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Two essays on the impact of rational and irrational investor sentiments on equity market return and volatility: Evidence from the U.S. and Brazil

Pablo Javier Calafiore
University of Texas-Pan American

TWO ESSAYS ON THE IMPACT OF RATIONAL AND IRRATIONAL INVESTOR SENTIMENTS ON EQUITY MARKET RETURN AND VOLATILITY: EVIDENCE FROM THE U.S. AND BRAZIL

A Dissertation

by

PABLO JAVIER CALAFIORE

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PABLO JAVIER CALAFIORE

Committee Members:

Dr. Gökçe Soydemir
Chair of Committee

Dr. Damian Damianov
Committee Member

Dr. Jan Smolarski
Committee Member

Dr. Dan Sutter
Committee Member

August 2010

ABSTRACT

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This dissertation consists of two essays on how investor sentiments affect the returns and volatility of the Brazilian stock market. Both essays share a similar methodological approach. The first one analyzes the effect of investor sentiments on the returns and volatility of the Brazilian stock market using a model that accounts for fundamentals (rational) and noise components (irrational) of investor sentiments on the Sao Paulo leading index Bovespa. This research finds a statistically significant positive (negative) impact of rational (irrational) sentiments on market returns. Moreover, there are statistically significant impacts of irrational components of the sentiment indexes on Bovespa volatility with immediate positive responses of the stock market volatility to irrational sentiments of investors but negative responses of stock market volatility to rational sentiments of investors corrected by positive responses in the upcoming periods. The results support the view that irrational sentiments of investors may be strong enough to impact the stock market returns and volatility. In addition we document an asymmetric impact of changes in sentiments on market returns and volatility.

In the second essay we focus on how rational and irrational sentiments of the U.S. individual and institutional investors affect stock market returns and volatility of an emerging market such as Brazil. In line with previous research for developed markets, the impact of rational sentiments on stock market returns is found to be greater than that of irrational

sentiments. There are immediate positive responses of Bovespa market returns to rational sentiments but insignificant responses to irrational sentiments while positive effects of past stock market returns on irrational sentiments but not on rational sentiments. There are negative responses of Bovespa market volatility to rational sentiments and no significant effect to irrational sentiments. Overall, these results support the economic fundamentals based arguments of stock returns providing limited evidence in favor of U.S. irrational sentiments impacting Bovespa returns and volatility

DEDICATION

Para Roxana y Gennarino. A mis padres.

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CHAPTER I

THE IMPACT OF BRAZILIAN INVESTOR SENTIMENT ON BOVESPA RETURNS AND VOLATILITY

1.1 Introduction

There is an increasing debate in the finance literature on whether noise traders acting as a group can influence stock prices and move them away from fundamentals. General noise trader models in finance provide evidence that it is possible for a group of investors who make decisions based on unrelated variables and not on variables associated with the company's fundamentals to affect stock prices. In the noise trader model of DeLong, Shleifer, Summers, and Waldmann (DSSW) (1990) a group of noise traders following signals produced by non-fundamental variables can influence prices beyond the short term and introduce a systematic risk component that is incorporated into asset prices. These price deviations from fundamentals are randomly derived from changes in investor sentiment. DSSW model of investor behavior shows that when noise traders are more bullish than informed investors, market volatility (as measured by the conditional variance) increases.

Most of the existing research focuses mainly on the impact of sentiments on stock returns. Therefore, authors analyze the first moment correlations between several alternative measures of sentiments and stock market returns. However, the effects of sentiments on stock return volatility or on second moments have not been thoroughly addressed. Verma & Verma (2007) analyze the effect of individual and institutional investor sentiments on the formation of conditional volatility for the U.S. stock market. They find significant negative effects for both

types of investor sentiments on stock volatilities and that investor errors are significant contributors of stock volatilities.

In the spirit of Verma & Verma (2007) this essay studies the impact of Brazilian investor sentiment on the returns and volatility of the Brazilian stock market. Using the theoretical noise trader framework provided by DSSW (1990), this research identifies whether rational risk factors, which are based on fundamentals, or noise trading which originate on unrelated variables, have an asymmetric impact in the Brazilian market return and volatilities for individual investor sentiments. Investor sentiments are difficult to measure since they are unobserved. The literature present several alternative measures for sentiment. This study uses the Brazilian consumer sentiment index as proxy for investor sentiment.

The major contributions of this chapter to the existing literature are fourfold. First, contrary to previous studies who only analyze developed markets, this is the first one to test the impact of individual investor sentiments on an emerging stock market conditional volatility. Second, this analysis separates rational sentiments based on fundamentals from irrational sentiments based on noise and considers their relative impact on the returns and volatility of the Brazilian stock market. Third, since the response of individual investor sentiments may be different depending on the stock market direction, this study explores the asymmetrical reaction of both types of sentiments on stock returns and volatility during bullish and bearish markets. Lastly, the effects of investor sentiments on stock market returns and volatility are investigated simultaneously in one model to differentiate between the two types of investor sentiments.

The results of the generalized impulses from VAR models present evidence for the following empirical results: First, the effect of a once and for all increase in rational investor sentiments on Bovespa returns is positive and significant during the first month and insignificant

thereafter while for irrational sentiments the effect is negative and significant lasting for about two months. Second, irrational investor sentiment has a greater effect on market returns than rational investor sentiment suggesting that irrational investor sentiments do have the potential to influence stock market returns consistent with DSSW model. Third, a one standard deviation positive shock to rational investor sentiments leads to a significant decrease in Bovespa index volatility during the first two months while a similar shock to irrational investor sentiments tends to significantly increase market volatility around the time of the second month, showing a delayed reaction. Lastly, rational sentiments have a more profound effect than irrational sentiments on Bovespa volatility providing evidence that economic fundamentals play a larger role in determining stock market returns and volatility. These findings are robust to different model specifications.

Results from this study have useful implications for policymakers and investors. Investors could improve their portfolio performance by regarding both rational and irrational sentiments as influencing stock returns and volatilities. It is important to establish the impact of non-fundamentals variables on conditional market volatility because volatility estimates are used in determining the prices of certain financial derivatives like stock options. Furthermore, knowing whether sentiment has disparate effects on volatility during bullish or bearish markets may assist investors in their portfolio decisions and policymakers when establishing new regulations since sentiment may be a factor affecting asset prices.

The remainder of this chapter is organized as follows: Section 1.2 reviews the existing literature on sentiments, stock prices and volatility while Section 1.3 presents the model. Section 1.4 presents the data and descriptive statistics. Section 1.5 describes the econometric methodology. Section 1.6 reports the empirical findings. Finally, section 1.7 concludes.

1.2. Literature Review

1.2.1 Noise traders and investor sentiment

Several studies suggest that investor sentiment and trading activities of noise traders influence stock prices. Chuang and Lee (2006) find that overconfident investors overreact to private information, underestimate risk and trade more aggressively increasing overall market volatility. The noise trader model of DSSW (1990) suggests that a group of noise traders, following signals produced by non-fundamental variables, can affect asset prices beyond the short term and introduce a systematic risk factor that is included in asset prices. This model shows that when noise traders are more bullish than informed investors, market volatility (as measured by the conditional variance) increases.

Research examining the influence of sentiments on stock returns based on the noise trader model of DSSW (1990) such as Brown and Cliff (2004, 2005); Lee, Jiang, and Indro (2002); Fisher and Statman (2000); Clarke and Statman (1998); Solt and Statman (1988); DeBondt (1993), provide evidence for the existence of strong comovements between investor sentiments and stock market returns. One of the major shortcomings in these studies of investor sentiment is that they fail to explain whether the effect of sentiment on market returns can be attributed completely to investor high spirits or to rational expectations or to a mixture of both. In general, these studies infer that sentiment is fully irrational. One of the first studies analyzing the simultaneous impact of sentiments of investors on U.S. stock market returns is Verma, Baklaci and Soydemir (2008) who find that rational sentiment has a larger impact than irrational sentiment on stock market returns. Using a VAR-GARCH model, Verma & Verma (2007) find

that rational sentiments have a larger impact on stock volatility than irrational investor sentiments for the U.S. stock market.

1.2.2 Investor Sentiment Measures

Investor sentiments are difficult to gauge since they are unobserved. The literature presents alternative measures of investor sentiments with varying results depending on the proxy selected. These measures include retail investor trades, mutual funds flow and cash position, market liquidity, closed-end fund discounts, option implied volatility, first-day returns on initial public offerings (IPO), IPO volume, equity issues, dividend premium, insider trading activity, combined set of measures, and surveys. Below there is a brief description of the major proxies for sentiments providing evidence for the choice of consumer confidence index as representative of individual investor sentiment for Brazil.

Retail Investor Trades: Using micro trading data, Kumar and Lee (2006) find support for noise trader models where systematic trading by retail investors explains return comovements for small-cap stocks with low-institutional ownership. Their results suggest that small investor sentiment, as measured by changes in a portfolio of certain basket of stocks, plays a role in determining market returns. Barber, Ocean, and Zhu (2009) employ TAQ/ISSM data to find that individual investors herd by systematically buying stocks with strong recent performance and with high trading volume. Similarly, Jackson (2004) finds that the trading of individual investors on the Australian stock market is coordinated. The inexperienced retail investor is more likely to be affected by market sentiment than the professional institutional investor.

Mutual Fund Flows and Cash Position: Studies that use the percent in cash held by mutual funds as a measure of sentiments include Gup (1973) and Branch (1976). These authors

argue that whenever mutual funds present an increasing cash position can be considered a bullish signal since mutual funds have cash to invest in equities; on the other hand, a decreasing cash ratio may be interpreted as a bearish sign since they are withholding funds from the market. Neal and Weahtley (1998) find that net mutual fund redemptions predict the size premium. Brown, Goetzmann, Hiraki, Shiraishi, and Watanabe (2002) and Randall and Tully (2003) suggest that daily mutual fund flows may be financial instruments for investor sentiment in the stock market. Frazzini and Lamont (2008) find that high individual investor sentiment, as proxied by mutual fund flows, predicts low future returns. Canbas and Kandir (2009) explain that mutual fund flows, used as estimates of investor sentiments, do not help predict future aggregate market returns in Turkey.

Market Liquidity: Other set of studies use market liquidity as an estimate of investor sentiment. For instance Amihud (2002) and Jones (2002) use trading volume, which is closely associated with market liquidity, to show that increased liquidity is associated with lower future returns. Baker and Stein (2004) present a model where overconfident noise traders are more likely to trade when they are optimistic than when they are pessimistic, using the bid-ask spread and share turnover as liquidity measures. Other measures of market liquidity include the price of a NYSE seat (Keim and Madhavan, 2000) which tends to increase in periods of high investor sentiment and the market turnover ratio (Baker and Wurgler, 2006) which also tends to increase when investor sentiments are high. However, in the latter case, the market turnover ratio does not seem to affect future stock returns.

Closed-end fund discounts: This is one of the earliest proxies for investor sentiment developed in the literature (Lee, Shleifer, and Thaler, 1991; Chopra, Lee, Schleifer, and Thaler, 1993; Swaminathan, 1996; Neal and Weahtley, 1998). Closed-end fund shares selling at prices

different from the fund Net Asset Value has given rise to the use of the discount or premium in closed-end fund shares as an indicator of individual investor sentiment. When investors are bearish, closed-end fund shares sell at a discount; on the contrary, fund shares sell at a premium when investors are bullish. Recent evidence (Brown and Cliff, 2004; Qiu and Welch, 2006; Baker and Wurgler, 2006; Lemmon and Portniaguina, 2006; Canbas and Kandir, 2009), however, suggest that closed-end fund discounts may not be a surrogate measure of investor sentiment.

Other sentiment measures: Dennis and Mayhew (2002) use the put-call parity ratio where a high ratio with large trading volume in puts indicates strong bearish sentiment and the prospect of a market bottom. Baker and Wurgler (2000) show that increases in corporate equity issuance participation on the total capital raised by a corporation, envisages lower stock market returns. Baker and Wurgler (2006) use the first-day return on IPOs which tends to be closely related to IPO volume since initial demand for IPOs tend to be larger during bullish market periods. One of the most widely used measures of volatility for U.S. markets is the market volatility index (VIX) obtained from the daily spread between options traded at the CBOE. The VIX is a measure of implied volatility of the S&P500 over the next 30 days representing expectations about future market fluctuations. Whaley (2009) suggests that the VIX can be interpreted as an investor fear gauge given that options prices tend to rise when the value of the underlying asset has greater expected volatility. In general, high VIX values imply higher volatility in the short term and investors demanding higher returns. Kaplanski and Levy (2009) introduce the Risk Sentiment Index as a measure of the residual risk contained in the VIX after considering the economic variables most predictive of future stock market volatility. Their results suggest that VIX may

contain an irrational component of risk, which is negatively related to stock returns, that rational investors may not have fully exploited.

Some studies create a combination of sentiment measures. Bandopadhyaya and Jones (2006) develop a regional equity market sentiment index based on historic volatility to explain short term stock price movements. Building an index based on the first principal components of several sentiment measures, Baker and Wurgler (2007) find that sentiments have a stronger effect on small-firm securities, which tend to be less liquid, difficult to arbitrage, and have a higher ownership by small investors. Small investors are closely linked with noise traders since they are more likely to be less informed than institutional investors.

Lastly, one of the most common ways of estimating investor sentiments consists of surveying market participants directly. These include consumer, individual and institutional investor sentiment surveys, among others. Fisher and Statman (2003) offer evidence of positive correlation between consumer confidence indexes and the investor sentiment index compiled by the American Association of Individual Investors (AAII) over the 1987-2000 period. Brown and Cliff (2004, 2005) and Kalotay, Gray, and Sin (2007) use three different survey measures (the Conference Board Consumer Confidence Index, the Investors' Intelligence Survey Index, and the University of Michigan Consumer Sentiment Index, UMichCCI) as proxies for investor sentiment in the U.S., finding that these indices help predict stock returns. Brown and Cliff (2005) find a negative relationship between sentiments and returns on the aggregate U.S. market. Using the same three sentiment measures, Ho and Hung (2009) show that including investor sentiment in asset pricing models helps capture the value, liquidity, and momentum effects on individual stock returns for the U.S. Chen (2008) suggests that including consumer confidence measures (such as UMichCCI) help the prediction of bear stock markets. Charoenrook (2003)

present evidence that changes in consumer confidence improve forecasts of aggregate market returns for the U.S. Qiu and Welch (2006) show that the UMichCCI is closely correlated with a direct measure of investor sentiment, such as the UBS/Gallup Survey of Investor Sentiments, whereas the closed-end fund discount is not correlated with investor sentiments measures. Schmeling (2006) finds that individual investor sentiment significantly impact aggregate market returns in Germany. In a recent study, Schmeling (2009) runs a panel of 18 industrialized countries and finds that consumer confidence, as a proxy for individual investor sentiment, affects the expected stock returns. He shows that irrational noise trader sentiment drives price away from their fundamentals-based pricing; moreover, he uncovers that when sentiment is high, future stock returns tend to be lower and vice versa.

Several authors (Baker and Wurgler, 2006; Lemmon and Portniaguina, 2006; and Brown and Cliff, 2005) contend that consumer sentiment indexes contain an irrational factor which makes them appropriate to measure noise trader sentiment. Doms and Morin (2004) present evidence that consumer confidence measures partially contains an irrational element given that at times consumer sentiment seems to be pushed away from what economic fundamentals would imply with consumers responding more to the tone and volume of news reports than by the content of news. Qiu and Welch (2006) assert that consumer sentiment should invariably be related to some macro variables or to returns given that investors become optimistic or pessimistic due to an array of positive or negative news.

The results described above provide evidence that consumer sentiment surveys, especially those based on the UMichCCI, are a good proxy for individual investor sentiments. In addition, not all sentiments have to be considered irrational given that the sentiment measure seems to incorporate both rational and irrational elements. The present study uses the monthly

Brazilian Consumer Confidence Index (ICC) compiled by the Federaçao do Comercio do Estado de São Paulo (FCESP) as a proxy for investor sentiment in the Brazilian stock market.

This study contributes to the current literature in a variety of ways. First, this is the first analysis conducted to test the impact of individual investor sentiments on an emerging stock market conditional volatility. Second, this study divides investor sentiments into rational sentiments based on fundamentals and irrational sentiments based on noise and considers their relative impact on the returns and volatility of the Brazilian stock market. Third, this analysis explores the asymmetrical reaction of both types of investor sentiments on stock returns and volatility during bullish and bearish markets. Lastly, this research considers the effects of investor sentiments on stock market returns and volatility simultaneously in one model.

1.3 Model

Given that sentiments partially contain rational expectations-based risk factors (Brown and Cliff, 2005, Shleifer and Summers, 1990), it is very likely that stock returns are affected by both fundamental and noise sentiments of sentiment. Hirshleifer's (2001) model relates expected returns to both risks and investor misvaluation. When an investor is bullish or bearish, then this could be a rational reflection of future period's expectation or irrational enthusiasm or a combination of both. Hence, first investor sentiment is decomposed into two elements: (i) rational sentiment based on the market fundamentals and (ii) irrational sentiment based on noise. Gobuleva and Uysal (2009) extract the non-fundamental component of consumer perception by regressing the UMichCCI readings on a set of macroeconomic variables. This approach is consistent with Chauvet and Guo (2003), Qiu and Welch (2006), Baker and Wurgler (2006), Lemmon and Portniaguina (2006), Dunn and Mirzai (2007), Verma *et al* (2008), and Schmeling

(2009) to name a few. Macroeconomic risk factors are regressed on sentiments in order to obtain a measure of irrational investor sentiment which is unrelated to macroeconomic factors[1]. We formulate equation (1.1) and model the rational and irrational effects of fundamentals and noise, respectively, on investor sentiments:

$$Sentt_{1t} = \gamma_0 + \sum_{j=1}^{J} \gamma_j Fund_{jt} + \xi_t \qquad (1.1)$$

where γ_0 is a constant, γ_j is the parameter to be estimated; and ξ_t is the random error term. $Sentt_{1t}$ represents the shifts in investor sentiments at time *t*. $Fund_{jt}$ is the set of fundamentals representing rational expectations based on risk factors that have been shown to carry non-redundant information in the asset pricing literature. The fitted values of equation (1.1) capture the rational sentiment of investors (for example $\hat{Sentt}_{1t}$). On the other hand the residual of equation (1.1) captures the irrational sentiment of investors (for example ξ_t).

Next, this work analyzes the extent to which Bovespa stock returns are affected by investor sentiments. Investor sentiments may be rational or irrational. Therefore, the sentiment variables are decomposed into the rational and irrational sentiments based on equation (1.1) and included in the return generating process as:

$$R_t = \alpha_0 + \alpha_1 \hat{Sentt}_{1t} + \alpha_2 \xi_t + \alpha_3 \sigma_t + \rho_t \qquad (1.2)$$

where α_0 is a constant while α_1 and α_2 are the parameters to be estimated; ρ_t is the random error term. The parameter α_1 captures the effects of sentiments induced by fundamental trading on the part of investors; while α_2 captures the effects of sentiments induced noise trading by investors. The parameter α_3 captures the monthly volatility of Bovespa

[1] Qiu and Welch (2006) mention the possibility for consumer confidence measures to capture some important macroeconomic information that is not included in the set of economic variables used to estimate the rational sentiments of individual investors.

Lastly, this research examines how investor sentiments affect Bovespa volatility. This study uses the standard deviation of the past month continuously compounded returns to determine this month's volatility[2] (trailing one-month realized volatility). The continuously daily compounded returns for Bovespa are estimated using the formula $u_t = \ln(R_t) - \ln(R_{t-1})$ where u_t is the continuously compounded return between the end of day *i* and between day *i-1*. To calculate an unbiased estimate of the standard deviation rate per day, σ, using the most recent *m* observations on the u_t the following formula is applied: [3]

$$\sigma_t = \sqrt{\frac{1}{m}\sum_{i=1}^{m} u_{t-1}^2} \tag{1.3}$$

In order to analyze the impact of investor sentiments on the volatility of Bovespa, the sentiment variable is separated into rational and irrational based on equation (1.1) and incorporated in the following equation:

$$\sigma_t = \alpha_0 + \alpha_1 \hat{Sentt}_{1t} + \alpha_2 \xi_t + \rho_t \tag{1.4}$$

where σ_t is the one-month trailing volatility for Bovespa as estimated using equation (1.3); α_0 is a constant while α_1 and α_2 are the parameters to be estimated; ρ_t is the random error term. The parameter α_1 captures the effects of sentiments induced by fundamental trading on the part of investors; while the parameter α_2 captures the effects of sentiments induced noise trading by investors.

