Financial Predictions Based on Investor Sentiments

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Abstract

Purpose: This paper studies whether investor sentiment can predict future Mexican stock market returns. Furthermore, the dynamic correlation between sentiment and returns is examined. Lastly, this article analyses whether sentiment innovations influence unexpected returns.

Design/Methodology/Approach: This study employs GMM regressions along with the diagonal BEKK model and GARCH model to investigate the impact of the Mexican investor sentiment on the future stock returns and the conditional volatility.

Findings: It was found that sentiment has significant predictive power up to 24 months ahead. Higher levels of sentiment today lead to lower returns in the future. The correlation between investor sentiment and equity returns varies over time. Finally, sentiment innovations are associated with unexpected returns. Overall, the results suggest that investor sentiment is an important risk factor for the Mexican stock market.

Originality/Value: This study seeks to deepen an insight into the non-traditional financial factors that drive stock market returns for an important Latin American country, Mexico. Mexican economy is ranked 2\textsuperscript{nd} largest in Latin America (based on stock market capitalization) and 15\textsuperscript{th} largest in the world (World Bank, 2014). Mexico is also classified as a highly collectivistic country that may exhibit high levels of herding behaviour in the stock market unlike the developed markets. This emerging stock market has unique cultural and social characteristics which make this nation worthy of a thorough investigation.
**Keywords:** Investor Sentiment, Mexico, Returns, Predictive Regressions

**JEL:** G02, G12, G150

1. **Introduction**

   It is becoming increasingly difficult to argue that investor sentiment does not exert a significant influence on equity markets. Over the last three decades, financial economists—and some psychologists—have shown that neoclassical finance cannot fully explain the observed behaviour of equity markets (e.g., Leroy and Porter, 1981; Shiller, 1981; De Bondt and Thaler, 1985; De Long, Shleifer, Summers, and Waldman, 1990; Lee, Shleifer, and Thaler, 1991; Loughran and Ritter, 1995; Lee, Jiang, and Indro, 2002; Brown and Cliff, 2004; Baker and Wurgler, 2007). As a result, scholars are now searching for non-traditional explanations (e.g., investor sentiment) for the observed asset price behaviour (Garcia, 2013; Da, Engleberg, and Gao, 2015). These studies, however, have mostly focused their efforts on the United States and other developed countries. In this paper, we argue that it is important for studies to centre their efforts on specific foreign stock markets. Specifically, the focus of our study is on Mexico.

   According to the International Monetary Fund (2014), from the 1990s to the Great Recession of 2008-2009, emerging countries’ economic growth has substantially outpaced that of developed nations. As a result of this growth, countries like Brazil, China, India, and Mexico have an ever increasing role to play in the global economy. For this reason, it is increasingly important that academics and practitioners alike enhance their understanding of the factors that drive these countries’ financial markets.
This study seeks to deepen our insight into the non-traditional financial factors that drive stock market returns for an important Latin American country, Mexico. So, why focus on Mexico? First, Mexico’s economy and stock market are both large. Its economy is ranked 2nd largest in Latin America and 15th largest in the world (World Bank, 2014). Furthermore, Mexico’s stock market is the 2nd largest in Latin America (based on stock market capitalization), 5th largest in the Americas, and 18th largest in the world (World Bank, 2012). The sheer size of this country’s economy and its stock market serve as indicators that we need to continue to enhance our knowledge of how both its economy and stock market function.

