The Stock Market Reaction to Earnings Announcements in the Presence of High Ambiguity

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Abstract

This paper investigates whether there are idiosyncratic factors that mitigate the stock market reaction to unfavorable corporate news in the presence of high ambiguity. Previous research shows that the stock market responds asymmetrically to earnings news in the presence of high ambiguity because investors follow a conservative approach and choose the worst-case scenario. In contrast, when ambiguity is low, bad and good earnings news are weighted similarly. We posit and test whether certain types of stocks provide a natural hedge during periods of high ambiguity. We focus on four characteristics of stocks that provide signals of future expected cash flows, and may thereby help resolve uncertainty, i.e. the dividend policy, the capital structure, the market-to-book ratio and the size of the firm.

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1. Introduction

This paper focuses on one type of uncertainty, namely Knightian uncertainty, also known as ambiguity (Knight, 1921). The concept of Knightian uncertainty is different from risk. Risk refers to situations characterized by uncertainty over payoffs (Savage, 1954), circumstances where although the outcome is unknown, we can associate a probability with each potential outcome. On the other hand, ambiguity refers to situations characterized by uncertainty about the probabilities over the payoffs (Williams, 2015), situations where the outcome is unknown, and we do not have the needed information to set accurate odds for each potential outcome. In illustrating the difference, Ricardo Caballero referred to risk as the “known unknowns” and ambiguity as the “unknown unknowns” in Donald Rumsfield’s famous quote:

> *“There are known knowns. These are things we know that we know. There are known unknowns. That is to say, there are things that we know we don't know. But there are also unknown unknowns. There are things we don't know we don't know.” (Donald Rumsfield, US Secretary of Defense, 1975-1977 and 2001-2006)*

As Caballero puts it, “…when institutions or people don’t truly understand what the risks are, they know or feel something is wrong but don’t know what and how likely it is, or how it will impact them.”[1] Uncertainty can affect individual expectations and decisions in a multitude of ways. Previous research shows that when investors make decisions in the presence of high Knightian uncertainty, the area in the brain responsible for fear and instincts (called amygdala) is activated (Hsu, Bhatt, Adolphs, Tranel, and Camerer, 2005). There is also evidence that investors behave differently in the presence of low vs. high Knightian uncertainty. More precisely, when uncertainty is high, investors tend to follow a conservative approach and choose the worst-case scenario (Ellsberg, 1961).

This paper investigates whether there are some idiosyncratic factors that can mitigate the stock market reaction to unfavorable corporate news in the presence of high ambiguity. Corporate news, such as earnings announcement move the stock market to a large extent via their effect on investors’ expectations (William, 2015). We posit that when there is high ambiguity, investors’ expectations become more sensitive to corporate announcements, which will therefore

[1] https://minneapolisfed.org/publications/the-region/interview-with-ricardo-caballero

affect their trading and investment decisions. How macro uncertainty impacts investor decisions, their trading behavior, and consequently how it influences the response of the market to news, is a concern for both policymakers and regulators (Bloom, 2009).

This study focuses particularly on the firms' earnings announcements, but the analysis can be easily applied to other corporate news. Previous research shows that the stock market responds asymmetrically to earnings news in the presence of high ambiguity because investors follow a conservative approach and choose the worst-case scenario. In contrast, when ambiguity is low, bad and good earnings news are weighted similarly (Williams, 2015). We posit and test whether certain types of stocks provide a natural hedge during periods of high ambiguity. We focus on four characteristics of stocks that provide signals of future expected cash flows, and may thereby help resolve uncertainty, i.e. dividend policy, capital structure, size, and market-to-book ratio (MTB).

We find that the firm's dividend policy can help reduce the reaction of stocks to bad earnings surprises in the presence of high ambiguity. This suggests that ambiguity-averse investors are generally better off by holding dividend stocks rather than non-dividend stocks. This result is in line with the bird in hand theory (Bhattacharya, 1979), according to which investors generally prefer dividends to capital gains, due to the uncertainty in the latter. Overall, we find that dividend stocks have smaller information asymmetry (on average) relative to non-dividend stocks, and can indeed be used as a natural hedge against periods of high ambiguity.