[2] One of the most popular ARCH-GARCH models used to represent volatility is Bollerslev's GARCH (1,1). The choice of historical monthly standard deviation is based on Ederington, Louis and Guan (2006) who suggest that historical standard deviation as a measure of volatility performs just as well as a GARCH (1,1) model.

[3] For details on estimating volatility see Hull (2006) pp. 461-462.

1.4. Data, Descriptive Statistics, and Characteristics of the Sao Paulo Stock Exchange

This section describes the data and the variables used in the empirical analysis; then we present summary statistics showing certain characteristics of the data, and lastly we portray a brief history of the Sao Paulo Stock Exchange.

1.4.1 Data

The data is in monthly intervals and cover from March 1995 to October 2009. This time period was selected because it avoids excessive fluctuations that experienced some Brazilian macroeconomic variables before the successful Plano Real, the early 1994 economic stabilization program launched by the Brazilian government which tamed inflation, and the late 1994 Mexican peso devaluation. There is complete data for all observations during the chosen period. All data is from Datastream Advance. We use the monthly Brazilian Consumer Confidence Index (ICC) compiled by the Federaçao do Comercio do Estado de São Paulo (FCESP) as a proxy for Brazilian investor sentiment. The ICC is produced monthly for the FCESP in the metropolitan region of São Paulo, Brazil's largest city. Being published since 1994, the ICC is the oldest confidence indicator for Brazil. This index evaluates how people's perception about the general situation of the country and their future economic conditions[4]. ICC's methodology is based on the U.S. Consumer Confidence Index created by the University of Michigan (UMichCCI) in 1950 to track consumer opinion about current and future economic conditions. One of the major differences between the ICC and the UMichCCI is that the former has a larger sample size (about 2,000 households per month are interviewed for the ICC versus about 500 for the UMichCCI). Another distinction is that the ICC questionnaire inquires about household

[4] The ICC is the average of two other indices: the Index of Condições Econômicas Atuais (Current Economic Conditions Index) and the Index of Expectativas (Expectations Index).

current financial conditions with that of the past 30 days whereas the UMichCCI uses the longer time frame of comparing current conditions versus that of the past twelve months. Since emerging markets such as Brazil tend to be more unstable it seems fit to ask consumers for their short term financial situation.

Lemmon and Portniaguina (2006), Qiu and Welch (2006), and Schmeling (2009), among others, show that consumer confidence surveys can serve as appropriate proxies for individual investor sentiments.

This study uses Bovespa index (Bovespa) returns to analyze the overall performance of the Brazilian stock market. This trade-weighted index is the main indicator of the Brazilian stock market's average performance and it reflects the variation of Bovespa's most traded stocks. The index comprises a theoretical stock portfolio and its components are adjusted every four months. Bovespa reflects not only the variation of the stock prices but also the impact of the distribution of benefits and is considered an indicator that evaluates the total return of its components stocks. This research uses the continuously compounded returns for Bovespa estimated by Datastream.

The monthly Bovespa volatility is estimated using formula (1.3). Figure 1.1 shows the annualized one-month trailing volatility for Bovespa from March 1995 to October 2009. Periods of high volatility coincide with economic crises influencing Bovespa returns. This is more notable around October 1998 (Russian financial crisis), February 1999 (Brazilian Real devaluation), and November 2008 (global financial crisis).

We use several variables that are representative of market fundamentals. These are some of the most commonly used in the asset pricing literature: (i) Economic growth (IIP): given the absence of GDP monthly series for Brazil, we use the monthly changes in the Brazilian industrial production index (IIP) as a surrogate for economic growth; (ii) Short term interest rates

(BT_Bill): measured as the effective yield on Letras do Tesouro Nacional issued by the Brazilian Central Bank (BCB) of 31 days or longer, calculated from the discount. The yield is that of the last issue of the month; (iii) Business conditions (Selic_FFR): measured as the average rate on loans between commercial banks. The Special Settlement and Custody System (SELIC) overnight rate is a weighted average rate on loans between financial institutions involving firm sales of or repurchase agreements based on federal securities in the SELIC. The rate is weighted by loan amounts; (iv) Country risk premia (EMBI): measured as the value of JPMorgan Emerging Markets Bond Index Plus (EMBI+ Brazil) which evaluates the risk spread of the Brazilian sovereign external debt over a general risk-free bond, in the case, the United States Treasury; it tracks total returns for actively traded external debt instruments in Brazil, including US-dollar denominated Brady bonds, Eurobonds, and traded loans issued by sovereign entities; (v) Currency fluctuation (ExchRate): measured as the changes in Brazilian Real to U.S. dollar exchange rate index; (vi) Dividend yield (Div): measured as the dividend yield for firms trading at the Sao Paulo stock exchange over the past 12 months calculated by Datastream as Bovespa does not currently calculate this data type; (vii) Inflation (CPI) measured as the monthly changes in the broad Brazilian consumer price index or IPCA; (viii) Terms of trade (BRTOT) for Brazil which consists of the monthly ratio between the export price index and the import price index. Export price index measures the changes in the prices of exports of merchandise from a country. The import price index measures the changes in the prices of imports of merchandise into a country. The index numbers for each month refer to prices of imports landed into the country during that period.

1.4.2 Descriptive Statistics

Table 1.1 presents the descriptive statistics of the variables previously introduced. The mean of the investor sentiment measure ($Sentt_1$) is approximately 16% suggesting that consumers have been bullish during most of the sample period. In addition, the measure of sentiment has a higher standard deviation than those of the stock market index, implying that sentiment has been highly volatile during this period.

The cross correlation between Bovespa returns and volatility, investor sentiment, and variables representative of market fundamentals are reported on Table 1.2. The low contemporaneous correlations between Bovespa returns, Bovespa volatility, and the measure of investor sentiments may entail the lack of feedback effect among them. Moreover, the low correlations among market fundamentals, with the exception of variables affected by interest rate changes (such as short-term interest rates, business conditions, consumer price changes), imply that each variable represents a distinctive characteristic of the market which is independent from each other.

1.4.3 Characteristics of the Sao Paulo Stock Exchange

Founded in 1890, the São Paulo Stock Exchange is the largest stock exchange in Brazil. As of September 1, 2009, the market capitalization of the 432 companies listed in the exchange was approximately $1.1 trillion dollars representing about 2.9% of total world market capitalization, a percent similar to that of the German stock market. It is the second largest market in the Americas (outside of the U.S.) by market capitalization with an average daily trading of $2.9 billion dollars which makes it the largest stock market by volume traded in Latin America. Early in 2008, the São Paulo Stock Exchange merged with the Brazilian Mercantile &

Futures Exchange creating the BM&FBOVESPA Securities, Commodities and Futures Exchange. The new entity is the third largest exchange worldwide measured in market value. BM&FBOVESPA offers equities, securities, OTC, financial assets, indices, interest rates, agricultural commodities, and foreign exchange futures and spot contracts.

The Bovespa index (Bovespa) is the leading index of the Brazilian stock market's average performance. Bovespa is an open-ended index which contains companies with the largest traded volume and the highest number of transactions in the previous twelve months of the BM&FBOVESPA. Bovespa includes companies which represent approximately 70% of the BM&FBOVESPA market capitalization. In the BM&FBOVESPA there are pure index funds, stock index options and futures derivatives currently replicating Bovespa. Additionally, there are four ETFs authorized to trade. Foreign investor participation in the BM&FBOVESPA has steadily increased since 2000 after the Brazilian government liberalized certain restrictions to asset ownership by foreigners.

During the 1990s many Latin American countries began economic liberalization processes which resulted in an increase in market integration, foreign investment participation, and globalization. Brazil is currently the ninth largest economy in the world and the second largest economy in the Americas as measured by total GDP.[5] The Brazilian economy is one of the fastest growing in the world and the leading economy in Latin America with several companies ranked as the largest multinational firms in the world. Brazil has undertaken domestic economic and political reforms steadily since the 1990s which helped position the country as a referent for Mercosur (the trade union it helped create with Argentina, Paraguay and Uruguay) and the G-20 (group of the twenty largest world economies). Recent internal reorganization of

[5] The Central Intelligence Agency (2009). *The World Fact Book: 2009 Edition*. Potomac Books, Washington DC.

international institutions, such as the IMF, UN, World Bank, has given emerging economies and Brazil in particular, a larger voice in setting the social agenda and in international politics.

1.5 Econometric Methodology

Several studies (Brown and Cliff, 2004; Lee et al., 2002; Verma *et al*., 2008) suggest that stock market returns and investor sentiments may act as a system. In order to examine the hypothesized link the Vector Autorregression (VAR) model (Sims, 1980) was chosen as adequate econometric methodology. The impulse response functions (IRFs) generated from the VAR model are used to analyze the effect of unanticipated changes in investor sentiment to both Bovespa returns and volatility. An IRF traces the effect of a one-time shock to one of the innovations on current and future values of the endogenous variables and allows overcoming potential misspecification problems. Litterman and Supel (1983), Hakkio and Morris (1984), Litterman (1984), and Webb (1999), among others, provide evidence that the prediction performance of VAR models is better than that of structural models.

Time delays in the generation, reporting, and assimilation of information by investors suggest that there may be lags between the observation of data regarding macroeconomic variables and the incorporation of this information into asset prices. A model which only accounts for the contemporaneous changes in variables at time *t* would be unrealistic, missing valuable information about the delayed effects of some variables. Consequently, this study uses the Akaike information criterion (AIC) and the Schwarz information criterion (SIC) to help in determining the proper lag lengths. The lags in the VAR model provide a good approximation to the true data generating process while capturing the dynamic relationships in a fairly unrestricted way. The VAR model is expressed as:

$$Z(t) = C + \sum_{s=1}^{m} A(s)Z(t-m) + \varepsilon(t) \quad (1.5)$$

where *Z(t)* is a column vector of variables under consideration, *C* is the deterministic sentiment comprised of a constant, *A(s)* is a matrix of coefficients, *m* is the lag length and *ε(t)* is a vector of random error terms.

Another advantage of VAR models is that researchers can integrate Monte Carlo simulations in order to obtain confidence bands around the point estimates (Doan, 1988; Hamilton, 1994). The IRFs show the likely response of one variable to a one time unit shock in another variable. Specifically, IRFs represent the behavior of the series in response to pure shocks while keeping the effect of other variables constant. These impulse responses tend to be non-linear functions of the estimated parameters. For this reason, confidence bands are built around the mean response. Impulse responses are considered statistically significant at the 95% confidence level whenever the upper and lower confidence bands hold the same sign. To avoid potential model misspecification this research uses the generalized impulses technique described by Pesaran and Shin (1998) in which an orthogonal set of innovations does not depend on the variable ordering. This technique prevents the model from being sensitive to variable ordering.

1.6 Estimation Results

In this section we first present the results of the Unit Root Tests on the variables used; then we show the results from several VAR models and interpret the IRFs graphs. Thirdly, we test for asymmetric responses in the model during upturns or downturns in sentiments. Lastly, we reveal results from alternative model specifications for robustness.

1.6.1 Unit Root Tests

We analyze the unit roots and univariate time series properties of the variables used in the present study. Table 1.3 reports the results of unit root tests using ADF test (Dickey and Fuller, 1979, 1981) and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test (Kwiatkowski, Phillips, Schmidt, and Shin, 1992). The appropriate number of lags is two after taking into account the loss in degrees of freedom and based on the *AIC* and *SIC* criteria (Diebold, 2003). In the case of the ADF test, the null hypothesis of non-stationarity is rejected. These results are robust after we include drift or trend terms in the ADF test equations. (Dolado, Jenkinson, and Sosvilla-Rivero, 1990). For the KPSS test, the null hypothesis of stationarity is not rejected.

1.6.2 VAR Model Results

Once the series were determined to be stationary, we decompose the sentiment variables into their rational and irrational components based on fitted and residuals of equation (1.1). In particular, an ordinary least square (OLS) regression based on equation (1.1) is estimated. The relatively low correlations among variables used as proxies for market fundamentals, as shown in Table 1.2, suggest the absence of multicollinearity in this analysis.

Table 1.4 reports the results from the OLS regression based on equation (1.1), presenting the effects of fundamentals on investor sentiments. Investor sentiment is significantly related to country risk premia (as measured by EMBI), changes in the dollar-real exchange rate (EXCHRATE), changes in inflation (as measured by CPI), and the terms of trade for Brazil (BRTOT). The regression has an R^2 of 0.49 meaning that about half of the variation in investor sentiment can be explained by economic fundamentals chosen. These results provide support to

Brown and Cliff (2005) observation that investor sentiments may contain a combination of both rational and irrational components and not necessarily only noise. The fitted values and residuals for regression (1.1) are generated to estimate the rational and irrational components of investor sentiments.

Next, a four variable VAR model with two lags is estimated in order to analyze the relative effects of rational and irrational investor sentiments on stock market returns and volatility as described in equation (1.2). The variables included in this VAR model are Bovespa index returns (BOVESPA), Bovespa index volatility (BovVol) as estimated using equation (1.3), rational sentiments of investors (RAT), and irrational sentiments of investors (IRRAT). Therefore, in addition to the returns on the market index and the volatility of returns on the market index, two new variables derived from equation (1.1) related to rational and irrational sentiments of investors[6] are included.

Sims (1980) points out that autoregressive systems are complicated to describe succinctly given that it is difficult to interpret the coefficients from the regression equations. Similarly, Enders (2003) show that the *t*-tests on individual coefficients are not reliable. Sims (1980) recommends focusing on the system's IRFs to typical random shocks. Consequently, we analyze the applicable IRFs figures while the VAR model estimation results are presented in Tables 1.6 through 1.9.

The IRFs from the VAR model depict the response of one variable to a one-standard-deviation shock to another variable in the system. Confidence bands are built around the mean response using Monte Carlo methods (Doan and Litterman, 1986). Whenever the upper and

[6] The results of the VAR estimates are available in Table 1.6. For this study, we use the generalized impulse responses as the impulse response definition. Results are materially similar when using Cholesky-difference adjusted as impulse response definition.

lower confidence bands hold the same sign, IRFs responses become statistically significant at the 95% confidence level.

Figures 1.2.a and 1.2.b show the impulse responses of Bovespa index returns to a one time standard deviation increase in the rational and irrational sentiments of investors respectively. A one time increase in rational sentiments affects positively Bovespa index returns. The effect of this positive and statistically significantly impact quickly disappears after the first month. On the other hand, the response of Bovespa index returns to irrational sentiments is negative and statistically significant suggesting that positive irrational sentiments tend to lower Bovespa returns at the time of the second period. In terms of magnitude, irrational sentiments have a much greater impact than rational sentiments. These findings present additional empirical support for both types of sentiments, rational and irrational, with irrational investor sentiment having a larger negative impact on Bovespa, thereby showing potential to influence stock market returns. Further, the positive and significant response of Bovespa returns to rational sentiments is consistent with Verma *et al* (2008) for the U.S. while the finding that higher levels of sentiment predict future lower returns is in line with Schmelling (2009). In short, a one-time positive shock to rational (irrational) investor sentiment leads to an increase (decrease) in stock market returns around the time of the second month.

Figures 1.3.a and 1.3.b present the relative impact of both types of investor sentiments on the volatility of Bovespa. In theory, when rational investor sentiments increase it should increase returns as well while decreasing volatility since there is more certainty about asset prices. Analysis of the impulse response function presented in Figure 1.3.a shows that a one standard deviation increase in rational sentiments of Brazilian investors decreases Bovespa market volatility around the second month. This implies that investors have a positive outlook consistent

with economic fundamentals. Therefore, they feel more certain about future prospect of the economy, creating expectations of a positive business environment, minimizing uncertainty, leading to a decrease in the variability of stock prices. Irrational investor sentiments, on the other hand, tends to increase market volatility around the second period as Figure 1.3.b shows. This pattern provides support to DSWW's view of irrational traders increasing overall market risk by trading on erroneous information.

1.6.3 Testing for Asymmetric Responses

To analyze the possible presence of response asymmetries on investor sentiments during months with positive market returns versus months with non positive market returns, we create a new variable called BovUp which results from the interaction between Bovespa returns and Bovespa up months (where Bovespa up months is an indicator variable taking a value of one if market return for a particular month is non negative). As presented in Figures 1.4.a and 1.4.b, results do not materially differ from the ones for the whole sample[7]. The interaction term BovUp is positive and significant for rational sentiments and negative and significant until the second period for irrational sentiments. A one time positive shock to rational sentiment leads to an increase in stock market returns around the time of the first period. On the other hand, the decrease on market returns during up months due to irrational sentiments is smaller than the decrease on returns during the whole sample.

Next, we examine the possibility of response asymmetries on Bovespa volatility to upturns or downturns in investor sentiment by creating a new variable, BovUpVol, from the interaction between Bovespa volatility (BovVol) and Bovespa up months (months where market return is non negative). In this sample there are 99 up return months and 83 down return months

[7] The results of the VAR estimates are available in Table 1.7.

for Bovespa. IRFs graphs[8] do not materially differ from the ones presented for the whole sample in Figures 1.3.a and 1.3.b. Consistent with previous findings a one standard deviation increase in rational sentiments decreases volatility during up months around the second period. The negative impact, however, is smaller during up months. Conversely, a one standard deviation increase in irrational sentiments significantly increases Bovespa volatility during up return months.

1.6.4 Robustness tests

We perform several analyses to evaluate the robustness of our original findings. First, we incorporate to the original model dummy variables representing the different calendar months in order to test for the presence of seasonality in this sample. There is no evidence of seasonality affecting Bovespa returns and volatility[9]. Next, we split the sample into pre- and post-2002 subsamples. In early 2000 The Sao Paulo Stock Exchange engaged in a series of institutional reforms that improved disclosure by market participants and streamlined the listing process for firms. The Stock Exchange created three new market listing segments, Level 1, Level 2, and the New Market (Novo Mercado[10]) to incorporate optional corporate governance practices based on the principles of transparency, accountability, and corporate social responsibility. These optional guidelines, which contain stronger corporate governance rules than Brazilian legal requirements, have become popular among publicly traded Brazilian firms. Firms listed in the New Market engage in several voluntary measures designed to improve disclosure and protect small investor rights. The increase in market transparency tends to improve asset pricing process, decreasing

[8] The results of the VAR estimates are available in Table 1.8.
[9] IRFs graphs for this model specification and results from VAR estimates are available upon request.
[10] In order to be listed in Novo Mercado, a firm has to issue only voting common shares, have a minimum free float of 25%, provide financial statements in compliance with either U.S. GAAP or IAS rules; provide rights to minority shareholders in case the company is taken over, among others. Level 2 listing is similar to Novo Mercado but permits firms to issue preferred shares; while Level 1 improve methods of market disclosure and disperse shares among the largest number of shareholders.

information asymmetries among market participants and raising trading volume (De Carvalho and Pennacchi, 2009). The creation of the New Market, among other measures, improved small investor as well as international investor participation rate in Bovespa. In 2000 foreign investors accounted for less than 25% of the total traded value at Bovespa whereas as of 2009 the foreign investors share has steadily grown to about 35% in a context of overall increase in market activity[11]. The first companies listed in the New Market started trading in 2002. Additionally, during this period, several Brazilian firms issued ADRs and opened their capital to external investors increasing capital free-float[12] which also improved stock market development[13]. Voluntary firm disclosure in conjunction with general public education campaigns about the benefits of investing in financial markets, helped improve the image of Bovespa among Brazilian individual investors (Grün, 2005). Finally, according to DSSW (1990) increased transparency benefits the role of arbitrageurs which tend to correct price deviations introduced by noise traders driving prices back to their fundamental values. This, in turn, reduces noise traders' activities while decreasing market wide volatility since prices now will tend to reflect their true value.

An analysis of the IRFs presented in Figures 1.6.a and 1.6.b shows that there is a significant and positive effect of rational sentiments on returns for the pre-2002 and a negative and significant impact of irrational sentiments on returns for the pre-2002 subsample. Results for this subsample are consistent with the ones obtained for the full sample. On the other hand, for the post-2002 subsample[14] there are no longer significant effects of investor sentiments in market

[11] According to data from the official Bovespa website obtained from http://www.bmfbovespa.com.br/renda-variavel/BuscarParticipacaoInvestimento.aspx on November 13th, 2009.
[12] Free-float is the percentage of shares outstanding, voting and non-voting, available for trading in the market. In the past free-float for Bovespa has been around 50 percent of total shares (Leal and Carvalhal, 2005).
[13] Liu (2007) presents international evidence that cross listing in the U.S. improves home-market pricing efficiency.
[14] The results of the VAR estimates are available in Tables 1.9 and 1.10 respectively.

returns. These results may provide evidence of the positive effect that increased market transparency brings to returns and volatility.