Second, and perhaps more interesting than its size, Mexico is classified as a highly collectivistic country (Hofstede and Hofstede, 2001). Research shows that financial variables might be influenced by cultural, country-specific factors (Chen, Dou, Rhee, Truong, and Veeraraghavan, 2015; Eun, Wang, and Xiao, 2015). For instance, studies suggest that the influence of investor sentiment on stock market returns might be greater in collectivistic cultures (Hofstede and Hofstede, 2001; Beckmann et al., 2008; Schmeling, 2009; Chui et al., 2010; Fang, 2014). One reason for this is that collectivistic countries’ financial markets tend to exhibit investor herding behavior. Beckmann et al. (2008) find that asset managers from collectivistic cultures are more likely to engage in herding behavior.[2] Furthermore, Eun, Wang, and Xiao (2015) find that stock prices exhibit a greater degree of co-movement in collectivistic countries, which in part could be due to investor herding. One of the key features of investor herding is that investors execute buy (or sell) orders without fully taking into account firms’ economic
fundamentals, which suggests the presence of sentiment-based trading. Studies have tested whether investor sentiment may explain investor herding. For instance, Liao, Huang, and Wu (2011) show that investor sentiment can explain mutual fund herding behaviour. Another reason sentiment might be greater in collectivistic countries is technical trading. Fang (2014) finds that technical trading profits are higher in collectivist countries.

Third, studies suggest that the intensity of the investor sentiment-stock returns relationship varies considerably by country (Corredor, Ferrer, and Santamaria, 2013). These differences may be explained by both stock characteristics and heterogeneity of cultures and institutions. Consequently, it is important to study in depth this relationship for each individual country.

Finally, Fang (2014) finds that technical trading profits are higher for emerging financial markets, suggesting that these markets are less efficient. Additionally, Lim and Brooks (2010) find that emerging stock markets exhibit greater price deviations from the random walk model, suggesting again that emerging markets might be less efficient. As a result, market inefficiency may give rise to noise trading. For all of the aforementioned reasons, we decide to focus our efforts on the investor sentiment-stock returns relationship for Mexico.

Until now, the role of investor psychology in Mexican financial markets has been largely ignored in the literature (Herrera and Lockwood, 1994; Curci et al., 2003; Ortiz et al., 2006; Diamandis, 2008; Lopez-Herrera and Ortiz, 2011; Lopez-Herrera et al., 2012; Roden et al., 2012). Only a couple of articles study how Mexican investor sentiment
influences *Mexican* stock market returns (Perez-Liston and Huerta, 2012; Perez-Liston et al., 2015). These two studies, naturally, have their limitations. First, they ignore the impact of investor sentiment on future stock market returns for various portfolios (e.g., value, growth, small-cap, and large-cap stocks). Additionally, they do not examine the joint predictably of investor sentiment across various forecast horizons. For the U.S. and various developed countries, studies have shown that periods of bullish sentiment are followed by periods of low returns (Brown and Cliff, 2005; Schmeling, 2009). We test this hypothesis for the Mexican stock market using predictive regressions. Second, they examine the correlation between sentiment innovations and unexpected returns for the market portfolio *only*. In this paper, we extend their analysis, and therefore add more insight, to a variety of stock portfolios (e.g., value, growth, small-cap, and large-cap stocks). Our analysis of sentiment innovations and unexpected returns allows us to test if unexpected investor optimism may lead to higher stock prices; positive correlations would be consistent with a behavioural story for Mexican stock prices (Schmeling, 2009). Third, these studies fail to examine the conditional correlation between investor sentiment and stock market returns. Studies have shown that the sentiment-stock market relationship may be time-variant. For example, Kurov (2010) finds that monetary policy exerts a significant influence on investor sentiment and that this influence depends on stock market conditions. As a result, we make use of a multivariate GARCH model to assess if the sentiment-stock returns relationship significantly changes over time. Due to the small number of existing articles that study the investor sentiment-stock market
returns relationship for Mexico, there are numerous questions that remain unanswered. Our study seeks to shed light on some of these questions.