Surprisingly, the results show that low MTB stocks seem to be a good hedge against bad earnings surprises in the presence of high ambiguity. We find that high MTB stocks have smaller information asymmetry (on average) relative to low MTB stocks. This is somehow expected, since growing firms, with more investment opportunities, can signal higher expected earnings growth, since future earnings are greatly influenced by investment opportunities. We would thus expect that when facing high ambiguity, high MTB stocks can help mitigate the stock market reaction to bad earnings news relative to low MTB stocks. Lakonishok, Shleifer, and Vishny (1994) find evidence for a 'torpedo effect', namely that high MTB firms experience more extreme responses to bad earning news than low MTB firms. Lakonishok et al. (1994) attribute this effect to overoptimistic expectational errors that are corrected upon the earnings announcement. Our results indicate that the 'torpedo effect' previously found in literature is characteristic to periods of high ambiguity only, and that periods of low ambiguity can exhibit a phenomenon opposite to the ‘torpedo effect’.

We also find that large size firms and firms with moderate level of leverage provide a natural hedge against bad earnings surprises in the presence of high ambiguity. Large firms have on average lower information asymmetry relative to small firms, since they reveal more information and are followed more intensively by security analysts. Similarly, firms with moderate levels of leverage have on average a lower information asymmetry relative to low leveraged firms. This is because in general, highly leveraged firms need to reveal more firm specific information when borrowing, and are subject to greater monitoring from creditors. Overall, the results indicate that a moderate level of leverage can help mitigate the stock market reaction to bad earnings news in the presence of extreme ambiguity.

This paper makes several contributions to the finance literature. First, it provides evidence that the dividend policy of a firm can weaken the reaction of stocks to bad corporate earnings news in the presence of high ambiguity. The findings suggest that dividend stocks should be preferred by ambiguity-averse investors when ambiguity is high. Second, it provides evidence on how the capital structure of firms (high vs. low leverage) can alleviate the reaction of stocks to bad earnings surprises. The results suggest that in the presence of extreme ambiguity, investors perceive moderate (towards high) leverage as a positive signal, since it reduces the manager’s ability to rent seek. Third, our analysis shows that the ‘torpedo effect’ previously found in literature is characteristic to periods of extreme ambiguity.

The remainder of the paper is organized as follows. Section 2 provides a short overview of the literature on how different types of stocks react to earnings announcements, and also reports the hypotheses. Section 3 describes the data and how ambiguity is measured, while Section 4 reports the results. The conclusions are summarized in Section 5.

2. Background and Hypotheses

> “*There is a fundamental distinction between the reward for taking a known risk and that for assuming a risk whose value itself is unknown*.” A known risk is “*easily converted into an effective certainty*”, while a “*true uncertainty*” is “*not susceptible to measurement*”.
>
> Frank Knight, 1921

2.1. Knightian Uncertainty

The concept of ambiguity or Knightian Uncertainy was introduced by Frank Knight (1921). Knight (1921) was the first to distinguish the concept of risk from uncertainty. According to him, risk applies to situations where we do not know the outcome of a given situation, but based on the information that we have, we can appropriately measure the probabilities of each potential outcome happening. On the other hand, uncertainty refers to situations where we do not know all the information needed to set accurate probabilities for each potential future outcome. In other words, risk refers to uncertainty over the payoffs, while ambiguity or Knightian uncertainty refers to situations characterized by uncertainty over the probabilities of such payoffs (Williams, 2015).

According to the traditional theory of choice under uncertainty, the variables influencing an uncertain choice are the judged probabilities of potential outcomes, and the evaluation of those outcomes. The confidence of these judged probabilities does not seem to play any role, although it can vary substantially. For example, when going to a casino and gambling on a Russian roulette, the probabilities of winning can be confidently judged based on past history, accepted theory, etc. However, when trying to judge the probability of a terrorist attack, these odds will be based on conflicting evidence, where important information is definitely missing (Hsu, Bhatt, Adolphs, Tranel, and Camerer, 2005). These two examples of uncertain events are called risky and ambiguous.

Based on the subjective expected utility theory, the probabilities of outcomes should influence choices, while confidence about these probabilities should not. However, experiments and empirical research have shown that people are more willing to bet on risky outcomes than on ambiguous ones, holding judged probability of outcomes constant (Ellsberg, 1961). In reality, people's choices do violate the postulates of the subjective expected utility, and one example is Ellsberg's paradox[2].