For rational investor sentiments, the impact of the pre-2002 subsample volatility is larger, negative, and more persistent than those for the complete sample, with the effect lasting about three months. Consistent with previous results for the pre-2002 subsample, the effects of irrational sentiments on volatility are positive, significant, and larger than those for the whole sample, suggesting that irrational investor sentiments had a larger effect on market volatility before Bovespa engaged in the series of structural reforms[15]. The benefits of market transparency are clearly present in the post-2002 subsample which shows that irrational investor sentiment has no significant impact on overall market volatility as presented in Figures 1.7.a through 1.7.d.

Lastly, there is a possibility that the results presented previously are model specific. We use an EGARCH (Exponential General Autoregressive Conditional Heteroskedasticity) model to test the asymmetric impact of sentiments on returns and volatility. ARCH and GARCH models have the ability to estimate and predict volatility over time. Many studies illustrate that volatility exhibits an asymmetric reaction to positive and negative events. One of the most widely used asymmetric models of volatility is the EGARCH developed by Nelson (1991). For the mean equation, the VAR model (Sims, 1980) is appropriate for analyzing the hypothesized relationships given that it does not impose restrictions on the structure of the system. The mean equation is:

$$R_{it} = \beta_{i0} + \sum_{j=1}^{2} \beta_{ij} R_{jt-1} + e_{it} \qquad \text{i, j = 1, 2;} \tag{1.6}$$

[15] The results of the VAR estimates are available in Tables 1.11 and 1.12 respectively.

Where R_{it} is the return on Bovespa (i=1), individual investor sentiments (i=2); e_{it} is the residual term while β_{i0} and β_{ij} are the parameters to be estimated. The parameter β_{ij} captures the degree of mean spillover effects across sentiments and returns.

The variance equation in this model is given by:

$$\log(h_t) = \gamma + \sum_{j=1}^{q} \varsigma_j \left| \frac{u_{t-j}}{\sqrt{h_{t-j}}} \right| + \sum_{j=1}^{q} \xi_j \left| \frac{u_{t-j}}{\sqrt{h_{t-j}}} \right| + \sum_{i=1}^{p} \delta_j \log(h_{t-i}) \qquad (1.7)$$

Where γ, the ςs, ξs and δs are parameters to be estimated. To test for asymmetries the parameters of importance are the ξs. When $\xi_1 = \xi_2 = \ldots = 0$ then the model is symmetric. When $\xi_j < 0$, then positive shocks generate less volatility than negative shocks.

As presented on Table 1.5, the coefficient of interest (ξ_j) is negative and significant at the 5% level suggesting that negative changes in sentiments have a larger impact on Bovespa volatility than positive events. Hull (2006) mentions that the volatility of a stock's price tends to be inversely related to price so that a negative shocks or news should have a bigger effect on volatility than positive shocks. Overall, results seem to provide support to Schwert (2002) who shows that volatility and market returns move in opposite directions. In general, when prices decrease, market wide volatility tends to increase.

Regarding the use of alternative measures of investor sentiment to increase the robustness of this study, unfortunately there is no data available for Brazil closed-end fund discounts during this period. As stated in the literature review, this measure has been used with limited success as a proxy for investor sentiment especially in studies analyzing U.S. markets. Possible paper extensions include performing the analysis in stock markets of countries showing increased foreign investor interest such as Russia, China, or India. To the best of our knowledge, however,

there are very limited data points in the extant consumer or investor confidence surveys for these markets, which may provide an incomplete picture of investor behavior.

1.7 Conclusion

The present study examines the relative effects of investor rational and irrational sentiments on Bovespa returns and volatility using VAR models. Major results from this study are as follows: First, the effect of a one time increase in rational (irrational) investor sentiments on Bovespa returns is positive (negative) and significant during almost the first two months and insignificant thereafter. Second, the impact of irrational investor sentiment is greater than that of rational investor sentiment on stock market returns. These results provide support to the stance that irrational investor sentiments do have the potential to influence stock market returns.

Third, the response of Bovespa index volatility to rational investor sentiments is negative and significant during the first two months while irrational investor sentiments tend to significantly increase market volatility with a delayed reaction around the time of the second month. In general, rational investor sentiments increase when investors have a positive outlook consistent with economic fundamentals. Investors feel more secure about a future state of the economy which in turn creates expectations of a positive business environment, minimizing uncertainty and leading to a decrease in market volatility. Irrational sentiments of investors tend to significantly increase market volatility. Lastly, rational sentiments have a more profound effect than irrational sentiments on Bovespa volatility. Although noise investors are significantly influencing stock market volatility, economic fundamentals play a larger role in determining stock market returns and volatility.

Previous studies treat investor sentiments as fully irrational behavior; however, this study provides evidence in favor of both types of sentiments affecting market returns and volatility. The results support the view that irrational sentiments of investors may be strong enough to impact the stock market returns and volatility. Investor sentiments are mostly a manifestation of the rational risk factors driving expected returns of stocks with irrational investor sentiments also having an impact, albeit smaller, on stock returns and volatility. Consequently, investors could improve their portfolio performance by considering both the rational as well as irrational sentiments as determinants of stock returns and volatilities.

Table 1.1 - Descriptive statistics

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
SENTT1	0.159	0.250	1.490	0.080	0.161	0.261	2.131
BOVESPA	0.014	0.024	0.247	-0.385	0.316	-1.155	6.731
BOVVOL	0.021	0.018	0.083	0.007	0.012	2.908	13.699
IIP	0.001	0.003	0.066	-0.134	0.023	-2.077	14.127
BT_BILL	0.016	0.015	0.052	0.007	0.007	2.039	9.445
SELIC_FFR	0.016	0.015	0.043	0.007	0.007	1.851	6.730
EMBI	0.057	0.051	0.178	0.014	0.032	1.147	4.552
EXCHRATE	1.977	1.955	3.746	0.849	0.718	0.228	2.324
DIV	0.003	0.003	0.007	0.001	0.001	0.203	2.860
CPI	0.006	0.005	0.029	-0.005	0.005	1.733	7.070
BRTOT	0.995	0.987	1.132	0.894	0.057	0.424	2.262

Notes: the variables are Brazilian investor sentiment (Sentt1), monthly returns on Bovespa index (Bovespa), monthly volatility of Bovespa returns (BOVVOL), Brazilian economic growth (IIP), short-term interest rate (BT_Bill), business conditions (Selic_FFR), Country risk premia (EMBI), Brazilian Real versus US dollar exchange rate, (Exchrate), inflation (CPI), and terms of trade (BRTOT).

Table 1.2 - Cross correlations

	SENTT1	BOVESPA	BOVVOL	IIP	BT_BILL	SELIC_FFR	EMBI	EXCHRATE	DIV	CPI	BRTOT
SENTT1	1										
BOVESPA	0.10	1									
BOVVOL	-0.17	-0.46	1								
IIP	0.08	0.29	-0.32	1							
BT_BILL	-0.14	-0.09	0.41	-0.19	1						
SELIC_FFR	-0.14	-0.07	0.39	-0.17	0.96	1					
EMBI	-0.05	-0.19	0.31	-0.08	0.53	0.49	1				
EXCHRATE	0.04	-0.03	-0.19	0.04	-0.42	-0.45	0.22	1			
DIV	-0.05	-0.13	0.19	-0.03	-0.19	-0.18	0.39	0.62	1		
CPI	-0.01	-0.02	0.08	-0.10	0.54	0.49	0.49	0.05	-0.15	1	
BRTOT	-0.07	-0.03	0.19	-0.06	0.13	0.15	-0.41	-0.73	-0.50	-0.19	1

Notes: the variables are Brazilian investor sentiment (Sentt1), monthly returns on Bovespa index (Bovespa), monthly volatility of Bovespa returns (BOVVOL), Brazilian economic growth (IIP), short-term interest rate (BT_Bill), business conditions (Selic_FFR), Country risk premia (EMBI), Brazilian Real versus US dollar exchange rate, (Exchrate), inflation (CPI), and terms of trade (BRTOT).

Table 1.3. Unit Root Tests

	ADF	Lag length	KPSS (4)
Levels			
SENTT1	-2.316	2	0.481***
BOVESPA	-1.668	2	0.662***
BOVVOL	-3.051*	2	0.145**
IIP	-1.781	2	0.612***
BT_BILL	-3.819	2	0.162**
SELIC_FFR	-3.115	2	0.316***
EMBI	-3.300*	2	0.332***
EXCHRATE	-1.275	2	0.740***
DIV	-2.709	2	0.422***
CPI	-2.848	2	0.433***
BRTOT	-3.157*	2	0.337***
First difference			
SENTT1	-9.331***	2	0.032
BOVESPA	-6.057***	2	0.157
BOVVOL	-11.488***	2	0.017
IIP	-14.539***	2	0.011
BT_BILL	-11.556***	2	0.031
SELIC_FFR	-8.805***	2	0.146
EMBI	-7.486***	2	0.032
EXCHRATE	-7.055***	2	0.241
DIV	-7.819***	2	0.081
CPI	-8.235***	2	0.127
BRTOT	-8.406***	2	0.178

*Notes: ***, ** and * denote rejection of the null hypothesis of unit roots for the Augmented Dickey–Fuller (ADF) tests at the 1%, 5% and 10% significance levels respectively*
****, ** and * denote rejection of the null hypothesis of stationarity for the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) tests at the 1%, 5% and 10% significance levels.*
Unit root tests were run with linear trend and intercept at levels, and intercept only at first differences.
Lag lengths were chosen using the Akaike Information Criterion (AIC) and the obtained residuals are white noise.

Table 1.4 - Effects of fundamentals on investor sentiments

Dependent Variable: SENTT1

Variable	Coefficient	SE	t-Statistic	Prob.
IIP	-41.05	40.56	-1.01	0.31
BT_BILL	0.04	0.34	0.12	0.91
SELIC_FFR	-0.17	0.31	-0.55	0.58
EMBI	-0.03	0.00	-7.80	0.00
EXCHRATE	8.44	2.51	3.36	0.00
DIV	0.35	0.95	0.37	0.71
CPI	5.99	2.39	2.51	0.01
BRTOT	0.58	0.25	2.35	0.02
C	58.89	28.49	2.07	0.04
R-squared	0.49			
AIC	7.82			
SC	7.98			
Sum squared resid	23366.86			
Log likelihood	-683.29			
F-statistic	19.95			
Prob(F-statistic)	0.00			

Notes: the variables are investor sentiment (Sentt1), Brazilian economic growth (IIP), short-term interest rate (BT_Bill), business conditions (Selic_FFR), country risk premia (EMBI), Brazilian Real versus US dollar exchange rate (Exchrate), inflation (CPI), Bovespa dividend yield (DIV), terms of trade (BRTOT).
The regression is estimated according to equation (1.1) as follows:

$$Sentt_{1t} = \gamma_0 + \sum_{j=1}^{J} \gamma_j Fund_{jt} + \xi_t$$

Table 1.5 Testing sentiments impact asymmetry on Bovespa returns

Variable	Coefficient	SE	z-Statistic	Prob.
β_{i0}	4.56	3.41	1.34	0.18
β_{ij}	0.96	0.03	33.94	0.00
	Variance Equation			
γ	1.11	0.50	2.23	0.03
ς_j	0.27	0.18	1.53	0.13
ξ_j	**-0.28**	0.08	-3.49	**0.00**
δ_j	0.61	0.17	3.66	0.00
R-squared	0.87	Mean dependent var		116.36
Adjusted R-squared	0.87	S.D. dependent var		15.90
S.E. of regression	5.82	Akaike info criterion		6.30
Sum squared resid	5956.50	Schwarz criterion		6.40
Log likelihood	-566.90	F-statistic		235.17
Durbin-Watson stat	1.71	Prob(F-statistic)		0.00

Notes: the dependent variable is investor sentiment (Sentt1). The mean equation is $R_{it} = \beta_{i0} + \sum_{j=1}^{2} \beta_{ij} R_{jt-1} + e_{it}$ where R_{it} is the return on Bovespa (i=1), individual investor sentiments (i=2); e_{it} is the residual term; β_{i0} is a constant while β_{ij} captures the degree of mean spillover effects across sentiments and returns.

The variance equation is given by:

$$\log(h_t) = \gamma + \sum_{j=1}^{q} \varsigma_j \left| \frac{u_{t-j}}{\sqrt{h_{t-j}}} \right| + \sum_{j=1}^{q} \xi_j \left| \frac{u_{t-j}}{\sqrt{h_{t-j}}} \right| + \sum_{i=1}^{p} \delta_j \log(h_{t-i})$$

Where γ, the ςs, ξs and δs are parameters to be estimated.

Table 1.6 - Vector Autoregression Estimates

	RAT	IRRAT	BOVESPA	BOVVOL
RAT(-1)	0.36	0.32**	-0.09	-0.01***
	(0.24)	(0.15)	(0.23)	0.00
RAT(-2)	0.49**	-0.21	0.01	0.01***
	(0.24)	(0.15)	(0.23)	0.00
IRRAT(-1)	-0.17	1.01***	-0.02	0.00
	(0.14)	(0.09)	(0.14)	0.00
IRRAT(-2)	0.15	-0.27***	0.09	0.00
	(0.14)	(0.09)	(0.14)	0.00
BOVESPA(-1)	5.57	3.46	3.62	0.48***
	(9.64)	(5.89)	(9.12)	-0.07
BOVESPA(-2)	-5.31	-4.58	4.82	0.10
	(8.29)	(5.07)	(7.84)	-0.07
BOVVOL(-1)	54.98	-67.58	1.58	0.48***
	(87.51)	(53.38)	(1.74)	(0.07)
BOVVOL(-2)	-54.37	16.67	-1.01	0.10
	(85.33)	(52.05)	(1.21)	(0.07)
C	16.17*	-13.31**	0.11	0.02**
	(8.89)	(5.44)	(0.08)	(0.01)
R-squared	0.44	0.66	0.03	0.52
Sum sq. resids	19656.71	7347.50	1.76	0.01
S.E. equation	10.78	6.59	0.10	0.01
F-statistic	21.95	53.97	0.41	25.35
Log likelihood	-664.71	-578.12	155.54	590.34
Akaike AIC	7.63	6.65	-1.69	-6.63
Schwarz SC	7.76	6.78	-1.56	-6.50
Mean dependent	115.78	-0.35	0.02	0.02
S.D. dependent	14.14	11.07	0.10	0.01

Notes: the variables are rational investor sentiments (RAT), irrational investor sentiments (IRRAT), returns on Bovespa (BOVESPA), and volatility of Bovespa returns (BOVVOL).

* ** and *** denote significance levels at the 10, 5, and 1% respectively. SEs are in the parentheses

Table 1.7 Vector Autoregression Estimates

	RAT	IRRAT	BovUp
RAT(-1)	0.34	0.33**	0.00
	(0.25)	(0.15)	(0.00)
RAT(-2)	0.50**	-0.22	0.00
	(0.25)	(0.15)	(0.00)
IRRAT(-1)	-0.18	1.01***	0.00
	(0.15)	(0.09)	(0.00)
IRRAT(-2)	0.16	-0.28***	0.00
	(0.15)	(0.09)	(0.00)
BovUp(-1)	4.59	5.25	0.06
	(26.57)	(16.28)	(0.16)
BovUp(-2)	23.32	-3.37	-0.06
	(26.55)	(16.26)	(0.16)
C	19.43*	-13.12**	-0.04
	(9.88)	(6.05)	(0.06)
R-squared	0.44	0.66	0.03
Sum sq. resids	19561.54	7341.22	0.67
S.E. equation	10.82	6.63	0.06
F-statistic	16.45	40.05	0.61
Log likelihood	-664.29	-578.04	240.70
Akaike AIC	7.65	6.67	-2.63
Schwarz SC	7.81	6.83	-2.47
Mean dependent	115.78	-0.35	-0.03
S.D. dependent	14.14	11.07	0.06

Notes: the variables are rational investor sentiments (RAT), irrational investor sentiments (IRRAT), and returns on Bovespa before 2002 (BOVESPA*Pre2002).

* ** and *** denote significance levels at the 10, 5, and 1% respectively. SEs are in the parentheses

Table 1.8 Vector Autoregression Estimates

	RAT	IRRAT	BovUpVol
RAT(-1)	0.43**	0.33***	-0.01**
	(0.23)	(0.14)	(0.00)
RAT(-2)	0.42*	-0.25*	0.00
	(0.23)	(0.14)	(0.00)
IRRAT(-1)	-0.18	0.98***	0.00
	(0.15)	(0.09)	(0.00)
IRRAT(-2)	0.16	-0.23***	0.00
	(0.15)	(0.09)	(0.00)
BovUpVol(-1)	79.70	-58.99**	-0.12
	(71.35)	(43.43)	(0.09)
BovUpVol(-2)	-41.41	31.05	-0.07
	(76.31)	(46.45)	(0.09)
C	16.19*	-8.93*	0.03***
	(10.50)	(6.39)	(0.01)
R-squared	0.44	0.66	0.18
Sum sq. resids	19495.93	7222.69	0.03
S.E. equation	10.80	6.58	0.01
F-statistic	16.57	41.05	4.69
Log likelihood	-663.99	-576.61	514.95
Akaike AIC	7.65	6.65	-5.75
Schwarz SC	7.81	6.82	-5.59
Mean dependent	115.78	-0.35	0.01
S.D. dependent	14.14	11.07	0.01

Notes: the variables are rational investor sentiments (Sentt1), irrational investor sentiments (Sentt1IR), and Bovespa monthly volatility of returns before 2002 (BOVVOL).

* ** and *** denote significance levels at the 10, 5, and 1% respectively. SEs are in the parentheses

Table 1.9 Vector Autoregression Estimates

	RAT	IRRAT	Bovespa*Pre2002
RAT(-1)	0.38*	0.36***	0.00
	(0.23)	(0.14)	(0.00)
RAT(-2)	0.48**	-0.25*	0.00
	(0.23)	(0.14)	(0.00)
IRRAT(-1)	-0.17	0.99***	0.00
	(0.15)	(0.09)	(0.00)
IRRAT(-2)	0.15	-0.26***	0.00
	(0.15)	(0.09)	(0.00)
Bovespa*Pre2002(-1)	8.29	-0.67	0.00
	(11.07)	(6.79)	(0.08)
Bovespa*Pre2002(-2)	-4.00	-0.27	0.01
	(10.04)	(6.16)	(0.07)
C	16.34*	-12.69**	0.15**
	(8.76)	(5.37)	(0.06)
R-squared	0.44	0.65	0.04
Sum sq. resids	19656.62	7394.56	1.08
S.E. equation	10.78	6.61	0.08
F-statistic	21.95	53.45	1.14
Log likelihood	-664.71	-578.68	198.49
Akaike AIC	7.63	6.66	-2.18
Schwarz SC	7.76	6.78	-2.05
Mean dependent	115.78	-0.35	0.01
S.D. dependent	14.14	11.07	0.08

Notes: the variables are rational investor sentiments (RAT), irrational investor sentiments (IRRAT), and returns on Bovespa index before 2002 (Bovespa*Pre2002).

* ** and *** denote significance levels at the 10, 5, and 1% respectively. SEs are in the parentheses

Table 1.10 Vector Autoregression Estimates

	RAT	IRRAT	Bovespa*Post2002
RAT(-1)	0.37	0.30**	0.00
	(0.25)	(0.15)	(0.00)
RAT(-2)	0.49**	-0.19	0.00
	(0.25)	(0.15)	(0.00)
IRRAT(-1)	-0.16	1.01***	0.00
	(0.15)	(0.09)	(0.00)
IRRAT(-2)	0.14	-0.27***	0.00
	(0.15)	(0.09)	(0.00)
Bovespa*Post2002(-1)	-8.43	7.93	0.07
	(16.71)	(10.17)	(0.10)
Bovespa*Post2002(-2)	-3.31	-11.65	0.11
	(16.66)	(10.14)	(0.10)
C	15.43*	-13.34**	-0.03
	(9.04)	(5.50)	(0.05)
R-squared	0.44	0.66	0.02
Sum sq. resids	19620.67	7267.81	0.67
S.E. equation	10.84	6.60	0.06
F-statistic	16.34	40.67	0.51
Log likelihood	-664.55	-577.16	240.24
Akaike AIC	7.65	6.66	-2.63
Schwarz SC	7.82	6.82	-2.47
Mean dependent	115.78	-0.35	0.01
S.D. dependent	14.14	11.07	0.06

Notes: the variables are rational investor sentiments (RAT), irrational investor sentiments (IRRAT), and returns on Bovespa index after 2002 (Bovespa*Post2002).