This paper contributes to the literature in the following distinct ways. First, we estimate predictive regressions to determine whether investor sentiment can predict expected returns at the 1-, 6-, 12-, 18-, and 24-month forecast horizons. We run these predictive regressions for a variety of portfolios; the market, large-cap, small-cap, value, and growth portfolios. Second, we estimate a bivariate GARCH model to determine how the conditional correlation between investor sentiment and stock returns has evolved over time. Third, we study the long-run correlation between sentiment innovations (i.e., sentiment that cannot be explained by prior sentiment) and unexpected returns (i.e., returns that cannot be explained by both prior sentiment and macroeconomic factors). Lastly, we draw more awareness to one of the largest stock markets in Latin America.

The main results show that high levels of investor sentiment in the current period, lead to lower future stock market returns. As the forecast horizon increases, investor sentiment has a lesser influence on future stock market returns. These results also hold for the large-cap, small-cap, value, and growth portfolios; however, the results are stronger and more pronounced for harder to arbitrage stocks (i.e., small-cap and value stocks). Second, results from the bivariate GARCH model show that the contemporaneous conditional correlation between investor sentiment and stock returns is mostly positive and increases during recessions. The correlation can be as low as 0.00 and as high as 0.70. Finally, the contemporaneous correlation between sentiment
innovations and unexpected stock returns is positive and significant for the various
portfolios.

The remainder of this paper is organized as follows. Section 2 describes the data
employed in the estimations; Section 3 explains the econometric methodology; Section 4
summarizes the empirical results; and Section 5 concludes.

2. Data and Descriptive Statistics

This study is conducted using monthly data obtained from DataStream. The
sample spans from January 1998 to December 2014, for a total of 204 monthly
observations. This study makes use of the following variables: the monthly percent
change in the industrial production index ($IIP_t$), which serves as a proxy for economic
growth; *Cetes 28-dias* ($IR_f^t$), proxy for the 1-month risk-free rate; the difference in the
91- and 28-day CETES government interest rates ($HB3_t$), which proxies for economic
risk premiums; the monthly percent change in the exchange rate measured in pesos per
U.S. dollar ($EXCH_t$); the monthly percent change in the consumer price index ($INFL_t$);
monthly returns on the Morgan Stanley Capital International Mexico index ($R_{t,MKT}$),
which proxies for the returns on the Mexican market portfolio; and levels in the Mexican
manufacturing business confidence index, published by El Banco de México (Mexico’s
Central Bank), which serves as our measure of investor sentiment. An increase in the
level of the index means that survey participants believe that business conditions will
improve. When we estimate the returns and first-differences we lose one observation;
therefore, the sample consists of 203 observations. Several studies have used the
manufacturing business confidence index as a proxy for investor sentiment (Grisse, 2008; Perez-Liston and Huerta, 2012; Perez-Liston et al., 2015).

Table 1 reports the descriptive statistics for all the variables in the study. The mean sentiment is 102.00, while the standard deviation is 8.71. The autocorrelation coefficient is 0.93 for sentiment which indicates that the variable has a large degree of persistence. Thus, a high level of sentiment today is followed by a slightly lower, but still relatively high level sentiment tomorrow. The average return for the Mexican stock market index is 0.97 percent per month (about 11.64 percent annualized), while the standard deviation is 6.53 percent per month (about 22.62 annualized). It is interesting to note that over the sampled period, the average return for small-cap stocks was considerably lower than the average returns for the large-cap stocks (0.53 for small-cap stocks versus 0.96 for large-cap stocks). This stands in contrast to the observed size premium found in U.S. studies (Banz, 1981). However, small-cap stocks had a higher maximum return compared to large-cap stocks (20.55 versus 15.83, respectively). Similarly, value stocks did not outperform growth stocks over this particular period. This is in contrast to some of the evidence found in the U.S., which shows a value premium (Fama and French, 1992, 1996; Lakonishok, Shleifer, and Vishny, 1994). Value stocks had a mean monthly return of 0.85 percent versus growth stocks that had a mean monthly return of 1.05 percent.