There has been a great amount of research on how people make decisions under different levels of probability (risk). In contrast, much less research has been done about decision-making

[2] We can imagine two decks of cards: one with 10 red and 10 blue cards (the risky deck), and the second one with 20 red or blue cards, but the composition of the red and blue cards is completely unknown (the ambiguous deck). A bet on a color pays a fixed sum if a card with the chosen color is drawn, and 0 otherwise. People would prefer the risky deck rather than the ambiguous one.

when probabilities are uncertain because of missing information (ambiguity). Although decision theory suggests that ambiguity about probabilities should not affect choices, it seems that ambiguity does matter. In fact, Hsu, Bhatt, Adolphs, Tranel, and Camerer (2005) use functional brain imaging and show that when people are forced to make decisions in the presence of ambiguity, the area in the brain responsible for fear and survival instincts (called amygdala) is activated. One main difficulty faced by empirical researchers is finding an appropriate ambiguity measure. One representative paper in this aspect is Williams (2015) who empirically investigates the role played by ambiguity shocks in shaping the response of stock market participants to firm-specific earnings news. Williams (2015) uses the VIX index as a proxy for the level of ambiguity, and finds that investors place greater weight on bad news following an increase in macro-uncertainty.

Another relevant paper is the study by Zhou (2015), who examines the role played by ambiguity around macroeconomic announcements. By accounting for ambiguity, he is able to understand some features of the data that were challenging the existing frameworks: why the stock market reacts stronger to bad news versus good news during crisis periods, and why almost 1/3 of the equity returns over 17 years of data occurs in the 10 minutes around the release of macroeconomic announcements. Zhou measures ambiguity by the Variance Risk Premium, computed as the difference between the risk-neutral and the physical expectations of the stock market return variance over a given horizon. The choice of the variance risk premium as a proxy for ambiguity is also motivated by Drechsler (2013), who considers that a representative investor has a range of models in mind about the dynamics of economic fundamentals, but is uncertain about the true model governing the economic fundamentals. Drechsler (2013) shows that the size of the variance risk premium is directly linked to the ambiguity in the model.

In this essay we proxy ambiguity by the variance risk premium computed similar to Zhou (2015). However, for measuring the physical expectations of the stock return variance, we use a different method, motived by Bekaert and Hoerova (2014). We investigate the role played by Knightian uncertainty around earnings announcements. More precisely, we examine whether there are some idiosyncratic factors that can mitigate the stock market reaction to unfavorable corporate news in the presence of high ambiguity. We anticipate that firms with smaller firm-specific information asymmetry might be able to offer some protection against news releases under high ambiguity scenarios. Thus, we test whether certain types of stocks provide a natural hedge during periods of high ambiguity. Particularly, we focus on four characteristics of stocks that provide signals of future expected cash flows, and can thereby help resolve uncertainty, i.e. dividend policy, capital structure, market-to-book ratio, and the size of the firm.

Such analysis is new to the literature. We believe that such a study is important for policymakers and regulators, by providing some insights about how macro uncertainty impacts investors' decisions, trading behavior, and hence how it influences the response of the stock market to news. In addition, such work is important for ambiguity-averse investors as well, because it can provide insights about what types of stocks can be used as natural hedge against high ambiguity scenarios.

2.2. Does Firm-Specific Information Asymmetry Matter?

> *"Under uncertainty, the brain is alerted that information is missing, and that choices based on the available information therefore carry more unknown (and potentially dangerous) consequences, and that cognitive and behavioral resources must be mobilized in order to seek out additional information from the environment."*
>
> *(Hsu, Bhatt, Adolphs, Tranel, and Camerer, 2005)*

The above quotation applied to our analysis is in line with our expectations that firms with greater information asymmetry react stronger to earnings announcements in the presence of high macro ambiguity. Most investors do not have a direct measure of each firm's information asymmetry in real time, but can still alleviate the information asymmetry problem by looking for stock specific signals or indicators.

2.2.1. Dividend vs. Non-Dividend Paying Stocks

According to Bhattacharya (1979), in the presence of information asymmetry, investors tend to use the dividend payments as signals of future expected cash flows, and hence of future expected earnings. In fact, stock prices adjust to dividend declarations before earnings announcement releases, and it can convey information about the firm's future earnings prospects before the actual earnings release (Miller and Rock, 1985).