* ** and *** denote significance levels at the 10, 5, and 1% respectively. SEs are in the parentheses

Table 1.11 Vector Autoregression Estimates

	RAT	IRRAT	BovVol*Pre2002
RAT(-1)	0.39*	0.31**	-0.01***
	(0.22)	(0.13)	(0.00)
RAT(-2)	0.41*	-0.27**	-0.01***
	(0.22)	(0.13)	(0.00)
IRRAT(-1)	-0.22	0.97***	0.00
	(0.15)	(0.09)	(0.00)
IRRAT(-2)	0.19	-0.24***	0.00
	(0.15)	(0.09)	(0.00)
BovVol*Pre2002(-1)	35.48	-88.82	0.54***
	(90.58)	(55.02)	(0.07)
BovVol*Pre2002(-2)	-93.89	10.68	0.24***
	(90.59)	(55.03)	(0.07)
C	23.17*	-3.59	0.02**
	(12.29)	(7.47)	(0.01)
R-squared	0.44	0.66	0.71
Sum sq. resids	19597.66	7230.45	0.01
S.E. equation	10.77	6.54	0.01
F-statistic	22.10	55.30	70.59
Log likelihood	-664.45	-576.70	597.14
Akaike AIC	7.63	6.63	-6.71
Schwarz SC	7.76	6.76	-6.58
Mean dependent	115.78	-0.35	0.01
S.D. dependent	14.14	11.07	0.02

Notes: the variables are rational investor sentiments (Sentt1), irrational investor sentiments (Sentt1IR), and monthly volatility of Bovespa returns before 2002 (BovVol*Pre2002).

* ** and *** denote significance levels at the 10, 5, and 1% respectively. SEs are in the parentheses

Table 1.12 Vector Autoregression Estimates

	RAT	IRRAT	BovVol*Post2002
RAT(-1)	0.39*	0.31**	0.00
	(0.22)	(0.14)	(0.00)
RAT(-2)	0.41*	-0.27**	0.01*
	(0.22)	(0.14)	(0.00)
IRRAT(-1)	-0.21	0.97***	0.00
	(0.15)	(0.09)	(0.00)
IRRAT(-2)	0.17	-0.24***	0.00
	(0.15)	(0.09)	(0.00)
BovVol*Post2002(-1)	-1.53	84.02	0.80***
	(177.88)	(108.17)	(0.08)
BovVol*Post2002(-2)	100.00	0.36	0.05
	(178.48)	(108.53)	(0.08)
C	22.94**	-3.61	0.00
	(12.36)	(7.51)	(0.01)
R-squared	0.44	0.66	0.80
Sum sq. resids	19549.27	7228.99	0.00
S.E. equation	10.82	6.58	0.01
F-statistic	16.47	41.00	83.52
Log likelihood	-664.23	-576.69	685.48
Akaike AIC	7.65	6.66	-7.69
Schwarz SC	7.81	6.82	-7.53
Mean dependent	115.78	-0.35	0.01
S.D. dependent	14.14	11.07	0.01

Notes: the variables are rational investor sentiments (Sentt1), irrational investor sentiments (Sentt1IR), and monthly volatility of Bovespa returns after 2002 (BOVVOL*Post2002).

* ** and *** denote significance levels at the 10, 5, and 1% respectively. SEs are in the parentheses

Figure 1.1 BOVESPA Annualized Monthly Volatility from March 1995 - October 2009

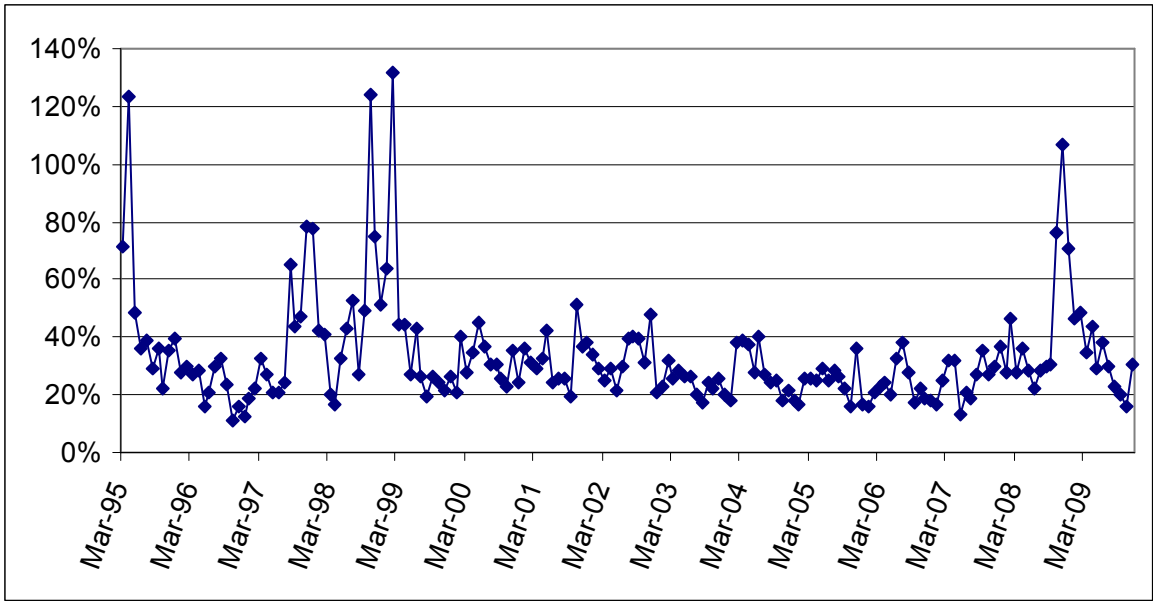
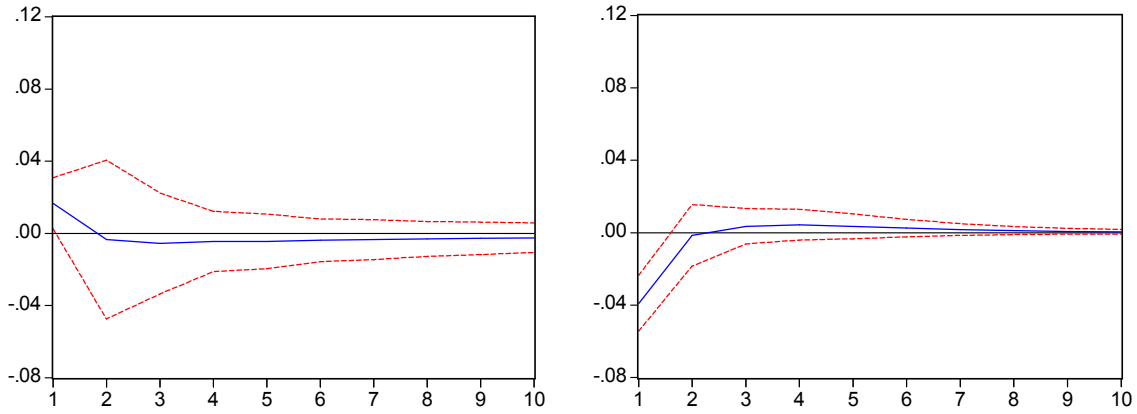


Figure 1.2 Response of Bovespa Returns to the Rational and Irrational Sentiments of Investors. (a) Rational sentiments; (b) Irrational sentiments

(a) Rational (RAT) Sentiments **(b) *Irrational (IRRAT) Sentiments***

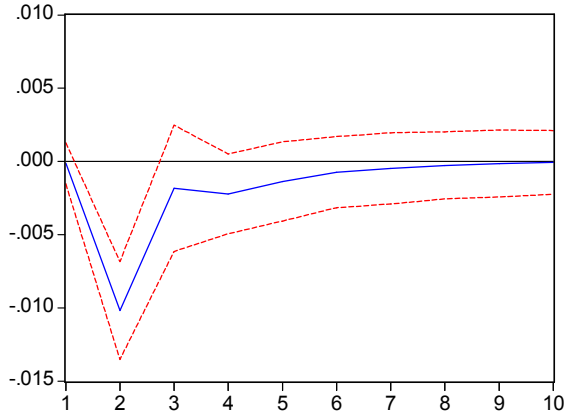


Notes: The dashed lines on each graph represent the upper and lower 95% confidence bands. When the upper and lower bounds carry the same sign the response becomes statistically significant.

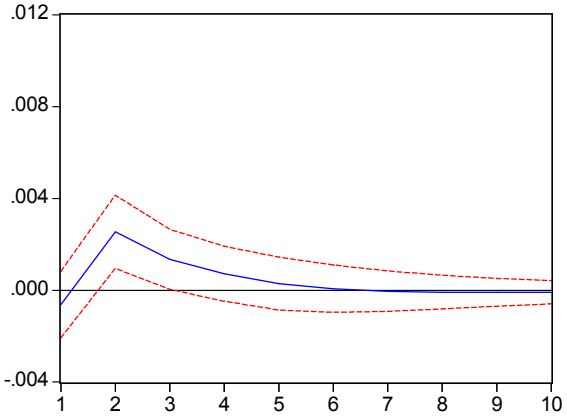
* On each graph, “percentage returns” are on the vertical and “horizon” is on the horizontal axis.

Figure 1.3 Response of Bovespa Volatility to the Rational and Irrational Sentiments of Investors. (a) Rational sentiments; (b) Irrational sentiments

(a) Rational (RAT) Sentiments



(b) *Irrational (IRRAT) Sentiments*

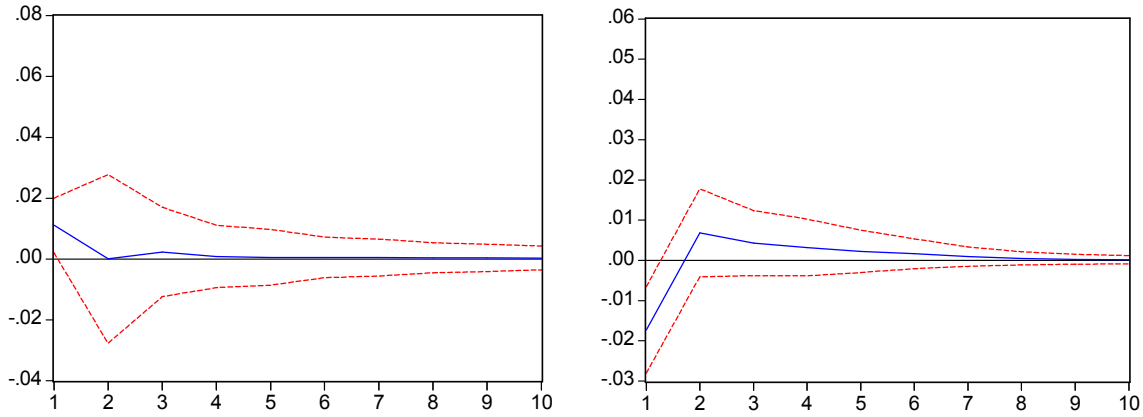


Notes: The dashed lines on each graph represent the upper and lower 95% confidence bands. When the upper and lower bounds carry the same sign the response becomes statistically significant.

* On each graph, “percentage returns” are on the vertical and “horizon” is on the horizontal axis.

Figure 1.4 Response of Bovespa Returns During Up Months to the Rational and Irrational Sentiments of Investors. (a) Rational sentiments; (b) Irrational sentiments

(a) Rational (RAT) Sentiments **(b) *Irrational (IRRAT) Sentiments***

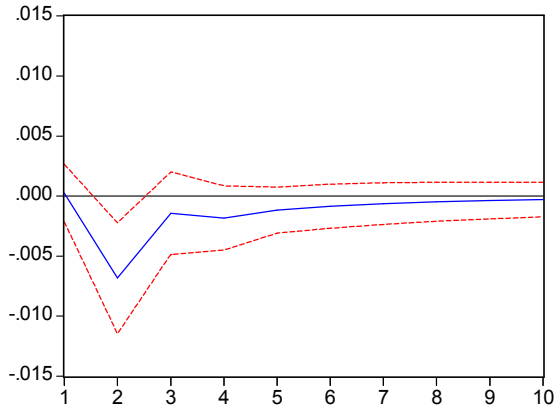


Notes: The dashed lines on each graph represent the upper and lower 95% confidence bands. When the upper and lower bounds carry the same sign the response becomes statistically significant.

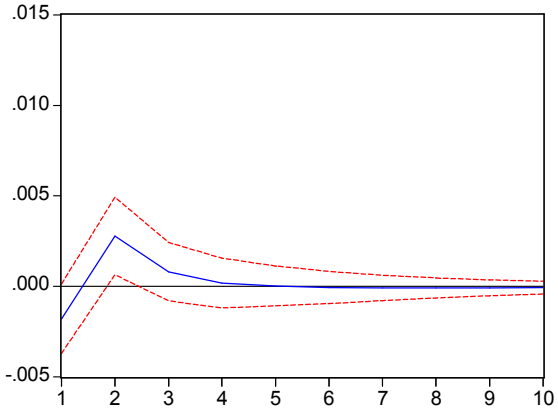
* On each graph, "percentage returns" are on the vertical and "horizon" is on the horizontal axis.

Figure 1.5 Response of Bovespa Volatility During Positive Changes in Bovespa Returns to the Rational and Irrational Sentiments of Investors. (a) Rational sentiments; (b) Irrational sentiments

(a) Rational (RAT) Sentiments



(b) *Irrational (IRRAT) Sentiments*

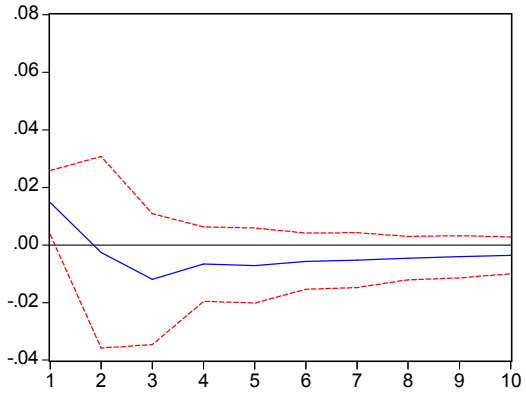


Notes: The dashed lines on each graph represent the upper and lower 95% confidence bands. When the upper and lower bounds carry the same sign the response becomes statistically significant.

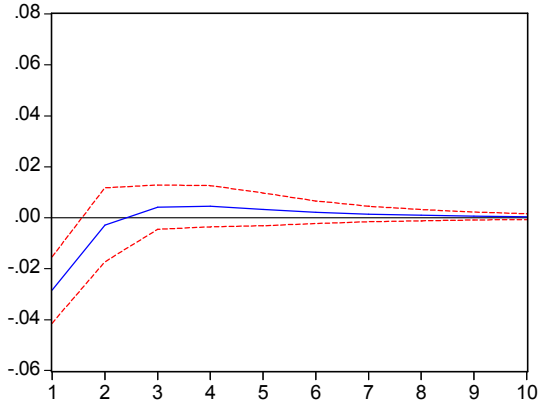
* On each graph, “percentage returns” are on the vertical and “horizon” is on the horizontal axis.

Figure 1.6 Response of Bovespa Returns to the Rational and Irrational Sentiments of Investors for the Pre and Post 2002 Subsamples. (a) Rational sentiments; (b) Irrational sentiments

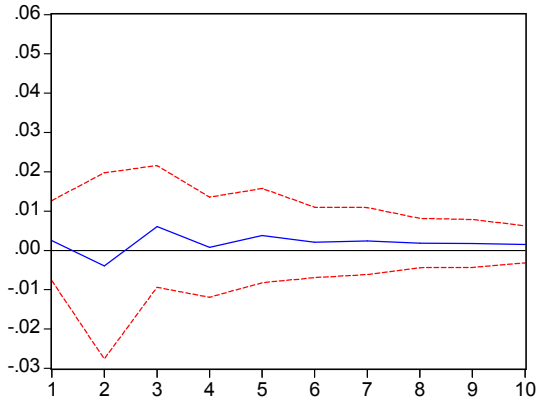
(a) Rational (RAT) Sentiments pre-2002



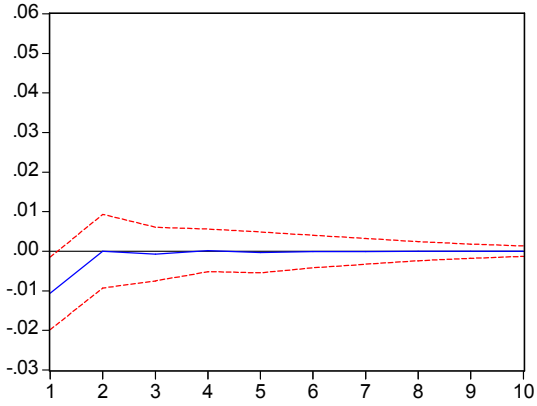
(b) *Irrational (IRRAT) Sentiments pre-2002*



(c) Rational (RAT) Sentiments post-2002



(d) *Irrational (IRRAT) Sentiments post-2002*

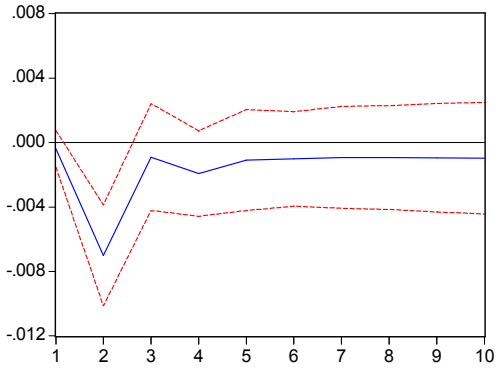


Notes: The dashed lines on each graph represent the upper and lower 95% confidence bands. When the upper and lower bounds carry the same sign the response becomes statistically significant.

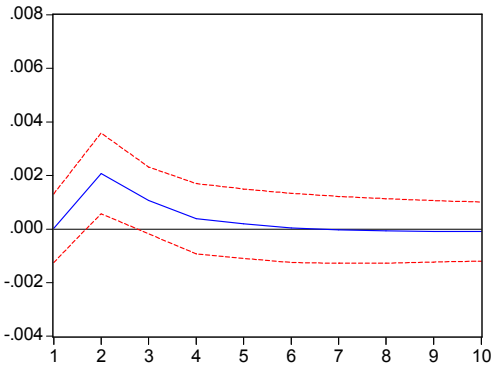
* On each graph, “percentage returns” are on the vertical and “horizon” is on the horizontal axis.

Figure 1.7 Response of Bovespa Volatility to the Rational and Irrational Sentiments of Investors for the Pre and Post 2002 Subsamples. (a) Rational sentiments; (b) Irrational sentiments

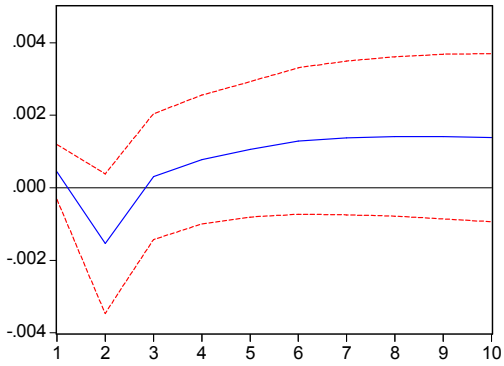
(a) Rational (RAT) Sentiments pre-2002



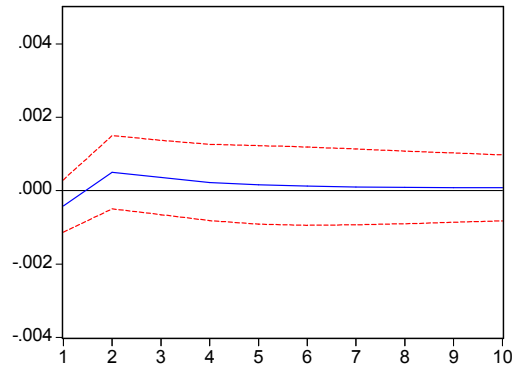
(b) *Irrational (IRRAT) Sentiments pre-2002*



(c) Rational (RAT) Sentiments post-2002



(d) *Irrational (IRRAT) Sentiments post-2002*



Notes: The dashed lines on each graph represent the upper and lower 95% confidence bands. When the upper and lower bounds carry the same sign the response becomes statistically significant.

* On each graph, “percentage returns” are on the vertical and “horizon” is on the horizontal axis.

CHAPTER II

THE IMPACT OF RATIONAL AND IRRATIONAL SENTIMENTS OF U.S. INDIVIDUAL AND INSTITUTIONAL INVESTORS ON BOVESPA INDEX RETURNS AND VOLATILITY

2.1 Introduction

This study examines the effect of U.S. investor sentiments on the returns and volatility of the Bovespa market index – an index reflecting the behavior of the largest Brazilian public firms. As implied by the empirical analysis undertaken in the previous chapter, it is possible for a group of noise traders to influence prices beyond the short term in line with the noise trader model of DeLong, Shleifer, Summers, and Waldmann (DSSW) (1990). The first chapter of this dissertation presented empirical evidence that these price deviations from fundamentals are unpredictably derived from changes in investor sentiment. In line with the DSSW model we pointed out that when noise traders are more bullish than informed investors, market volatility increases.