Table 2 reports the Augmented Dickey-Fuller (1979) unit root tests for the variables in the study. The results indicate that most of the variables, with the exception of the risk-free rate, are stationary. That is, the null hypothesis of a unit root is rejected.\[5\]
3. Methodology

3.1 Predictive Regressions

To test whether investor sentiment has an influence on future stock market returns we follow Schmeling (2009) and estimate long-horizon return regressions:

$$\frac{1}{k} \sum_{k=1}^{k} r_{t+k} = \gamma_0 + \gamma_1 \text{sent}_t + X_t \gamma + \epsilon_{t+1 \rightarrow t+k}$$  \hspace{1cm} (1)

where $r_t$ is the return on one of the MSCI indexes (e.g., market, value, growth, small-, and large-cap), $\text{sent}_t$ is the proxy for investor sentiment, and $X_t$ is a matrix that includes a set of macro variables. In the matrix, $X_t$, we include the following control variables: industrial production index ($IPP_t$), which proxies for economic growth; the difference in monthly returns on 3-month and 1-month Treasury bills ($HB3_t$), which proxies for economic risk premiums; exchange rate ($EXCH_t$); the inflation rate ($INFL_t$); and Cetes 28-dias ($Rf_t$), which serves as the 1-month risk-free rate.[6]

As a result, the average $k$-period return (left-hand side of the equation) is a function of investor sentiment and a set of control variables (right-hand side of the equation).[7] Notice that we use information up to time $t$ to forecast mean returns beginning in month $t+1$. We estimate returns for the 1-, 6-, 12-, 18-, and 24-month forecast horizons. To attenuate some problems in estimating equation (1), we employ a block-bootstrap procedure to estimate the coefficients and standard errors.[8]

Next, we estimate equation (1) jointly for the various forecast horizons (1-, 6-, 12-, 18-, and 24-months). In essence, we estimate a system of equations using GMM. This
allows us to test whether the coefficient on investor sentiment ($\gamma_1$) is statistically significant across the various forecast horizons. That is, we test the following hypothesis:

$$\gamma_1^1 = \gamma_1^6 = \gamma_1^{12} = \gamma_1^{18} = \gamma_1^{24},$$

where the superscript indicates the forecast horizon. This joint test of predictability at various forecast horizons has been employed by other researchers (Mark, 1995; Ang and Bekaert, 2007; Schmeling, 2009).

3.2 Diagonal BEKK Model

Correlations are critical inputs for portfolio managers and individual investors. Academics and practitioners have long sought reliable estimates of correlations between financial assets and other important macroeconomic variables (Engle, 2002). To examine whether the co-movement (correlation) of investor sentiment and Mexican portfolio returns various over time, we estimate Engle and Kroner’s (1995) BEKK model:

$$H_t = \Omega \Omega' + A \varepsilon_{t-1} \varepsilon_{t-1}' A' + B H_{t-1} B' \quad (2)$$

where $H_t$ is the conditional covariance matrix and $\varepsilon_t$ is a vector of residuals. $\Omega, A,$ and $B$ are matrices of coefficients to be estimated. We estimate a bivariate GARCH (1,1) model where the variables included in the GARCH equations are the market portfolio returns (or small-cap returns) and investor sentiment (Engle, 1982). This methodology will allow us to examine if the correlation between sentiment and stock returns has changed during important events (e.g., recessions, financial crises).

3.3 Sentiment innovations and unexpected returns

Following Pastor and Stambaugh (1999) and Schmeling (2009), we estimate the following equations:
\[ r_{t+1} = \delta_0 + \delta_1 \text{sent}_t + X_t \gamma + \xi_{t+1} \quad (3) \]
\[ \text{sent}_{t+1} = \alpha_0 + \alpha_1 \text{sent}_t + \eta_{t+1} \quad (4) \]
to examine the correlation between unexpected returns \((\xi_{t+1})\) and sentiment innovations \((\eta_{t+1})\). According to Schmeling (2009), these two variables might be positively correlated if waves of unexpected sentiment push prices above their equilibrium values. But under a rational expectations story we would observe a negative correlation between these two variables.\[^9\]

4. Estimation Results

4.1 Predictive Regressions

Table 3 shows the Granger (1969) causality tests between investor sentiment and the various portfolios. In the second column, second row of the table the results indicate that the market portfolio Granger causes investor sentiment (the \(F\)-statistic is 1.49 and is significant at the 10% level). The results also indicate that investor sentiment Granger causes market portfolio returns (the \(F\)-statistic is 1.68 and is also significant).