Whether dividends are good predictors of subsequent firm's earnings is still debated in the literature. For instance, Nissim and Ziv (2001) find a positive association between current dividend changes and future earnings changes, but assume a linear form of mean reversion in earnings. On the other hand, Grullon, Michaely, Benartzi, and Thaler (2005) correct for the nonlinearity pattern in the behavior of earnings, and show that dividend changes are poor indicators of both earnings and profitability levels. Some other papers mention that dividends might not be accurate predictors of subsequent earnings releases, if firms decide to pay more dividends on purpose to run up the price (as in Miller and Rock, 1985), although this means declining investments. Market participants would learn in time about the manager's temptation to take advantage of the information asymmetry, and they would consequently adjust downwards the price they are willing to pay for the stock.

If dividends are indeed accurate signals of future expected cash flows, and ambiguity-averse investors can use them to reduce the information asymmetry, then we would expect to see a weaker reaction to earnings announcements news for dividend stocks relative to non-dividend paying stock, in the presence of high ambiguity. This mainly summarizes the first hypothesis.

Hypothesis 1: In the presence of high macro ambiguity, relative to non-dividend paying stocks, dividend stocks have a weaker reaction to earnings new.

This hypothesis is also consistent with the *bird in hand* theory. According to this theory, investors tend to prefer the certainty of dividends to potential substantial, but uncertain, future capital gains (Bhattacharya, 1979) because of the inherent uncertainty in the latter. It may therefore be argued that investors holding dividend stocks are more averse to uncertainty in general, i.e. more ambiguity-averse.

2.2.2. High vs. Low Market-To-Book Stocks

Growing firms with more investment opportunities usually have higher expected earnings growth, since future earnings are greatly influenced by the investment opportunities. From this perspective, high Market-to-Book (MTB) stocks could alleviate the firm-specific information asymmetry. On the other hand, high MTB stocks can be thought of as having a greater potential of inside information (and hence greater information asymmetry) because the managers of these firms are familiar with the investment plans and the expected cash flows. While these two views would potentially lead to contrasting roles for MTB in the presence of ambiguity, the extant literature largely finds that stocks with a high MTB ratio exhibit a 'torpedo effect', namely they seem to experience relatively more extreme responses to bad earnings news than low MTB ratio stocks (Skinner and Sloan, 2002). These findings have been attributed to overoptimistic expectational errors of investors (Lakonishok, Schleifer, and Vishny, 1994), errors that are subsequently corrected upon the earnings announcement.

We therefore investigate whether the torpedo effect is a general characteristic of high MTB ratio stocks, or whether it depends on the level of macro uncertainty and state the second hypothesis as:

Hypothesis 2: In the presence of high macro ambiguity, relative to low MTB stocks, high MTB stocks have a weaker reaction to earnings news.

2.2.3. Stocks of Large vs. Small Firms

Large firms usually reveal more information relative to small firms, are followed more intensively by security analysts because investors pay more attention to their stocks, and are usually older firms. We would thus expect that large firms have lower information asymmetry relative to small firms. Therefore we expect that large firms would experience a weaker reaction to earnings surprises in periods of both high and low ambiguity.

Hypothesis 3: In the presence of high macro ambiguity, relative to stocks of small firms, stocks of large firms have a weaker reaction to earnings news.

2.2.4. Stocks of Firms with High vs. Low Leverage

We also investigate whether the capital structure of a firm can help mitigate the reaction of stocks to bad earnings news, in the presence of high ambiguity. Highly leveraged firms can be associated with smaller information asymmetry, since they usually need to reveal firm specific information when borrowing, and they are subject to greater monitoring from the creditors (Demerjian, 2007). We would therefore expect that highly leveraged firms (lower information asymmetry) experience a weaker reaction to earnings surprises.

Hypothesis 4: In the presence of high macro ambiguity, relative to stocks of low leveraged firms, stocks of firms with high levels of leverage exhibit a weaker reaction to bad earnings news.

3. Data

For our empirical analysis, we use all common stocks available in CRSP from March 6, 2000 until June 18, 2015. We collect financial accounting data from Compustat, and earnings announcement releases and analysts' earnings forecasts from Bloomberg. To be included in the sample a firm must have a complete set of financial variables and quarterly announcement dates. In addition to the firm data, we collect the VIX data from the Chicago Board Options Exchange (CBOE) website. We eliminate those observations with prices less than or equal to $5 before the event window to reduce the effect of market frictions (similar to Ball, Kothari, Shanken (1993) and Williams (2015)). The final sample consists of 4138 individual stocks, with a total of 103,204 earnings announcements over the entire sample period. For each earnings announcement, we compute the earnings announcement surprise, as the difference between the actual released value of earnings (A_t), and its Bloomberg consensus forecast ($E_{t-\tau}(A_t)$). Then we standardize the announcement surprise by dividing $A_t - E_{t-\tau}(A_t)$ by its own sample standard deviation.