The influence of noise traders on domestic asset prices has been widely documented. However, it is possible that the sentiments of investors from a major stock market such as the U.S. exert an influence on asset prices in emerging stock markets (Ratanapakorn and Sharma, 2002; Meric *et al*, 2001). If U.S. investor sentiments were to influence the Brazilian stock market, its effect should be more evident in the sentiments of institutional investors who tend to be more informed and be subject to lesser constrains than individual investors.

Viceira (2007) shows that U.S. investor equity allocations are heavily biased towards U.S. stocks with investors interpreting international stocks as riskier than domestic stocks. However, this may be a flawed investment decision as evidenced by the work of French and Poterba (1991) who indicate that a well-diversified equity portfolio of U.S. investors is supposed to have a significant allocation to international assets.

Using the framework provided by Verma *et al.* (2008), in this study we employ a monthly database of U.S. investor sentiments at the individual compiled by the American Association of Individual Investors and of U.S. investor sentiments at the institutional level provided by Investors Intelligence to study the influence of U.S. investor sentiments on the Brazilian stock market.

The results of the generalized impulses generated from a vector auto regression (VAR) model reveal the following empirical results. First, the rational sentiments of U.S. investors significantly affect Brazilian market returns and volatility implying that U.S. investor sentiments have the ability to influence an emerging market returns and volatility. Second, there are immediate positive responses of Bovespa returns to U.S. irrational individual investor sentiments whereas no significant response of Bovespa returns to U.S. irrational institutional investor sentiments. Third, an increase in the rational sentiments of both classes of U.S. investors tend to decrease Bovespa volatility in line with the market fundamentals view where informed investors bring less uncertainty to asset prices. Fourth, there are no significant effects of past stock performance or past market volatility on rational or irrational sentiments of either class of investors. Lastly, rational sentiments have a more rapid and pronounced effect than irrational sentiments on Bovespa stock market returns and volatility. Contrary to the findings of Verma *et al* (2008) we do not find that irrational sentiments of U.S. investors have an effect on Bovespa

returns and volatility. Our results provide support to the view that there are spillover effects from rational sentiments of U.S. investors who base their decisions on an analysis of market fundamentals.

These results have practical suggestions for investors. People considering an investment in Bovespa should regard the sentiments of U.S. investors as well since rational sentiments of U.S. investors seem to have an effect on Brazilian stock market return and volatility. We find evidence that U.S. rational investor sentiment has a larger impact on Bovespa returns and volatility; therefore, sentiment from investors in developed markets may influence the returns and volatility of less deep emerging stock markets providing support to the presence of spillover effects. These effects may have become more pronounced in recent years as the participation rate of foreign investors[16] trading in Bovespa steadily increased to reach more than a third of the total traded volume in the exchange[17]. Moreover, our empirical results suggest the need to incorporate rational investor sentiments on international asset pricing models, in particular sentiments from investors trading in the U.S. which is considered one of the most influential stock markets worldwide.

The remainder of this chapter is organized as follows. Section 2.2 reviews the existing literature on investor sentiments and its influence on stock returns and volatility. Section 2.3 presents the model whereas Section 2.4 presents the data and descriptive statistics. Section 2.5

[16] Bovespa does not disclose the country of origin of foreign investors as well as whether the foreign investor is an individual or an institution.

[17] Foreign investor participation rate in Bovespa was about 22% of the total exchange traded volume in 2000. By 2009 their participation rate represented more than 37%. In October 2009 the Brazilian government began levying a 2% tax on short term foreign capital buying Brazilian firms debt and equity. This measure was intended to discourage short term capital from generating an investment bubble in the country while avoiding an overvaluation of the Real, the Brazilian currency. Brazilian market brokers initially feared this new tax would shift trading offshore to New York where foreign investors can buy and sell ADRs (American Depositary Receipts) in Brazil's biggest companies. However, traded volume in Bovespa has remained at about the same levels as before the new tax was instituted.

describes the econometric methodology. Section 2.6 presents empirical findings. Lastly, section 2.7 summarizes the major findings and concludes.

2.2 Literature review

One of the first authors to consider the role of investor sentiments and noise trading in the financial markets is Black (1986). He argues that "noise" makes trading in financial markets possible but also makes them imperfect as people sometimes trade on noise as if it were information. Trueman (1988) extends Black's assertion and explains why anyone would rationally want to trade on noise to benefit from noise traders misinformation. DSSW (1990), building upon Black's (1986) noise trader framework, present a model where noise traders acting as a group can influence stock prices in equilibrium. In this model the deviations in price from fundamental value, created by changes in investor sentiment, introduce a systematic risk which is priced. DSSW shows that risk created by the unpredictability of investor sentiment reduces the attractiveness of information traders to carry out arbitrage.

DSSW (1991) present a model of portfolio allocation by noise traders and show noise traders as a group can earn expected returns higher than rational investors and can survive in terms of wealth gain in the long run, due to unpredictability in their sentiments. Shleifer and Summers (1990) introduce a model in which limited arbitrage may prevent traders from taking advantage of short term mispricing in some assets. Shefrin and Statman (1994) present the behavioral capital asset pricing theory where noise traders interact with information traders. They show that the effect of noise traders in the market depends on specific cognitive errors committed. In contrast to information, noise traders' sentiment may act as a driver moving the market away from efficiency.

Lakonishok, Shleifer and Vishny (1992) suggest that institutional investors influence prices in small markets (stocks with small market capitalization). Palomino (1996) extends the DSSW (1990) model for an imperfectly competitive market. Palomino (1996) shows that in an imperfectly competitive market with risk averse investors, noise traders may earn higher return and obtain higher expected utility than rational investors. This implies that if relative success breeds imitation, then noise traders will likely survive in the long run. Overall, these models suggest that due to the randomness in investor sentiment, noise traders acting as a group may be able to introduce a systematic risk that is incorporated in asset prices.

In line with these predictions, several empirical studies have examined the role of sentiment on stock pricing. These studies have either used indirect measures or direct measures of investor sentiment. Studies using indirect measures include the following proxies: close-ended fund's discount (Gemmill and Thomas, 2002; Baker & Wurgler, 2006; Sias, Starks and Tinic, 2001; Neal and Whitney, 1998; Swaminathan, 1996; Elton, Gruber and Busse, 1998; Chan, Kan and Miller, 1993; Lee, Shleifer and Thaler, 1991); market performance based measures (Brown and Cliff, 2004); trading activity based measures (Brown and Cliff, 2004; Neal and Whitney, 1998); derivative variables (Brown and Cliff, 2004); dividend premium (Baker and Wurgler, 2006); and IPOs related measures (Baker & Wurgler, 2006; Brown and Cliff, 2004). Overall, these studies do not provide a consensus on whether the proxies chosen are appropriate measures of investor sentiment; in addition, they tend to show mixed results about the connection between investor sentiments and stock returns.

Other studies use direct measures based mainly on sentiment surveys data to establish the expectations of market participants. Research related to individual investors sentiment find strong comovements with stock market returns (Brown and Cliff, 2004; DeBondt, 1993) and

mixed results regarding its role in short term predictability of stock prices (Brown and Cliff, 2004; Fisher and Statman, 2000). Similarly, studies examining institutional sentiment find significant comovements with stock market returns (Brown and Cliff, 2004) and mixed results regarding its short run implications on stock prices (Brown and Cliff, 2004; Lee, Jiang and Indro, 2002; Clarke and Statman, 1998; Solt and Statman, 1988). In addition, Brown and Cliff (2005) examine the long run implications of institutional investor sentiment and find strong relationships with long horizon stock returns. Overall, research using direct measures of investor sentiments provides powerful and consistent empirical support for the hypothesis that stock prices are affected by individual and institutional investor sentiments.

One major drawback in these studies is that they fail to explain whether the effect of sentiment on stock returns can be attributed entirely to investor exuberance or fully to rational expectations or to a combination of both. A recent study by Verma *et al* (2008) examines the role of investor sentiment on U.S. stock market returns analyzing their simultaneous impact. They find that rational sentiments have a larger impact than irrational sentiments on stock market returns.

The effects of domestic investor sentiments on a foreign stock market returns and volatilities have not been properly documented. Verma *et al* (2006) suggests that U.S. investor sentiments are propagated abroad with different degrees of impact, with the response of individual investors being more erratic than that of institutional investors. However, they do not consider whether the volatility of returns in a foreign market is affected by domestic investor sentiments in the same econometric model. Moreover, in order to avoid turbulent times in foreign markets, we begin our analysis in 1995. Our choice of this date is based on several market developments that substantially changed the Brazilian economy around that period. First,

in February 2004 the Brazilian government launched Plano Real, a program that successfully controlled inflation and brought monetary stability. Second, since the beginning of the century many Brazilian firms increased their international presence by cross listing in other international stock exchanges, mainly from developed countries such as the U.S., the U.K. and Germany. Furthermore, Bovespa engaged in a series of institutional changes that increased transparency by promoting voluntary corporate disclosure, granted greater protection to local and foreign minority investors, and simplified company listing processes which lead to increased individual investor participation. In order to analyze how the increased presence of foreign investors may influence Bovespa, we estimate the effect of U.S. investor sentiments on the returns and volatility of iShares MSCI Brazil Index Fund (EWZ) ETF. U.S. investors are more likely to invest in instruments trading locally and regulated by U.S. law. EWZ is one of the preferred vehicles used by U.S. investors to obtain international diversification in the Brazilian market as it tracks the performance of the Bovespa index and is widely traded in U.S. stock markets. This highly liquid ETF, managed by Blackrock Institutional Trust Company (formerly known as Barclays Global Investors), began trading in July 2000 in line with the increase in foreign investor participation rate in Brazil. There is no information about the place of origin of foreign investors but we hypothesize that since EWZ trades in the U.S. and most investors tend to trade in markets physically close to their place of residence (French and Poterba, 1991), it is very likely that U.S. investors account for a large segment of the total investment on EWZ.

The above mentioned market facts may lead to differing results from Verma *et al* (2006) while making our analysis more relevant to current market conditions.

2.3 Model

There is evidence that U.S. stock market developments affect emerging stock markets (Ratanapakorn and Sharma, 2002; Meric *et al*, 2001). Following the model presented in Verma and Soydemir (2006) we analyze the international propagation of U.S. investor sentiments on Bovespa stock market returns and volatility.

Several authors (Shleifer and Summers, 1990; Brown and Cliff, 2004) document that investor sentiments contain rational expectations based risk factors. We hypothesize that there exists a possibility that both types of sentiment components, fundamental and noise, affect stock returns and volatility. Moreover, Hirshleifer (2001) and Shefrin (2005) also relate expected returns to both risks and investor misvaluation. Investor expectations about future market direction could be based on a rational analysis of market fundamentals or irrational optimism or due to a combination of both types of sentiments. Moreover, excessive optimism or pessimism on the part of investors may drive asset prices away from their intrinsic value. For these reasons we present a two-step model in this study. First we decompose investor sentiments into two components: (i) a rational component based on the fundamentals and (ii) an irrational factor based on the noise.

In order to model the rational and irrational effects of fundamentals and noise respectively on sentiments of individual and institutional investors, we formulate equations (2.1) and (2.2) and model:

$$Sent_{1t} = \gamma_0 + \sum_{j=1}^{J} \gamma_j Fund_{jt} + \xi_t \qquad (2.1)$$

$$Sent_{2t} = \theta_0 + \sum_{j=1}^{J} \theta_j Fund_{jt} + \vartheta_t \qquad (2.2)$$

where γ_0 and θ_0 are constants, γ_j and θ_j are the parameters to be estimated; ξ_t and ϑ_t are the random error terms. $Sent_{1t}$ and $Sent_{2t}$ represent the changes in sentiments of individual and institutional investors respectively at time *t*. $Fund_{jt}$ is the set of fundamentals representing rational investor expectations based on several risk factors that are consistently used in the asset pricing literature as providing useful information about asset prices. The fitted values of equations (2.1) and (2.2) capture the rational component of sentiments (i.e. $\hat{Sent}_{1t}$ and $\hat{Sent}_{2t}$). Conversely, each residual term of equations (2.1) and (2.2) captures the irrational component of sentiments (i.e. ξ_t and ϑ_t).

It is important to note that the sentiments of individual and institutional investors are included in the same model in order to avoid misspecification (Verma & Verma, 2007) and to correctly interpret the effect of different type of sentiments have on stock returns and volatility.

In the second step, we evaluate the effects of sentiments on stock returns and volatility. It is important to note that investor sentiments may be classified as rational or irrational. In order to examine how investor sentiments affect stock returns we decompose the sentiment variables are into the rational and irrational components based on the previously estimated equations (2.1) and (2.2). These factors are then modeled as follows:

$$R_t = \alpha_0 + \alpha_1 \hat{Sent}_{1t} + \alpha_2 \hat{Sent}_{2t} + \alpha_3 \xi_t + \alpha_4 \vartheta_t + \alpha_5 \sigma_t + \rho_t \qquad (2.3)$$

where α_0 is a constant while $\alpha_1, \alpha_2, \alpha_3$ and α_4 are the parameters to be estimated; ρ_t is the random error term. In this model, the parameters α_1 and α_2 capture the effects of sentiments induced by fundamental trading on the part of individual and institutional investors respectively; whereas α_3 and α_4 capture the effects of sentiments induced noise trading by individual and institutional investors respectively. Lastly, the parameter α_5 captures Bovespa volatility.

Lastly, we evaluate how investor sentiments affect stock market volatility. We estimate the standard deviation of the past month continuously compounded returns to determine this month's volatility[18] (trailing one-month realized volatility). The stock market continuously daily compounded returns are calculated using the formula $u_t = \ln(R_t) - \ln(R_{t-1})$ where u_t is the continuously compounded return between the end of day *i* and between day *i-1*. To calculate an unbiased estimate of the standard deviation rate per day, σ, using the most recent *m* observations on the u_t the following formula is applied: [19]

$$\sigma_t = \sqrt{\frac{1}{m}\sum_{i=1}^{m} u_{t-1}^2} \qquad (2.4)$$

In order to analyze the impact of investor sentiments on stock market volatility, similar to equation (2.3) we separate the sentiment variable into the rational and irrational components obtained in equation (2.1) and incorporate them in the following equation:

$$\sigma_t = \alpha_0 + \alpha_1 \hat{Sent}_{1t} + \alpha_2 \hat{Sent}_{2t} + \alpha_3 \xi_t + \alpha_4 \vartheta_t + \rho_t \qquad (2.5)$$

where σ_t is the one-month trailing volatility for the stock market; α_0 is a constant while α_1, α_2, α_3 and α_4 are the parameters to be estimated; ρ_t is the random error term. The parameters α_1 and α_2 capture the effects of sentiments induced by fundamental trading on the part of individual and institutional investors respectively; while α_3 and α_4 capture the effects of sentiments induced noise trading by individual and institutional investors respectively.

[18] One of the most popular ARCH-GARCH models used to represent volatility is Bollerslev's GARCH (1,1). The choice of historical monthly standard deviation is based on Ederington, Louis and Guan (2006) who suggest that historical standard deviation as a measure of volatility performs just as well as a GARCH (1,1) model.
[19] For details on estimating volatility see Hull (2006) pp. 461-462.

2.4 Data and Descriptive Statistics

The data is in monthly intervals and cover the period from January 1995 to May 2010. The extant literature presents several alternatives to measure the sentiments of market participants. For this study we use survey data about sentiments of U.S. individual and institutional investors. In general, institutional investors tend to participate in the market for a living; individual investors, on the contrary, do not make a living off the stock market (Brown and Cliff, 2004) and are seen as less sophisticated investors or noise traders (Baker and Wurgler, 2006).

Following DeBondt (1993), Fisher and Statman (2000), and Brown and Cliff (2004), among others, we use the survey data of the *American Association of Individual Investor (AAII)* as the individual investor sentiment index. The *AAII*, with approximately 100,000 members, conducts a weekly survey[20] asking its members for the likely direction of the stock market during the next six months. There are only three choices available in this survey: market will go up, down or stay the same. On a weekly basis, *AAII* compiles the results of the survey answers labeling answers of those expecting the market to go up, down, or remain the same as bullish, bearish or neutral respectively. These results are readily available to any interested party by visiting *AAII's* website. In line with the previous literature, the sentiment index for individual investors is computed as the spread between the percentage of bullish investors and percentage of bearish investors (Bull-Bear). Given that this survey is targeted towards individual investors, it is a feasible proxy measure of individual investor sentiments.

Regarding the institutional investor sentiment index we follow Solt and Statman (1988), Clarke and Statman (1998), Lee et al. (2002), and Brown and Cliff (2004) which use the survey

[20] In order to add greater flexibility, current *AAII* members can submit an electronic vote about future market conditions using this webpage http://www.aaii.com/sentimentsurvey/

data of *Investors Intelligence (II)*. *II* is an investment service which since 1963 compiles data based on a survey of hundreds of independent market newsletters, assessing each investment advisor newsletter stance on the market: bullish (positive view of the market), bearish (expecting a market correction), or hold. The sentiment index for the institutional investor is calculated as the spread between the percentage of bullish investors and percentage of bearish investors. According to *II*, this sentiment indicator provides a view of the broad market, especially industry practitioners. With the purpose of avoiding investment newsletters bias towards buy recommendation, the *II* sentiment index excludes letters from brokerage houses. In line with past literature the *II* index is interpreted as representative of institutional investor sentiments.

In order to determine the overall performance of the Brazilian stock market, we use the returns of Bovespa index (Bovespa). This trade-weighted index is the main indicator of the Brazilian stock market's average performance, reflecting the variation of the most liquid stocks traded at the Sao Paulo Stock Exchange. The index comprises a theoretical stock portfolio with its components adjusted every four months. Bovespa reflects not only the variation of the stock prices but also the impact of the distribution of benefits and is considered an indicator that evaluates the total return of its component stocks. In this study we use the monthly continuously compounded returns for Bovespa estimated by Datastream.

The monthly volatility of Bovespa returns is estimated using formula (2.4). Figure 1.1 shows the annualized one-month trailing volatility for Bovespa from January 1994 to May 2010. Periods of high volatility coincide with economic crises influencing Bovespa returns (notice for example the Russian financial crisis around October 1998 or the Brazilian Real devaluation of February 1999 or the recent global financial crisis of October 2008).

In line with Verma *et al* (2006) we utilize several variables as representative of market fundamentals. These are some of the most commonly used variables in the asset pricing literature: (i) Economic growth (IIP) (Fama, 1970; Schwert, 1990) measured as the monthly changes in the U.S. industrial production index (ii) Short term interest rates (STR) (Campbell, 1991) measured as the yield on one month U.S. Treasury Bill (iii) Economic risk premia (ERP) (Ferson and Harvey, 1991; Campbell, 1987) measured as the term structure of interest rates (difference in monthly yields on three month and one month U.S. Treasury bills (iv) Future economic expectations variables (FUTEC) (Fama, 1990) measured as the term spread (yields spread on the 10 year U.S. Treasury bond and three month U.S. Treasury bill) (v) Business conditions (BUSC) (Fama and French, 1989; Keim and Stambaugh, 1986) measured as the default spread (difference in yields on Baa and Aaa corporate bonds) (vi) Dividend yield (DIV) (Hodrick, 1992; Fama and French, 1988; Campbell and Shiller, 1988a, 1988b) measured as the dividend yield for the value-weighted Center for Research in Security Prices (CRSP) index over the past 12 months. The dividend yield is the ratio of the ordinary dividends of an index to the previous price. (vii) Inflation (INFL) (Sharpe, 2002; Fama and Schwert, 1977) measured as the monthly changes in the broad U.S. consumer price index (viii) Excess returns on market portfolio (RM) (Lintner, 1965; Sharpe, 1964) measured as the value-weighted returns on all NYSE, AMEX, and NASDAQ stocks minus the one-month U.S. Treasury bill rate (ix) Premium on portfolio of small stocks relative to large stocks (SMB) (Fama and French, 1993). SMB (Small minus Big) is the average return on three small portfolios minus the average return on three big portfolios (x) Premium on portfolio of high book/market stocks relative to low book/market stocks (HML) (Fama and French, 1993). This Fama/French benchmark factor is constructed from six size/book-to-market benchmark portfolios that do not include hold ranges

and do not incur transaction costs. HML (High minus Low) is the average return on two value portfolios minus the average return on two growth portfolios. (xi) Momentum factor (UMD) (Jegadeesh and Titman, 1993). UMD (Up minus Down) is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios (xii) Currency fluctuation (Elton and Gruber, 1991) measured as the weighted average of the foreign exchange value of the U.S. dollar against the currencies of a broad group of major U.S. trading partners (major trading partners include the Euro Area, Canada, Japan, Mexico, China, United Kingdom, Taiwan, Korea, Singapore, Hong Kong, Malaysia, Brazil, Switzerland, Thailand, Philippines, Australia, Indonesia, India, Israel, Saudi Arabia, Russia, Sweden, Argentina, Venezuela, Chile and Colombia).