Furthermore, the Granger causality tests seem to support the notion that investor sentiment Granger causes the various portfolios (i.e., value, growth, large-, and small-cap). However, the \(F\)-statistic for value stocks is higher than the one for growth stocks. Similarly, small stocks have a higher \(F\)-statistic than large stocks. These results could indicate that investor sentiment has a stronger influence on harder-to-arbitrage stocks (i.e., value and small-cap stocks). Conversely, the Granger causality tests show that the market, growth, and small-cap portfolios Granger cause investor sentiment. In general,
the Granger causality tests suggest that there is a bi-directional influence between investor sentiment and equity returns; these results are similar to those found in the literature (see, Perez-Liston et al., 2015).

Table 4 presents the results of the predictive regressions. For the aggregate market portfolio with a 1-month forecast horizon, the coefficient on investor sentiment (-0.64) is negative, but statistically insignificant (although it has the correct sign). This result indicates that high investor sentiment in the current period can lead to lower returns during the following month. The same results are observed for the 6-, 12-, 18-, and 24-month forecast horizons; the coefficients are -0.81, -0.70, -0.62, and -0.63, respectively. However, notice that most of coefficients are statistically significant at the 1 percent level. The negative impact of sentiment seems to strengthen from the first month to the sixth month (the 1-month coefficient is -0.64 and the 6-month coefficient is -0.81), after which the coefficients begin to get smaller (at the 6-month forecast horizon the coefficient is -0.81, but the 24-month coefficient is -0.63), indicating that sentiment begins to lose its influence as the forecast horizon increases. These results are similar to those found in Schmeling (2009); he finds coefficients as large as -0.42 for the market portfolio.

Panel B shows the sentiment coefficient estimates for value stocks at the various forecast horizons. The pattern is similar to that found for the aggregate market; however, the coefficients are somewhat larger for value stocks. Finally, Panel C presents the sentiment coefficients for growth stocks. The magnitude and direction (sign) of the
coefficient estimates are relatively similar to those of the aggregate market and value stocks.

Table 5 presents the results of the predictive regressions for the large-cap, small-cap and size premium portfolios. In comparison to large stocks, investor sentiment seems to have more predictive power for small stocks. The sentiment coefficient estimates for small-cap stocks are generally larger in magnitude than the ones found for large-cap stocks. Additionally, the change in adjusted $R$-squared is higher for small-cap stocks than it is for large-cap stocks; again suggesting that sentiment has greater predictive power for harder to arbitrage stocks, such as small-cap stocks.

Table 6 presents the results of estimating all four predictive regressions for each individual portfolio (e.g., small-cap stock) as a system of equations. The table reports the mean of all four sentiment coefficients across the various forecast horizons for each individual portfolio. We test the null hypothesis ($H_0: \gamma_{1,1} = \gamma_{1,6} = \gamma_{1,12} = \gamma_{1,24} = 0$) that all of the sentiment coefficients are zero across the various forecast horizons for each portfolio. That is, we test the null hypothesis that investor sentiment has no predictive power across all four forecast horizons. The final column of the table reports the $p$-values of the Wald test. The $p$-values suggest that the null hypothesis may be rejected at the 1 percent level for all five portfolios. That is, investor sentiment has predictive power for each of the five portfolios (i.e., market, value, growth, small-cap, and large-cap). By looking at the size of the coefficients-in the second column of the table-we can see that investor sentiment has the strongest influence on the small-cap portfolio (the mean coefficient is -1.17), followed by the value portfolio (the mean coefficient is -0.82).
These results suggest that harder to arbitrage stocks, like small-cap stock and value stocks are more susceptible to investor sentiment.