3.1.The Ambiguity Measure

We proxy ambiguity by the Variance Risk Premium (VRP), computed as the difference between the risk-neutral (Q measure) and the physical (P-measure) expectations of the stock market return variance over a one month (22 trading day) horizon:

$$VRP_{t,T} = E_t^Q\left[RV_{t+1,T}\right] - E_t^P[RV_{t+1,T}] \quad (1)$$

Expectations are taken at time t for realized variance from t+1 to T. The motivation for choosing the variance risk premium as a proxy for ambiguity is Zhou (2015) and Drechsler (2013). Prior papers show that this premium is relatively well captured by the difference between the option-implied expectation of stock return variance (which corresponds to VIX), and a statistical (true) expectations of return variance. Zhou (2015) argues that this premium exists because investors do not only care about the uncertainty of the stock return itself, but also about the uncertainty of the return variance. When holding a position in a stock option, investors hedge against high realized variance, and therefore demand a positive variance risk premium for this insurance.

Drechsler (2013) argues that the option implied expectation ($E_t^Q\left[RV_{t+1,T}\right]$) is equivalent to the price of a variance swap, a contract whose buyer receives the realized variance over the maturity of the swap. Buying the swap provides the buyer with protection against high realized variance. So, the difference between the swap price and the true expectation of variance is the (variance) premium investors pay for this hedge. Because it is costless to enter such a strategy, and by no arbitrage opportunities, the variance swap rate needs to equal the risk neutral expectations of the return variance ($E_t^Q[RV]$) (Zhou, 2015), which is the first component of the expression in (1). The investor having a long position in the variance swap protects himself against high realized variance, and the price of such protection is the variance risk premium.

Zhou (2015) relates the concept of VRP to ambiguity and investigates whether such ambiguity affects the reaction of the stock market to macroeconomic announcements. In addition, Drechsler (2013) directly ties the VRP to ambiguity. He considers a representative investor with a range of models in mind about the dynamics of the economic fundamentals data. The investor is uncertain about the true model underlying the fundamentals, and because he is ambiguity-averse, he chooses the worst-case model, a model where the realized variance is high and options have high payoffs. Options hedge investor's model uncertainty, and this results in a variance risk premium.

We compute a daily series for the VRP by following a similar procedure to Bekaert and Hoerova (2014), where:

$$VRP_t = \frac{VIX_t^2}{12} - E_t[RV_{t+1}^{(22)}] \qquad (2)$$

VIX is the implied option volatility of the S&P 500 index for contracts with a maturity of one month, while $RV_{t+1}^{(22)}$ is the realized variance of the E-mini S&P 500 futures returns over the next month (22 trading days) using 5 minute returns. $RV_t^{(22)}$ is defined as the sum of the daily realized variances RV over the 22 days: $RV_t^{(22)} = \sum_{j=1}^{22} RV_{t-j+1}$. The daily realized variance is the sum of squared 5-minute[3] log returns on E-mini S&P 500 futures from 9:30 AM ET to 4:00 PM ET and the squared close-to-open log return.

[3] We use 5 minutes because it is long enough to avoid the artificial volatility induced by bid-ask bounce, and short enough to truly sample intraday volatility. (See Andersen, et al. (2003)).

Consistent with the relation in (1), VIX^2 captures the expected stock market return variance constructed using a 'risk-neutral' probability measure, while the conditional variance uses the 'actual physical' probability measure. We want to compute the conditional variance premium as described in (2), which requires physical conditional expected value of the future realized variance. A simple approach for solving this is by using empirical projections of the realized variance on the variables in the information set. The problem is reduced to a problem of variance forecasting. Thus, to forecast the realized variance $RV_t^{(22)}$, we follow the general forecasting framework proposed by Bekaert and Hoerova (2014) (BK from here forward). BK consider 10 potential explanatory variables for $RV_t^{(22)}$, and look at 31 different OLS forecasting models for the realized variance to identify the model with the best out-of-sample forecasting performance.