The data on economic growth, business conditions and inflation are from Datastream; short term interest rates, economic risk premium, future economic variables and currency fluctuations are obtained from Federal Reserve Bank of St. Louis (Federal Reserve Economic Database, FRED); dividend yield is from CRSP; excess return on market portfolio (RM), SMB, HML and UMD factors are from Kenneth French's Data Library at Dartmouth College.

Table 2.1 reports the descriptive statistics for all the variables used in this study. The mean of $Sent_1$ and $Sent_2$ are approximately 10% and 18% respectively, suggesting that individual and institutional investors have been on average bullish during most of the sample period. Institutional investors have been more bullish on average than individual investors. The mean return of Bovespa is 4.4% while the volatility of Bovespa returns is approximately 2.5%. The two sentiment measures have higher standard deviations than that of Bovespa market index returns, suggesting that investor sentiments have been highly volatile during the sample period.

The cross correlation between Bovespa returns and volatility, investor sentiment measures, and variables representative of market fundamentals are reported on Table 2.2 The correlations between the two sentiments variables is approximately 0.50, which is comparable to Fisher and Statman (2000)'s result of 0.49 and Verma *et al* (2006) figure of 0.50. Such high correlation indicates a possible link between individual and institutional investor sentiments. It is likely that individual investor sentiments are influenced by institutional investor sentiments, or vice versa. This possibility provides additional support for our decision of modeling sentiments in the same multivariate setting first, while isolating their individual effects on the stock market returns and volatility in the second stage.

The contemporaneous correlation between Bovespa returns and institutional investor sentiments is higher than that with individual investor sentiments. This may imply that institutional investors are more likely to invest in foreign markets than individual investors in line with previous research showing that U.S. investors' portfolios holding less foreign securities than implied by predictions of standard mean-variance portfolio optimization models (French and Poterba, 1991; Errunza, Hogan and Hung, 1999; Pastor, 2000). There seems to be a high correlation (0.82) between the variables business conditions (BUSC) and dividend yield (DIV) which we will take into consideration when estimating the model to avoid multicollinearity. On the other hand, the low correlations among the remaining variables representative of fundamentals hints that each variable measures different constructs and that they are independent from each other. Lastly, the variability, as expressed by the standard deviation, of the variables representative of market fundamentals is lower than that of the investor sentiment proxies and that of Bovespa returns and volatility.

2.5 Econometric methodology

Previous research (Brown and Cliff, 2004; Lee et al., 2002; Verma *et al*, 2008) suggest that it is likely for stock market returns and investor sentiments to operate as a system. We think that a VAR model as proposed by Sims (1980) is the suitable econometric methodology to study the relationships between sentiments and market returns and volatility. Among the advantages of VAR models is that all variables are treated as endogenous and model estimation is very simple. Additionally, there has been extensively documented that forecasts obtained with VAR models are better than those obtained through most complex simultaneous equation models (Mahmoud, 1984; Litterman, 1984; McNees, 1986; Lupoletti and Webb, 1986; and Webb, 1999). Given that the coefficients obtained from a VAR model are difficult to interpret since they lack a theoretical background, we analyze the impulse response functions (IRFs). An IRF traces the effect of a one-time shock to one of the innovations on current and future values of the endogenous variables and allows overcoming potential misspecification problems. Hence, we use the IRFs generated from the VAR model to analyze the effect of unanticipated changes (surprises or innovations) in U.S. investor sentiment to both Bovespa returns and volatility.

It is very likely that there exist time delays between the generation and reporting of information and its application to a particular strategy by investors. Therefore, for a model to be a reasonable representation of reality, it has to take into consideration time lags between variables not just the contemporaneous changes in variables at a particular point in time. This fact is especially relevant for the macroeconomic variables used as representative of market fundamentals. Hence, in line with previous studies, we use the Akaike information criterion (AIC) and the Schwarz information criterion (SIC) to determine the appropriate lag lengths. As Verma *et al* (2006) point out the lags in the VAR model provide a decent approximation to the

true data generating process while capturing the dynamic relationships in a fairly unrestricted way. We express the VAR model as:

$$Z(t) = C + \sum_{s=1}^{m} A(s)Z(t-m) + \varepsilon(t) \qquad (2.6)$$

where, $Z(t)$ is a column vector of variables under consideration, C is the deterministic component comprised of a constant, $A(s)$ is a matrix of coefficients, m is the lag length and $\varepsilon(t)$ is a vector of random error terms.

An added advantage of VAR models is that it let researchers integrate Monte Carlo simulations in order to obtain confidence bands around the point estimates from the IRFs (Doan, 1988; Hamilton, 1994). As previously described, the IRFs show the likely response of one variable to a one time unit shock in another variable. Specifically, IRFs represent the behavior of the series in response to pure shocks while keeping the effect of other variables constant. These impulse responses tend to be non-linear functions of the estimated parameters. For this reason, adding confidence bands around the mean response estimated using Monte Carlo simulations help researchers identify statistically significant responses. IRFs are said to be statistically significant at the 95% confidence level whenever the upper and lower confidence bands hold the same sign.

Lastly, we use the generalized impulses technique of Pesaran and Shin (1998) who construct an orthogonal set of innovations that is independent from variable ordering. The generalized impulses technique prevents the model from being sensitive to variable ordering as it happens when researchers use the more traditional Choleski factorization of VAR innovations.

2.6 Estimation results

This section presents the results of the Unit Root Tests on the variables used. Then results from several VAR models and the interpretation of the IRFs graphs are shown. Lastly, for robustness this section concludes with the results from alternative model specification using iShares Brazil (EWZ) as the market index return.

2.6.1 Unit Root Tests

Table 2.3 reports the results of unit root tests using ADF test (Dickey and Fuller, 1979, 1981) and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test (Kwiatkowski, Phillips, Schmidt, and Shin, 1992). These tests are conducted in order to check the time series properties of each variable. The appropriate number of lags is two after taking into account the loss in degrees of freedom and based on the *AIC* and *SIC* criteria (Diebold, 2004). In the case of the ADF test, the null hypothesis of non-stationarity is rejected. These results do not materially change when we include drift or trend terms in the ADF test equations. (Dolado, Jenkinson, and Sosvilla-Rivero, 1990). For the KPSS test, the null hypothesis of stationarity is not rejected. Overall, unit root tests suggest that the series used in this study are stationary.

2.6.2 VAR Model Results

First, the individual and institutional investor sentiments variables are decomposed into rational and irrational components based on the fitted and residual values of equations (2.1) and (2.2). In particular, we estimate two ordinary least squares (OLS) regressions based on equations (2.1) and (2.2). The relatively high correlation ($\rho=0.82$) between (BUSC) and dividend yield (DIV) as shown in Table 2.2 suggest the presence of collinearity. Therefore, we drop BUSC

from the current analysis and estimate the model with the remaining variables representative of fundamentals which exhibit low cross correlations. The relatively low values of the Durbin-Watson statistics (1.38 and 1.53 respectively) after estimating the OLS regressions of equations (2.1) and (2.2) suggest the presence of positive first-order serial correlations. Following Diebold (2004) and Verma *et al* (2006) we include an AR(1) process in both OLS regressions to remove the serial correlation in error terms. The Durbin-Watson statistics drastically improve after incorporating the AR(1) term (2.05 and 2.02) implying that there is no first-order serial correlation in both cases.

Table 2.4 shows the results after estimating equation (2.1). Individual investor sentiments are significantly related to economic risk premium, dividend yield, inflation, excess returns on the market, HML, and MOM. Similarly, Table 2.5 presents the results after estimating an OLS regression based on equation (2.2). In this particular case, institutional investor sentiments are significantly related to short term interest rates, economic risk premium, future economic conditions, dividend yield, excess returns on the market, and the trade-weighted exchange rate.

The regressions have an R^2 of 0.32 and 0.66 respectively, meaning that about the set of economic fundamentals chosen are better in explaining the variation in institutional investor sentiment. These results are consistent with the argument of Brown and Cliff (2005) that investor sentiments may contain a combination of both rational and irrational components and not necessarily just noise. We generate the fitted values and residuals for each regression (2.1 and 2.2) to compute the rational and irrational components of individual and institutional U.S. investor sentiments.

To analyze the effects of the relative effects of rational and irrational U.S. investor sentiments on Bovespa stock market returns and volatility, as depicted in equation (2.3), we

estimate a six variable VAR model with two lags. The variables included in this VAR model are Bovespa index returns, Bovespa volatility, rational sentiments of U.S. individual and U.S. institutional investors ($\hat{Sent}_{1t}$ and $\hat{Sent}_{2t}$) and irrational sentiments of U.S. individual and U.S. institutional investors (ξ_t and ϑ_t). This implies that in order to measure the effects of investor sentiments on the Brazilian market, in addition to the returns and volatility of Bovespa, we include the four new variables derived from equations (2.2) and (2.3) related to rational and irrational sentiments of U.S. individual and institutional investors.

Table 2.6 present the results of the VAR estimates. Sims (1980) mentions that it is difficult to make sense of VAR estimates by examining the coefficients in the regression equations themselves. Enders (2003) show that the *t*-tests on individual coefficients are not very reliable guides. Given that Sims (1980) recommends interpreting IRFs instead of focusing on the estimated coefficients of the VAR model, we analyze the relevant IRFs. We build the generalized impulse responses (Pesaran and Shin, 1996) from the VAR model to trace the response of one variable to a one-standard-deviation shock to another variable in the system. Confidence bands are built around the mean response using Monte Carlo methods (Doan and Litterman, 1986). Whenever the upper and lower confidence bands hold the same sign, IRFs responses become statistically significant at the 95% confidence level.

Figure 2.1.a and 2.1.b plot the impulse responses of Bovespa returns to a one time standard deviation increase in the rational and irrational sentiments of U.S. individual investors respectively. The effect of the rational component is positive and significant around the second month and insignificant thereafter. The response to the irrational component is positive and significant during the first month insignificant during the remaining months. In addition, the response to the rational component is much greater than the response to the irrational component

perhaps indicating that a positive rational sentiment has a tendency to increase returns and a positive irrational sentiment to lower returns after two periods. This result may suggest that the sentiments induced fundamental trading has a delayed but greater statistically significant effect than the sentiments induced noise trading by U.S. individual investors in the Brazilian market perhaps reflecting investor reaction after careful and thorough analysis of fundamentals which may require longer time to conduct analysis than trading induced by irrational sentiments. These findings thus provide empirical support for both rational and irrational sentiments contradicting the previous findings of Verma *et al* (2006) who show no transmission effect from U.S. investor sentiments to Brazilian stock market returns.

Figures 2.2.a and 2.2.b plot the impulse responses of Bovespa volatility to rational and irrational sentiments of the U.S. individual investors. The effect of the rational component is negative and marginally significant around the third month signaling a delayed decrease in Bovespa volatility when there is an increase in the rational sentiments of U.S. individual investors. Irrational sentiments of U.S. individual investors have no effect on Bovespa volatility, perhaps due to their limited involvement in emerging markets trades.

The response of Bovespa returns to the rational sentiments of U.S. institutional investors, as plotted in Figure 2.3.a, show a significant increase in returns peaking around the second period when there is a one-standard deviation increase in the rational sentiments. The effect of this positive and statistically significantly impact of rational investor sentiments lasts for about two months. Figure 2.3.b presents the insignificant effect of irrational sentiments of U.S. institutional investors on Bovespa returns. These results support the view that the effect of the rational component is much greater than that of the irrational components suggesting that U.S. institutional investors carefully analyze market fundamentals before investing in Brazil,

providing support to the view that institutional investors are more sophisticated and better informed than individual investors. Moreover, the greater effect of rational components of U.S. institutional investor sentiments may suggest that the sentiments induced fundamental trading has much greater effect than the sentiments induced noise trading by institutional investors on Bovespa returns.

Figures 2.4.a and 2.4.b present the effects of U.S. institutional investor sentiments on the volatility of Bovespa. A one-time positive shock to rational (irrational) U.S. institutional investor sentiments leads to a decrease (no effect) in Bovespa volatility around the time of the second month having a significant negative effect lasting for several periods. These findings are in line with the view that informed investors after a careful analysis of market fundamentals reduce uncertainty and noise in markets.

Overall, these IRFs figures present evidence consistent with the traditional finance view that informed institutional investors trade after careful analysis of the market fundamentals, thereby reducing the noise in financial markets. In terms of magnitude, rational sentiments have a much greater impact than irrational sentiments. These findings present additional empirical support for both types of sentiments, rational and irrational, with rational (irrational) investor sentiments having a larger (insignificant) positive impact on Bovespa returns (volatility), thereby showing potential to influence stock market behavior. Further, stock returns appear to respond to rational sentiments at a slower speed than irrational sentiments perhaps reflecting relatively longer time required to carry out thorough analysis processing news contained in fundamentals rather than the quicker response of investors generally trading on very little information. In addition, the magnitude of the response of rational sentiments of U.S individual and institutional

investors is larger than irrational sentiments, perhaps indicating more prudent and careful behavior of the better informed investors.

Figures 2.5.a through 2.5.d plot the impulse responses of U.S. individual investor rational and irrational sentiments to Bovespa returns and volatility. The responses of rational sentiments are not significant in both cases (Figures 2.5.a and 2.5.c) suggesting the sentiments induced fundamental trading is not affected by past stock market performance in line with the weak form of the efficient market hypothesis (Fama, 1970; 1976) which claims that past stock prices do not predict future stock prices. The responses of the irrational sentiments of U.S. individual investors are also not significant. Overall, these results imply that sentiments induced fundamental trading is not affected by past stock market performance not providing support to DeBondt's (1993) traders 'positive feedback effect' whereby past positive market returns engenders increased short term bullishness whereas recent negative returns increases market bearishness. It is also feasible that the relative low U.S. investor participation rate in foreign markets may be the reason for the inexistence of this positive feedback effect in our sample.

Figures 2.5.a through 2.5.d plot the impulse responses of U.S. institutional investor rational and irrational sentiments to Bovespa returns and volatility. The insignificant responses of stock returns and volatility to the rational sentiments of U.S. institutional investors are in line with the efficient market hypothesis (Fama, 1970; 1976). For this sample, we do not find support to the behavioral model since there is no positive feedback effect (DeBondt. 1993) contrary to the results from previous studies such as Verma *et al* (2006).

2.6.3 Robustness Test

U.S. investors are more likely to invest in instruments trading locally regulated by U.S. law. French and Poterba (1991) showed that most investors tend to trade in firms and markets physically close to their place of residence. In order to analyze how the increased presence of foreign investors may influence Bovespa, we estimate the effect of U.S. investor sentiments on the returns and volatility of iShares MSCI Brazil Index Fund (EWZ) ETF. EWZ, which tracks the performance of the Bovespa index, is highly correlated with Bovespa (ρ=0.99) and widely traded in U.S. This highly liquid ETF, managed by Blackrock Institutional Trust Company began trading in July 2000 in line with the increase in foreign investor participation rate in Brazil. Although there is no information about the place of origin of foreign investors, it is very likely that U.S. investors account for a large segment of the total investment on EWZ that since EWZ trades in the U.S. under U.S. jurisdiction.

From Datastream we obtain the monthly return and volatility for EWZ since inception in July 2000 and estimate a VAR model (based on Equation 2.3) with six variables: EWZ returns, EWZ volatility, and the rational and irrational sentiments of individual and institutional investors respectively. Results from the VAR model are summarized in Table 2.7. Figures 2.7.a and 2.7.c present the effect of a one-time shock to the rational sentiments of individual and institutional investors respectively leads to a statistically significant increase in EWZ returns around the second period. These effects are similar to the ones on Bovespa returns described in Figures 2.1.a and 2.3.a but the returns of EWZ react more dramatically than those of Bovespa. Contrary to the IRF figure for Bovespa (see Figure 2.3.b) Figure 2.7.d portraits a positive response of EWZ returns to the irrational sentiments of U.S. institutional investors. This provides some support to the behavioral theory that irrational trading by institutional investors tends to increase EWZ

prices in the short run deviating prices from their fundamental values. This result contrasts with that of Verma *et al* (2006) who found no significant effect of the irrational sentiments of investors on Bovespa returns.

Figures 2.8.a through 2.8.d illustrate the effect of rational and irrational sentiments of individual and institutional to EWZ volatility. These results are similar to the ones previously described for Bovespa presented in Figures 2.2 and 2.4 respectively. The main difference is that the significant decrease in EWZ volatility when there is a one-standard deviation shock in the rational sentiments of investors is stronger than the reaction described for Bovespa. This suggests that informed investors trading in EWZ may react more quickly and efficiently to new information which is in line with increased transparency and liquidity in the ETF market.

2.7 Conclusion

In this study, we investigate the relative effects of rational and irrational sentiments of U.S. individual and institutional investors on Bovespa market index returns and volatility. We decompose the measure of investor sentiments into rational and irrational factors. We estimate a six variable VAR model finding the following overall results. First, the rational sentiments of U.S. investors significantly influence Brazilian market returns and volatility implying that U.S. investor sentiments has the ability to influence an emerging market returns and volatility. Second, there are immediate positive responses of Bovespa returns to U.S. irrational individual investor sentiments whereas there is no significant response of Bovespa returns to U.S. irrational institutional investor sentiments. Third, an increase in the rational sentiments of both classes of U.S. investors tend to decrease Bovespa volatility in line with the market fundamentals view where informed investors bring less uncertainty to asset prices. Fourth, there are no significant

effects of past stock performance or past market volatility on rational or irrational sentiments of either class of investors. Lastly, rational sentiments have a more rapid and pronounced effect than irrational sentiments on Bovespa stock market returns and volatility. Overall our results suggest that the sentiments induced fundamental trading on Bovespa has much greater effect than the sentiments induced noise trading by both U.S. individual and institutional investors. Our empirical results suggest the need to incorporate rational investor sentiments on international asset pricing models, in particular sentiments from investors trading in the U.S. which is considered one of the most influential stock markets.

Table 2.1 Descriptive Statistics

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
$Sent_1$	0.098	0.101	0.561	-0.368	0.184	-0.075	2.925
$Sent_2$	0.185	0.196	0.433	-0.296	0.135	-0.702	3.524
BOVESPA	0.044	0.030	0.777	-0.409	0.140	1.079	7.063
BOVVOL	0.025	0.021	0.065	0.010	0.011	1.509	5.390
IIP	0.002	0.002	0.020	-0.039	0.007	-1.426	9.306
STR	0.008	0.001	0.016	-0.023	0.076	-0.489	2.974
ERP	0.006	0.004	0.087	-0.077	0.025	-0.263	5.869
FUTEC	0.001	0.001	0.003	-0.001	0.001	-0.012	1.715
BUSC	0.009	0.008	0.034	0.006	0.005	3.042	13.584
DIV	0.002	0.001	0.003	0.001	0.000	0.705	2.752
INFL	0.002	0.002	0.014	-0.018	0.003	-1.739	15.868
RM	0.000	0.001	0.009	-0.015	0.004	-0.865	4.514
SMB	0.000	0.000	0.018	-0.014	0.003	0.809	10.817
HML	0.000	0.000	0.012	-0.010	0.003	-0.014	5.323
MOM	0.000	0.001	0.015	-0.029	0.005	-1.586	12.245
USD	0.004	0.001	0.078	-0.031	0.014	1.988	10.058

Notes: The variables are U.S. individual investor sentiments ($Sent_1$), U.S. institutional investor sentiments ($Sent_2$), returns on Bovespa index (BOVESPA), Bovespa index volatility of returns (BOVVOL), economic growth (IIP), short term interest rates (STR), economic risk premium (ERP), future economic conditions (FUTEC), business conditions (BUSC), dividend yield (DIV), inflation (INF), excess returns on market portfolio (RM), premium on portfolio of small stocks relative to large stocks (SMB), premium on portfolio of high book/market stocks relative to low book/market stocks (HML), momentum factors (UMD), and currency fluctuations (USD).

