETCH

Mr. Johnk graduated from North Dakota State University in 1984 with a Bachelor of Science degree in Mechanical Engineering. After graduating he proceeded to work in the business world, eventually becoming an expert in metals and electronics manufacturing. During this time he worked under various positions of increasing responsibility, holding job titles such as Manufacturing Engineer, Manufacturing Engineering Manager, Senior Engineering and Operations Manager, Site Manager, and Plant Manager. He acquired a great deal of international experience during that time, working for maquiladoras (assembly plants located across the border in Mexico, which legally cross parts for assemble, while only being charged import/export taxes on the assembly labor while in Mexico).While working in the business world, he went back to school part-time and earned a Master of Science degree in Management of Technology from the University of Texas at San Antonio, graduating in 1998.

Several years ago he began working full-time on his Ph.D., the completion and defense of this dissertation being the end of that long journey. Upon graduating he is looking forward to finding a tenure-track assistant professorship position in the subject area of finance, where he can continue to teach and do research. Mr. Johnk's research interests include investor sentiment, asset pricing, international finance, and consumer credit default modeling. He has peer-reviewed journal publications in the *North American Journal of Finance and Banking Research* and the *International Journal of Services and Standards*. His research has been presented at several conferences including the Southern Finance Association and Midwest Finance Association. You may contact Mr. Johnk at: djohnk@gmail.com.