4.2 Diagonal BEKK Model

Figure 1 shows the conditional standard deviations of investor sentiment and the market portfolio. After 2003, there appears to be less stock market volatility—with the exception of the 2008-2010 period—in the Mexican equities market. Also, investor sentiment seems to be less volatile after 2001; again, with the exception of the Great Recession period.

Figure 2 displays the conditional correlation between investor sentiment and the returns of the market portfolio. The mean conditional correlation of the market with investor sentiment is 0.27. Furthermore, Figure 3 displays the conditional correlation between investor sentiment and the small-cap portfolio returns. The mean conditional correlation of the small-cap portfolio with investor sentiment is 0.21. A Satterthwaite-Welch $t$-test of equal means for the conditional correlations of the market portfolio and the small-cap portfolios indicates that the means are statistically different from each other.\footnote{10} We also perform the Bartlett test of equal variances for the conditional correlations and find that they are statistically the same (the variance for the market portfolio is 0.0136 and for the small-cap portfolio it is 0.0154).\footnote{11} These results suggest that the conditional correlations for both the market and small-cap portfolios have about equal variability about their means. The results show that during crisis (e.g., the Asian Crisis, the DotCom Bubble, and the Financial Crisis) investor sentiment and small-cap stock returns seem to have a higher correlation.
4.3 Sentiment innovations and unexpected returns

Table 7 presents the correlation estimates between sentiment innovations and unexpected returns for the various portfolios. Table 7 shows that sentiment innovations and unexpected market portfolio returns are positively and significantly correlated at the 1 percent level; the correlation coefficient is 0.28. This correlation is higher than the one found in Schmeling (2009). They find that the average correlation of unexpected returns with sentiment innovations is 0.10; so, the results we find for Mexico are stronger than those in Schmeling (2009). That is, when compared to the average developed country, Mexican sentiment seems to have a stronger influence on stock market returns. The table also shows the correlations between sentiment innovations and the rest of the portfolios (i.e., value, growth, size premium, large-cap, and small-cap). The results show that unexpected returns--for each of the five portfolios--are correlated with sentiment innovations. Correlations range from as high as 0.28 to as low as 0.26. More importantly, value stocks have a greater degree of correlation with investor sentiment than do growth stocks. Similarly, small-cap stocks seem to have a higher level of co-movement with sentiment than do large-cap stocks. Overall, Table 7 suggests that higher levels of sentiment are associated with higher returns, which is consistent with a behavioural story.\[12\]

5. Conclusion

For the most part, the influence of investor sentiment in the Mexican stock market has been ignored in the literature (Herrera and Lockwood, 1994; Curci et al., 2003; Ortiz
et al., 2006; Diamandis, 2008; Lopez-Herrera and Ortiz, 2011; Lopez-Herrera et al., 2012; Roden et al., 2012). Despite the large size of the Mexican market and its importance in the global economy and Latin America, only a few papers focus their attention on how investor sentiment influences Mexican stock market returns (Perez-Liston and Huerta, 2012; Perez-Liston et al., 2015). This study is an attempt to fill this gap in the literature.

In this paper, we estimate predictive regressions to test whether investor sentiment can predict future equity returns across various forecast horizons (specifically, the 1-, 6-, 12-, 18-, and 24-month forecast horizons). We estimate these predictive regressions for a variety of equity portfolios (i.e., market, large-cap, small-cap, value, and growth portfolios). Second, using a bivariate GARCH model, we model the conditional correlation between investor sentiment and market (small-cap) portfolio returns to test whether the correlation between these two variables significantly changes over time. Third, we estimate the correlation coefficients between sentiment innovations and each of the unexpected returns of five equity portfolios. This allows us to test whether unwarranted high stock prices may result from excessive investor optimism.