Table 2.2 Cross Correlations

	$Sent_1$	$Sent_2$	BOVESPA	BOVVOL	IIP	STR	ERP	FUTEC	BUSC	DIV	INFL	RM	SMB	HML	MOM	USD
$Sent_1$	1.00															
$Sent_2$	0.50	1.00														
BOVESPA	0.21	0.35	1.00													
BOVVOL	-0.11	-0.35	-0.25	1.00												
IIP	0.21	0.28	0.10	-0.15	1.00											
STR	0.17	0.33	0.08	-0.28	0.25	1.00										
ERP	0.16	0.26	0.18	-0.10	0.31	0.12	1.00									
FUTEC	-0.03	-0.03	0.02	-0.05	-0.05	-0.44	-0.07	1.00								
BUSC	-0.36	-0.45	-0.09	0.30	-0.45	-0.44	-0.21	0.43	1.00							
DIV	-0.44	-0.44	-0.07	0.14	-0.32	-0.25	-0.15	0.41	0.82	1.00						
INFL	-0.08	0.18	0.21	-0.30	0.08	0.14	0.09	-0.13	-0.31	-0.23	1.00					
RM	0.36	0.41	0.05	-0.05	0.03	0.13	0.06	0.01	-0.12	-0.04	0.03	1.00				
SMB	0.11	0.17	0.08	-0.08	-0.04	-0.10	0.08	0.15	0.05	-0.02	0.06	0.24	1.00			
HML	0.05	0.07	0.10	-0.20	0.07	0.07	0.03	-0.02	-0.12	-0.11	0.07	-0.26	-0.36	1.00		
MOM	-0.11	-0.04	-0.11	-0.04	0.07	-0.04	0.20	-0.07	-0.22	-0.23	0.07	-0.32	0.09	-0.16	1.00	
USD	-0.11	-0.43	-0.36	0.35	0.02	0.00	-0.20	-0.03	0.04	0.04	-0.21	-0.38	-0.15	-0.06	0.22	1.00

Notes: The variables are U.S. individual investor sentiments (Sent1), U.S. institutional investor sentiments (Sent2), returns on Bovespa index (BOVESPA), Bovespa index volatility of returns (BOVVOL), economic growth (IIP), short term interest rates (STR), economic risk premium (ERP), future economic conditions (FUTEC), business conditions (BUSC), dividend yield (DIV), inflation (INF), excess returns on market portfolio (RM), premium on portfolio of small stocks relative to large stocks (SMB), premium on portfolio of high book/market stocks relative to low book/market stocks (HML), momentum factors (UMD), and currency fluctuations (USD).

Table 2.3 Unit Root Tests

	ADF	Lag length	KPSS (4)
Levels			
$Sent_1$	-2.558	2	0.261***
$Sent_2$	-2.035	2	0.221***
BOVESPA	-1.959	2	0.201***
BOVVOL	-3.036*	2	0.147**
IIP	-1.570	2	0.839***
STR	-2.148	2	0.167**
ERP	-2.475	2	0.569**
FUTEC	-1.743	2	0.195**
BUSC	-2.718*	2	0.147**
DIV	-2.031	2	0.733***
INFL	-1.533	2	0.057***
RM	-1.261	2	0.056***
SMB	-1.345	2	0.079***
HML	-3.011*	2	0.127*
MOM	-1.568	2	0.159**
USD	-2.070	2	1.072***
First difference			
SENTT1	-13.081***	2	0.015
SENTT2	-11.283***	2	0.026
BOVESPA	-14.389***	2	0.026
BOVVOL	-10.586***	2	0.015
IIP	-6.693***	2	0.027
STR	-9.492***	2	0.042
ERP	-10.468***	2	0.017
FUTEC	-6.395***	2	0.157
BUSC	-6.779***	2	0.029
DIV	-5.987***	2	0.200
INFL	-7.538***	2	0.023
RM	-13.897***	2	0.021
SMB	-13.677***	2	0.014
HML	-14.278***	2	0.014
MOM	-14.354***	2	0.012
USD	-12.089***	2	0.122

Notes: The variables are U.S. individual investor sentiments (Sent1), U.S. institutional investor sentiments (Sent2), returns on Bovespa index (BOVESPA), Bovespa index volatility of returns (BOVVOL), economic growth (IIP), short term interest rates (STR), economic risk premium (ERP), future economic conditions (FUTEC), business conditions (BUSC), dividend yield (DIV), inflation (INF), excess returns on market portfolio (RM), premium on portfolio of small stocks relative to large stocks (SMB), premium on portfolio of high book/market stocks relative to low book/market stocks (HML), momentum factors (UMD), and currency fluctuations (USD).
****, ** and * denote rejection of the null hypothesis of unit roots for the Augmented Dickey–Fuller (ADF) tests at the 1%, 5% and 10% significance levels respectively.*
****, ** and * denote rejection of the null hypothesis of stationarity for the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) tests at the 1%, 5% and 10% significance levels.*
Unit root tests were run with linear trend and intercept at levels, and intercept only at first differences. Lag lengths were chosen using the Akaike Information Criterion (AIC) and the obtained residuals are white noise.

Table 2.4 Effects of fundamentals on U.S. individual investor sentiments

The variables are U.S. individual investor sentiments ($Sent_1$), economic growth (IIP), short term interest rates (STR), economic risk premium (ERP), future economic conditions (FUTEC), dividend yield (DIV), inflation (INF), excess returns on market portfolio (RM), premium on portfolio of small stocks relative to large stocks (SMB), premium on portfolio of high book/market stocks relative to low book/market stocks (HML), momentum factors (UMD), and currency fluctuations (USD).

$$Sentt_{1t} = \gamma_0 + \gamma_j \sum_{j=1}^{J} Fund_{jt} + \xi_t$$

Dependent Variable: $Sent_1$				
Variables	Coefficient	Std. Error	t-Statistic	Prob.
IIP	0.52	1.74	0.30	0.76
STR	0.33	0.20	1.63	0.11
ERP	0.85	0.39	2.20	0.03
FUTEC	20.73	16.37	1.27	0.21
DIV	-197.49	39.03	-5.06	0.00
INFL	-10.79	4.20	-2.57	0.01
RM	13.27	3.35	3.96	0.00
SMB	3.84	3.82	1.01	0.32
HML	8.07	4.44	1.82	0.07
MOM	-4.71	2.54	-1.86	0.07
USD	0.64	1.00	0.64	0.52
C	0.39	0.06	6.58	0.00
Adj. R-squared	0.3225			
S.E. of regression	0.1529			
Sum squared residual	4.2543			
Log-likelihood	96.2510			
Durbin-Watson Stat	1.3809			
F-statistic	8.6952			
Prob(F-statistic)	0.0000			

Table 2.5 Effects of fundamentals on U.S. institutional investor sentiments

Notes: The variables are U.S. institutional investor sentiments ($Sent_2$), economic growth (IIP), short term interest rates (STR), economic risk premium (ERP), future economic conditions (FUTEC), dividend yield (DIV), inflation (INF), excess returns on market portfolio (RM), premium on portfolio of small stocks relative to large stocks (SMB), premium on portfolio of high book/market stocks relative to low book/market stocks (HML), momentum factors (UMD), and currency fluctuations (USD).

$$Sentt_{2t} = \theta_0 + \theta_j \sum_{j=1}^{J} Fund_{jt} + \vartheta_t$$

Dependent Variable: *Sent₂*				
Variables	Coefficient	Std. Error	t-Statistic	Prob.
IIP	-0.50	0.90	-0.56	0.58
STR	0.44	0.20	2.24	0.03
ERP	0.65	0.27	2.42	0.02
FUTEC	39.60	15.92	2.49	0.01
DIV	-216.91	45.55	-4.76	0.00
INFL	-0.34	2.22	-0.15	0.88
RM	6.54	1.67	3.92	0.00
SMB	2.74	1.78	1.54	0.13
HML	2.21	2.20	1.01	0.32
MOM	-0.35	1.20	-0.30	0.77
USD	-1.96	0.62	-3.14	0.00
C	0.45	0.06	6.95	0.00
Adj. R-squared	0.6606			
S.E. of regression	0.0791			
Sum squared residual	0.9134			
Log-likelihood	184.5667			
Durbin-Watson Stat	1.5301			
F-statistic	26.6248			

Table 2.6 Vector Autoregression Estimates

The variables are rational sentiments of U.S. individual investors (Sent1_r), irrational sentiments of U.S. individual investors (Sent1_ir), rational sentiments of U.S. institutional investors (Sent2_r), irrational sentiments of U.S. institutional investors (Sent2_ir), returns on Bovespa index (BOVESPA), and volatility of Bovespa index returns (BOVVOL).
*, ** and *** denote significance levels at the 10%, 5% and 1%, respectively. Standard errors are in the parentheses.

	Sent1_r	Sent1_ir	Sent2_r	Sent2_ir	BOVESPA	BOVVOL
Sent1_r (-1)	0.58***	-0.272	0.16**	0.159	-0.138	0.02***
	(0.13)	(0.24)	(0.08)	(0.12)	(0.12)	(0.01)
Sent1_r (-2)	-0.084	0.191	-0.106*	-0.078	-0.070	-0.005
	(0.09)	(0.18)	(0.06)	(0.09)	(0.09)	(0.01)
Sent1_ir (-1)	0.282***	-0.043	-0.011	-0.063	-0.007	0.005
	(0.05)	(0.09)	(0.03)	(0.04)	(0.04)	(0.00)
Sent1_ir (-2)	-0.088	0.136	-0.040	-0.026	0.012	-0.006
	(0.06)	(0.11)	(0.04)	(0.05)	(0.06)	(0.00)
Sent2_r (-1)	0.033	0.667*	0.671***	0.066	1.195***	-0.073***
	(0.19)	(0.36)	(0.13)	(0.17)	(0.18)	(0.01)
Sent2_r (-2)	0.169	-0.511*	0.154	-0.156	-0.767***	0.039***
	(0.15)	(0.29)	(0.10)	(0.14)	(0.15)	(0.01)
Sent2_ir (-1)	-0.235**	-0.103	0.498***	0.026	0.347***	-0.014**
	(0.09)	(0.17)	(0.06)	(0.08)	(0.09)	(0.01)
Sent2_ir (-2)	-0.163	-0.185	-0.133	0.035	-0.645***	0.045***
	(0.15)	(0.28)	(0.10)	(0.14)	(0.14)	(0.01)
BOVESPA(-1)	0.021	-0.073	-0.003	0.045	-0.045	-0.025***
	(0.08)	(0.15)	(0.05)	(0.07)	(0.08)	(0.01)
BOVESPA(-2)	0.138*	-0.160	0.065	0.057	0.009	0.012**
	(0.08)	(0.15)	(0.05)	(0.07)	(0.08)	(0.01)
BOVVOL(-1)	0.494	-1.975	-0.155	1.517	-0.363	0.584
	(1.12)	(2.10)	(0.74)	(1.02)	(1.07)	(0.08)
BOVVOL(-2)	0.246	1.648	0.739	-1.365	1.339	0.026
	(1.01)	(1.89)	(0.67)	(0.92)	(0.96)	(0.07)
C	0.003	-0.021	0.013	0.002	-0.065	0.013
	(0.03)	(0.06)	(0.02)	(0.03)	(0.03)	(0.00)
Adjusted R-squared	0.368	0.621	0.528	-0.012	0.767	0.016
Sum sq. resids	0.885	0.005	0.981	3.455	0.427	0.816
S.E. equation	0.078	0.006	0.083	0.155	0.054	0.075
F-statistic	8.571	22.340	15.542	0.846	43.843	1.218
Log likelihood	183.707	592.063	175.614	76.816	240.950	190.060
Akaike AIC	-2.175	-7.377	-2.072	-0.813	-2.904	-2.256
Schwarz SC	-1.922	-7.124	-1.818	-0.560	-2.651	-2.002
Mean dependent	0.013	0.023	0.115	-0.013	0.186	0.001
S.D. dependent	0.099	0.009	0.120	0.154	0.113	0.076

Table 2.7 Vector Autoregression Estimates

The variables are rational sentiments of U.S. individual investors (Sent1_r), irrational sentiments of U.S. individual investors (Sent1_ir), rational sentiments of U.S. institutional investors (Sent2_r), irrational sentiments of U.S. institutional investors (Sent2_ir), returns on iShares MSCI Brazil Index Fund ETF (EWZ), volatility of returns on iShares MSCI Brazil Index Fund ETF (EWZVOL).
*, ** and *** denote significance levels at the 10%, 5% and 1%, respectively. Standard errors are in the parentheses.

	Sent1_r	Sent1_ir	Sent2_r	Sent2_ir	EWZ	EWZVOL
Sent1_r (-1)	0.46***	-0.275	0.137	0.37**	0.009	0.14***
	(0.17)	(0.30)	(0.10)	(0.15)	(0.16)	(0.05)
Sent1_r (-2)	-0.124	0.147	-0.13*	-0.083	-0.24**	-0.041
	(0.12)	(0.21)	(0.07)	(0.10)	(0.11)	(0.04)
Sent1_ir (-1)	0.28***	0.006	0.013	-0.015	0.031	0.012
	(0.06)	(0.10)	(0.03)	(0.05)	(0.05)	(0.02)
Sent1_ir (-2)	-0.022	0.141	-0.021	-0.065	-0.091	-0.011
	(0.07)	(0.13)	(0.04)	(0.06)	(0.07)	(0.02)
Sent2_r (-1)	0.156	0.478	0.70***	-0.278	1.22***	-0.54***
	(0.27)	(0.49)	(0.17)	(0.24)	(0.26)	(0.08)
Sent2_r (-2)	0.066	-0.367	0.175	0.056	-0.67***	0.28***
	(0.23)	(0.41)	(0.14)	(0.20)	(0.22)	(0.07)
Sent2_ir (-1)	-0.142	-0.097	0.55***	-0.110	0.33***	-0.09**
	(0.12)	(0.22)	(0.07)	(0.11)	(0.12)	(0.04)
Sent2_ir (-2)	-0.203	0.019	-0.093	0.191	-0.68***	0.34***
	(0.20)	(0.36)	(0.12)	(0.18)	(0.19)	(0.06)
EWZ(-1)	-0.095	-0.212	-0.062	0.101	0.056	-0.05*
	(0.09)	(0.16)	(0.06)	(0.08)	(0.09)	(0.03)
EWZ(-2)	0.136	-0.238	0.090	0.021	0.21**	-0.05*
	(0.09)	(0.16)	(0.06)	(0.08)	(0.09)	(0.03)
EWZVOL(-1)	-0.152	-0.788	0.038	0.238	-0.280	0.62***
	(0.29)	(0.51)	(0.18)	(0.25)	(0.27)	(0.09)
EWZVOL(-2)	-0.218	0.273	0.009	-0.148	0.71***	-0.24***
	(0.25)	(0.45)	(0.15)	(0.22)	(0.24)	(0.08)
C	0.069	0.038	0.014	0.010	-0.12***	0.11***
	(0.05)	(0.08)	(0.03)	(0.04)	(0.04)	(0.01)
Adjusted R-squared	0.516	-0.018	0.810	0.004	0.443	0.757
Sum sq. resids	0.798	2.524	0.298	0.622	0.723	0.075
S.E. equation	0.088	0.157	0.054	0.078	0.084	0.027
F-statistic	11.110	0.837	41.452	1.037	8.563	30.631
Log likelihood	122.661	56.409	179.284	136.976	128.300	258.895
Akaike AIC	-1.907	-0.755	-2.892	-2.156	-2.005	-4.276
Schwarz SC	-1.597	-0.445	-2.582	-1.846	-1.695	-3.966
Mean dependent	0.091	-0.019	0.183	0.008	0.012	0.112
S.D. dependent	0.127	0.156	0.124	0.078	0.113	0.055

Figure 2.1 Response of Bovespa Returns to the Rational and Irrational Sentiments of U.S. Individual Investors.

Figure 2.1.a

Response of Bovespa returns to the rational sentiments of U.S. individual investors

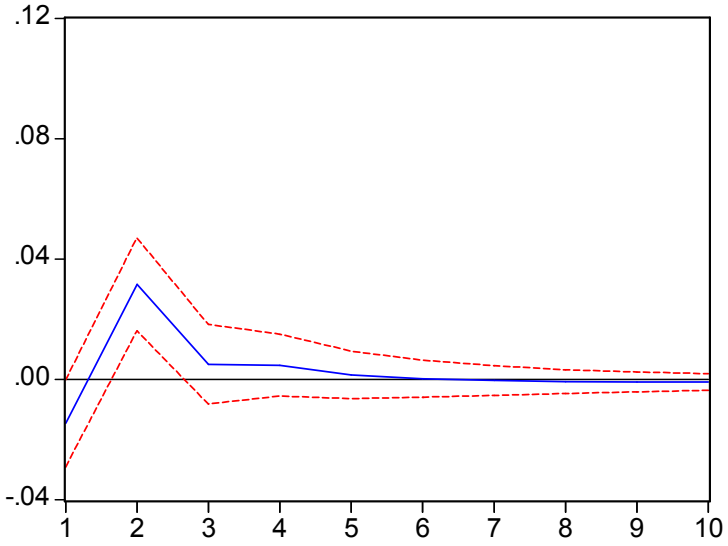
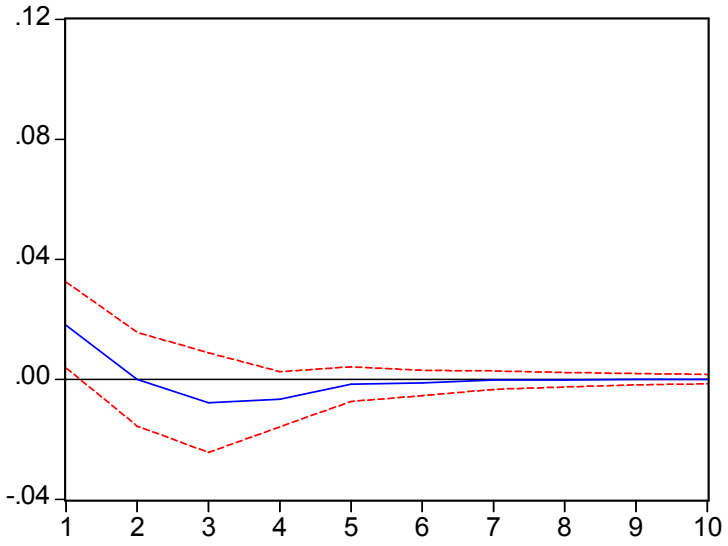


Figure 2.1.b

Response of Bovespa returns to the irrational sentiments of U.S. individual investors



The dashed lines on each graph represent the upper and lower 95% confidence bands. When the upper and lower bounds carry the same sign the response becomes statistically significant.

* On each graph, “percentage returns” are on the vertical and “horizon” is on the horizontal axis.

Figure 2.2 Response of Bovespa Volatility to the Rational and Irrational Sentiments of U.S. Individual Investors

Figure 2.2.a
Response of Bovespa volatility to the rational sentiments of U.S. individual investors

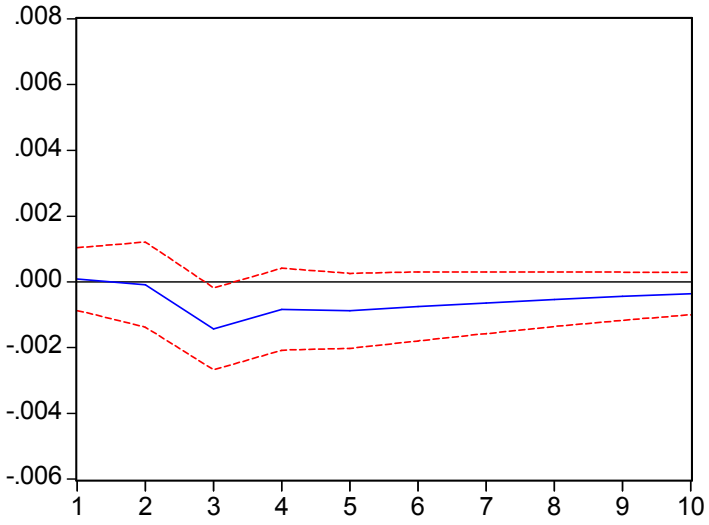
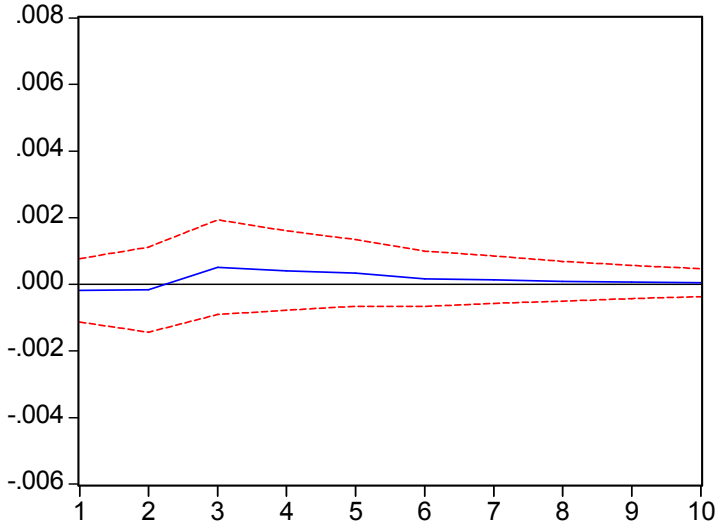


Figure 2.2.b
Response of Bovespa volatility to the irrational sentiments of U.S. individual investors



The dashed lines on each graph represent the upper and lower 95% confidence bands. When the upper and lower bounds carry the same sign the response becomes statistically significant.

* On each graph, "percentage returns" are on the vertical and "horizon" is on the horizontal axis.

Figure 2.3 Response of Bovespa Returns to the Rational and Irrational Sentiments of U.S. Institutional Investors.

Figure 2.3.a

Response of Bovespa returns to the rational sentiments of U.S. institutional investors

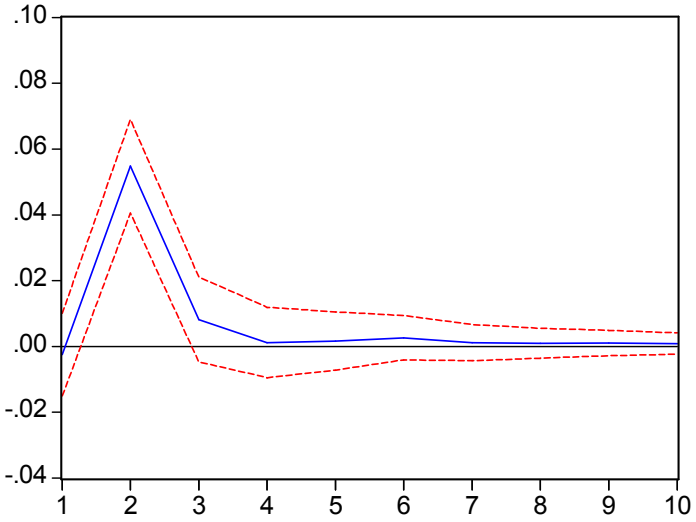
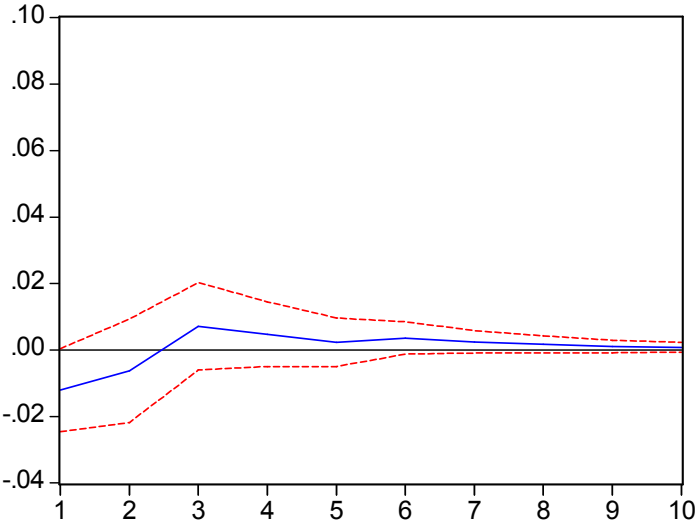


Figure 2.3.b

Response of Bovespa returns to the irrational sentiments of U.S. institutional investors



The dashed lines on each graph represent the upper and lower 95% confidence bands. When the upper and lower bounds carry the same sign the response becomes statistically significant.

* On each graph, “percentage returns” are on the vertical and “horizon” is on the horizontal axis.

Figure 2.4 Response of Bovespa Volatility to the Rational and Irrational Sentiments of U.S. Institutional Investors

Figure 2.4.a
Response of Bovespa volatility to the rational sentiments of U.S. institutional investors

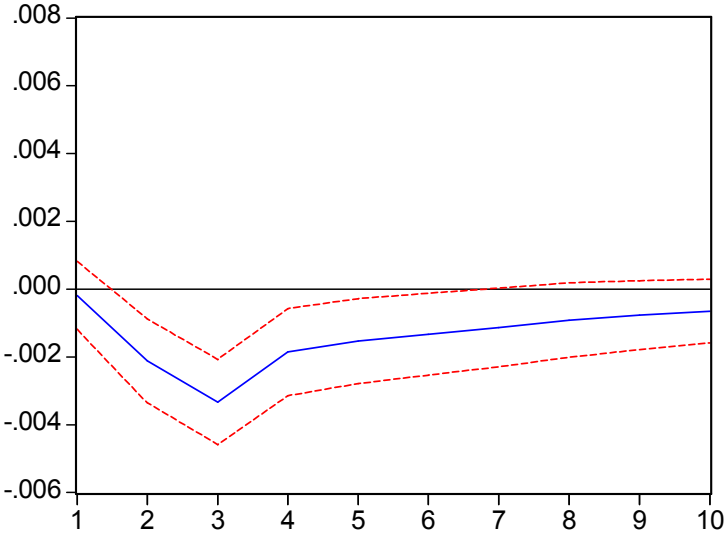
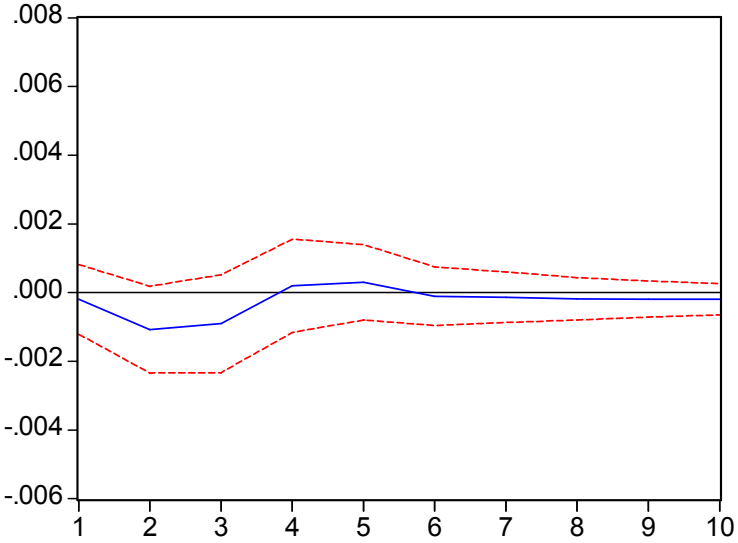


Figure 2.4.b
Response of Bovespa volatility to the irrational sentiments of U.S. institutional investors



The dashed lines on each graph represent the upper and lower 95% confidence bands. When the upper and lower bounds carry the same sign the response becomes statistically significant.

* On each graph, "percentage returns" are on the vertical and "horizon" is on the horizontal axis.

Figure 2.5 Response of U.S. Individual Investor Sentiments to Bovespa Returns and Volatility

Figure 2.5a
Response of rational sentiments of U.S. individual investors to Bovespa returns

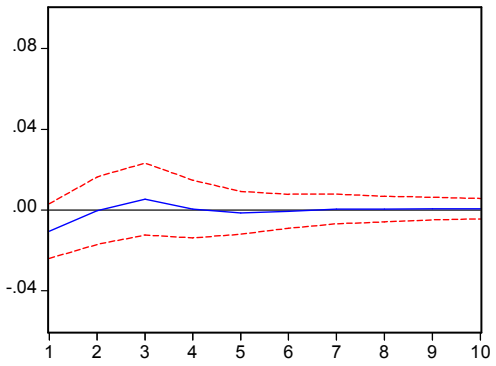


Figure 2.5b
Response of irrational sentiments of U.S. individual investors to Bovespa returns

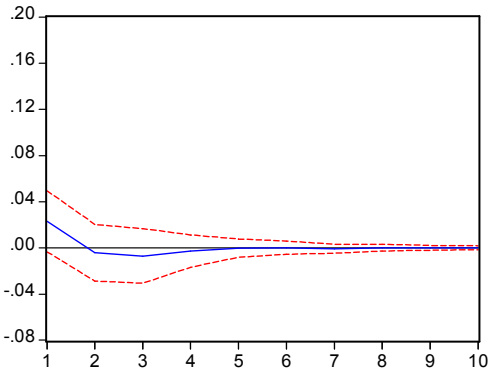


Figure 2.5c
Response of rational sentiments of U.S. individual investors to Bovespa volatility

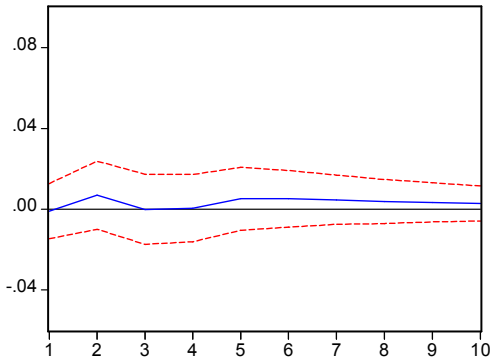
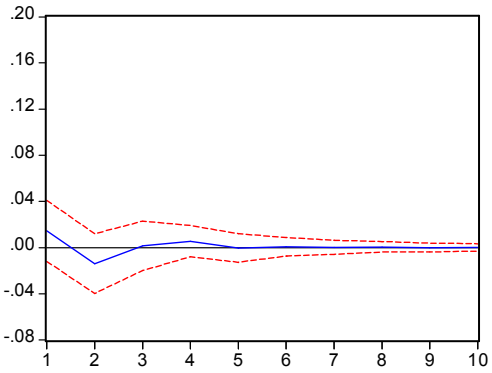


Figure 2.5d
Response of irrational sentiments of U.S. individual investors to Bovespa volatility



The dashed lines on each graph represent the upper and lower 95% confidence bands. When the upper and lower bounds carry the same sign the response becomes statistically significant.

* On each graph, “percentage returns” are on the vertical and “horizon” is on the horizontal axis.

Figure 2.6 Response of U.S. Institutional Investor Sentiments to Bovespa Returns and Volatility

Figure 2.6a
Response of rational sentiments of U.S. institutional investors to Bovespa returns

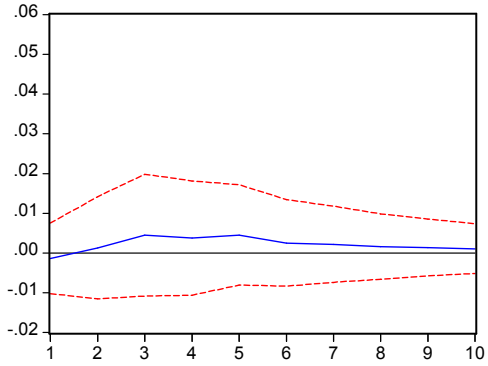


Figure 2.6b
Response of irrational sentiments of U.S. institutional investors to Bovespa returns

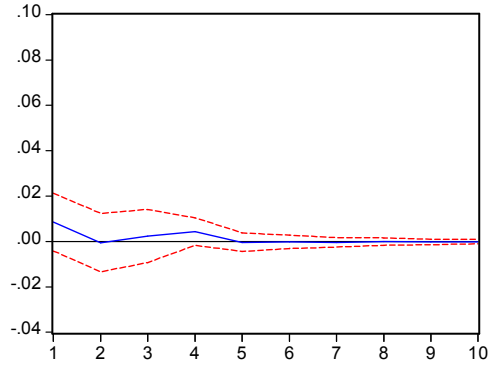


Figure 2.6c
Response of rational sentiments of U.S. institutional investors to Bovespa volatility

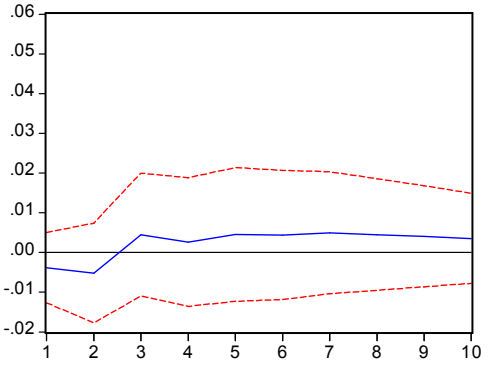
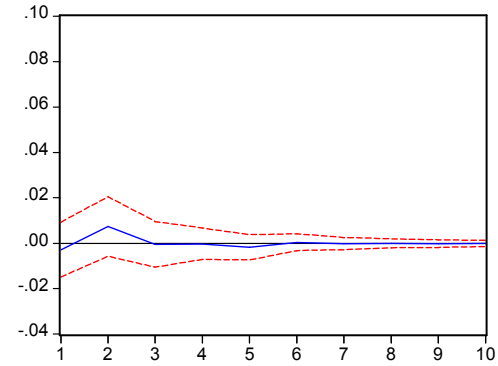


Figure 2.6d
Response of irrational sentiments of U.S. institutional investors to Bovespa volatility



The dashed lines on each graph represent the upper and lower 95% confidence bands. When the upper and lower bounds carry the same sign the response becomes statistically significant.

* On each graph, “percentage returns” are on the vertical and “horizon” is on the horizontal axis.

Figure 2.7 Response of MSCI Brazil Index Fund (EWZ) Returns to the Rational and Irrational Sentiments of U.S. Individual and Institutional Investors

Figure 2.7.a
Response of EWZ to the rational sentiments of U.S. individual investors

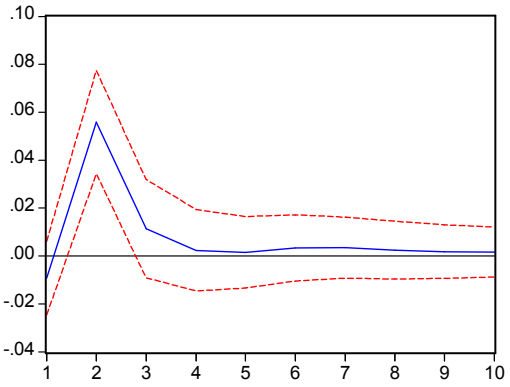


Figure 2.7.b
Response of EWZ to the irrational sentiments of U.S. individual investors

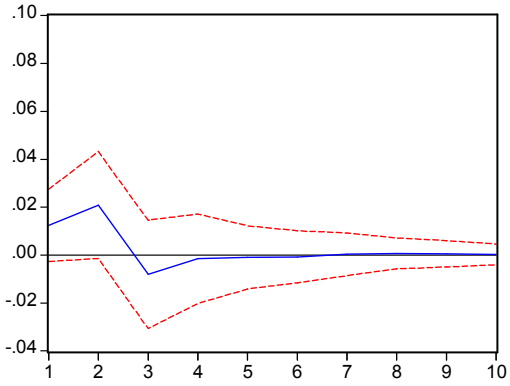


Figure 2.7.c
Response of EWZ to the rational sentiments of U.S. institutional investors

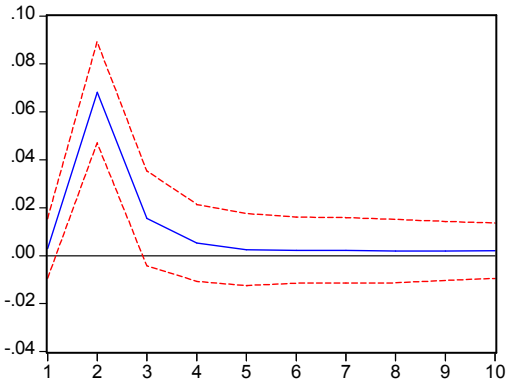
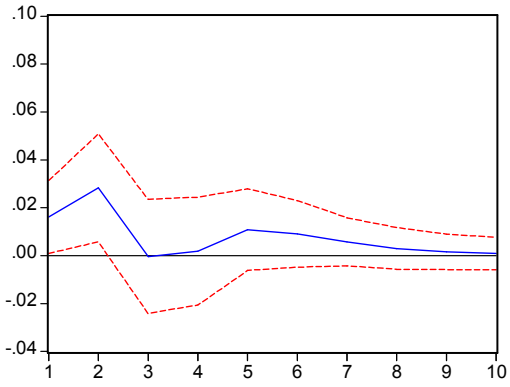


Figure 2.7.d
Response of EWZ to the irrational sentiments of U.S. institutional investors



The dashed lines on each graph represent the upper and lower 95% confidence bands. When the upper and lower bounds carry the same sign the response becomes statistically significant.

* On each graph, "percentage returns" are on the vertical and "horizon" is on the horizontal axis.

Figure 2.8 Response of MSCI Brazil Index Fund (EWZ) Volatility to the Rational and Irrational Sentiments of U.S. Individual and Institutional Investors

Figure 2.8.a
Response of EWZ volatility to the rational sentiments of U.S. individual investors

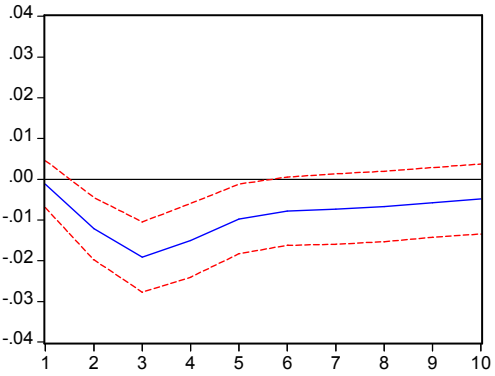


Figure 2.8.b
Response of EWZ volatility to the irrational sentiments of U.S. individual investors

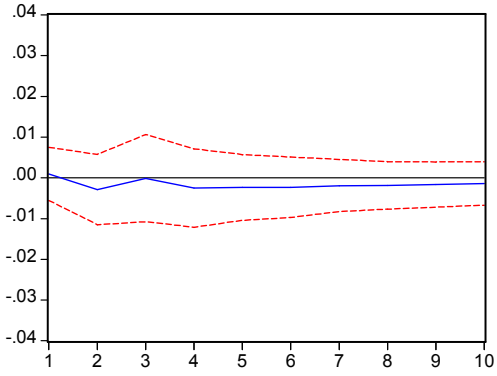


Figure 2.8.c
Response of EWZ volatility to the rational sentiments of U.S. institutional investors

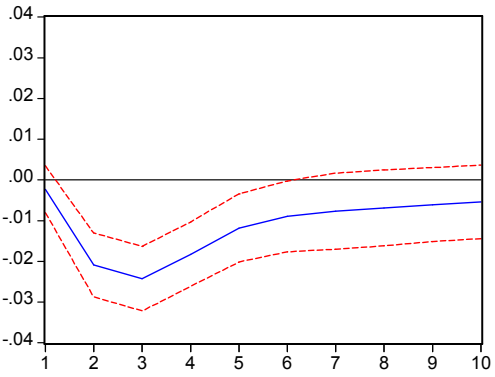
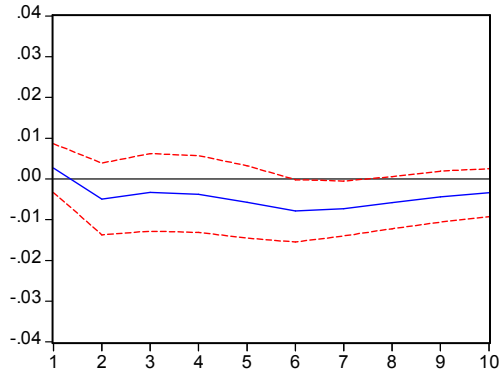


Figure 2.8.d
Response of EWZ volatility to the irrational sentiments of U.S. intitutional investors



The dashed lines on each graph represent the upper and lower 95% confidence bands. When the upper and lower bounds carry the same sign the response becomes statistically significant.

* On each graph, “percentage returns” are on the vertical and “horizon” is on the horizontal axis.

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BIOGRAPHICAL SKETCH

Pablo Javier Calafiore was born and brought up in Argentina, where he attended River Plate University completing there his bachelor degrees in management and accounting in 1997. From 1997 until 2002 he worked at the accounting department of a recognized Argentinean food processing company as well as a cost accountant for a hospital.

Upon completing a Master in Business Administration at the University of Texas Pan-American in 2003, Mr. Calafiore worked as a small business counselor at the University of Texas Pan-American Small Business Development Center until 2006. In addition, during that period Mr. Calafiore taught different business courses at both the University of Texas-Brownsville and the University of Texas Pan-American.

Mr. Calafiore earned his Ph.D. degree in Business Administration, Finance, at the University of Texas Pan-American in August, 2010. Mr. Calafiore research interests focus primarily in corporate finance, financial markets and institutions, emerging markets, and behavioral finance, among others. He has four papers published in journals such as Journal of Current Research in Global Business and Journal of Economics and Finance Education. Furthermore, Mr. Calafiore has presented eight papers at different professional conferences (Academy of Economics and Finance, and Southern Finance Association).