Our main finding shows that high levels of investor sentiment in the current period, lead to lower future stock market returns over the next 1-, 6-, 12-, 18-, and 24-months. Furthermore, we observe that the influence of current sentiment on stock returns decreases as the forecast horizon increases. These results suggest that excessively high prices today are corrected in the near future for this important emerging market. Second, results from the bivariate GARCH model show that the contemporaneous conditional
correlation between investor sentiment and both the market portfolio and the small-cap portfolios are positive and significant. Furthermore, the correlations seem to change over time, indicating that there are periods where sentiment has a greater (lesser) influence on stocks market returns. The results also indicate that the correlation of both portfolios with investor sentiment seems to increase during crises (i.e., Asian Crisis, Dotcom Bubble, Great Recession). Finally, the contemporaneous (current) correlation between sentiment innovations and unexpected stock returns is positive and significant for each of the five equity portfolios. This result suggests that excessive mispricing is due to noise trading. In particular, we observe that value (small-cap) stocks have larger correlation coefficients with investor sentiment than do growth (large-cap) stocks. A plausible explanation might be that these harder-to-arbitrage equity portfolios might be more prone to noise trading than large-cap stocks and growth stocks (Baker and Wurgler, 2006).

In general, the results for Mexico support the view that investor sentiment is an important factor in the Mexican stock market. Institutional and individual investors need to consider the effects that current and future levels of Mexican investor sentiment can have on the expected returns and volatilities of their portfolios. Furthermore, when valuing stocks during periods of excessive optimism, investors should avoid over paying for stocks.
Notes


[2] Investor herding maybe defined as a group of investors (institutional or individual) purchasing (or selling) similar stocks within the same time frame.


[4] Abugri (2008) and Hsing et al. (2012) suggest that macroeconomic variables, such as inflation and the risk-free rate are important determinants of stock returns for Latin American countries.

[5] We tried other tests (e.g., Kwiatkowski et al. (1992) (KPSS) and Phillips-Perron (PP)) and the results were qualitatively the same.

[6] In order to compare our results to those of Schmeling (2009), we standardize all right-hand side variables.

[7] Other studies also net out the effect of macroeconomic risk factors on sentiment (see, Baker and Wurgler, 2006; Lemmon and Portniaguina, 2006; Schmeling, 2009; Perez-Liston et al., 2015).

[8] The left-hand side of equation (1) uses a variable that has overlapping observations, which can lead to estimation errors (see, Stambaugh, 1999). Furthermore, persistent predictive variables may also be a problem.

That is, we test the following null hypothesis: $H_0: \bar{\rho}_{t,sm} = \bar{\rho}_{t,mkt}$.

For the Bartlett test, we test the following null hypothesis: $H_0: \text{Var}(\rho_{t,sm}) = \text{Var}(\rho_{t,mkt})$.

Under a rational (or traditional) story of returns, we would expect to see a negative correlation between sentiment innovations and unexpected returns (see, Schmeling (2009) for a discussion on this topic).
References


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Figure 1. Conditional Standard Deviations.

Notes: This figure shows the conditional standard deviations of the Mexican stock market portfolio (top graph) and the conditional standard deviations of investor sentiment (bottom graph). Standard deviations are estimated using a bi-variate diagonal BEKK GARCH model. The sample spans from January 1998 to December 2014.
Figure 2. Conditional Correlations.

Notes: This figure shows the time-varying conditional correlations between the Mexican stock market portfolio and investor sentiment. The correlations are estimated using a bivariate diagonal BEKK GARCH model. The sample spans from January 1998 to December 2014.
Figure 3. Conditional Correlations.

Notes: This figure shows the time-varying conditional correlations between the small-cap portfolio and investor sentiment. The correlations are estimated using a bi-variate diagonal BEKK GARCH model. The sample spans from January 1998 to December 2014.