BK analyze the following explanatory variables: (VIX_{t-22}^2, $C_{t-22}^{(22)}$, $C_{t-22}^{(5)}$, $C_{t-22}^{(1)}$, $J_{t-22}^{(22)}$, $J_{t-22}^{(5)}$, $J_{t-22}^{(1)}$, $r_{t-22}^{(22)-}$, $r_{t-22}^{(5)-}$, $r_{t-22}^{(1)-}$). The first independent variable VIX_{t-22}^2 is expected to have a positive impact on realized variance. The next six variables split the realized variance into a continuous and a discontinuous ("jump") component at the monthly, weekly and daily frequencies, respectively, following Andersen, Bollerslev and Diebold (2007). To isolate the jumps contribution to the quadratic variation, we use standardized bipower variation BPV_t as in relation (5) in Andersen, Bollerslev, and Diebold (2007), and define the daily jump as: $J_t = \max[(RV_t - BPV_t), 0]$. The continuous component of the realized variance is then computed as: $C_t = RV_t - J_t$. Weekly (h=5) and monthly (h=22) variables are averaged and we express all variables in monthly units: $J_t^{(h)} = \frac{22}{h}\sum_{j=1}^{h} J_{t-j+1}$ and $C_t^{(h)} = \frac{22}{h}\sum_{j=1}^{h} C_{t-j+1}$. Similarly to BK, we add negative returns over the past day, week or month, to incorporate a potential leverage effect. To model the leverage effect at different frequencies, we define $r_t^{(h)-} = \min\left(r_t^{(h)}, 0\right)$ where $r_t^{(h)} = \frac{22}{h}\sum_{j=1}^{h} r_{t-j+1}$.

[Insert Figure 1 about here]

To forecast $RV_t^{(22)}$ we use the same explanatory variables as in BK (2014), but do not assume any functional form between the explanatory variables and the realized variance. We believe that using OLS and assuming a linear relationship between the variables might not be the best approach to use, given the fact that such relationship can be time dependent or nonlinear. Instead, we predict $RV_t^{(22)}$ non-parametrically through a locally weighted least squares. We plot both the predicted $RV_t^{(22)}$ and the true $RV_t^{(22)}$ in Figure 1. The prediction of the realized variance seems to be reasonable, both the true and the predicted $RV_t^{(22)}$ following the same pattern, peaks, and drops.

In the next step, we compute the daily variance risk premium as the difference between $\frac{VIX_t^2}{12}$ and the predicted $RV_t^{(22)}$. The daily VRP and the predicted realized variance are plotted together in Figure 2. This daily measure of VRP seems to fluctuate in a well behaved manner most of the time, but it also has some wide swings (similar patterns observed in Zhou, 2015 and BK, 2014). Because of this, we compute the 22 days moving average for the VRP as: $VRP_t = \frac{1}{22} * \sum_{j=1}^{22} VRP_{t-j}$, and we plot this 1-month moving average VRP across time in Figure 3. The 1-month moving average VRP seems to capture important events that were true macroeconomic shocks for the stock market. For instance, peaks of the monthly VRP are associated with the terrorist attack of September 11, 2011, the recent financial crisis of 2008- 2009, the large drops in the stock market in August 2011, due to fear of contagion of the European sovereign debt crisis to Spain and Italy, concerns about France's AAA rating, and also concerns about the US credit rating being downgraded. In the subsequent analysis, we use this time series of 1-month moving average VRP[4] as the main proxy for ambiguity, after we winsorize it at the 5% and 95% percentiles.

[Insert Figure 2 about here]

[Insert Figure 3 about here]

3.2.Descriptive Statistics

Table 1 reports the descriptive statistics for the main variables used in our analysis during periods of low and high ambiguity. We consider periods of low (high) ambiguity those months when the VRP was below (above) its sample median. Table 1 indicates that the winsorized 1-month moving average VRP is definitely smaller and has a smaller standard deviation as well, in periods of low ambiguity, relative to periods of high ambiguity (as expected). In addition, firms

[4] We will refer to it simply as variance risk premium

making earnings announcements during periods of high ambiguity are usually (i.e. on average) smaller, have a low MTB and a higher level of leverage. The market return is smaller on average during high ambiguity intervals. However, the magnitude of the negative or the positive earnings surprises during low vs. high ambiguity scenarios is quite similar. That is, both positive and negative earnings surprises appear to have similar mean and median values. The cumulative abnormal return (CAR) computed over the window (-1, +1) days around each earnings announcement seems to be greater on average for the firms making earnings announcements during high ambiguity periods. In Table 2 we report summary statistics for the CAR around earnings announcements of different types of stocks. Overall, the stocks experiencing greater cumulative abnormal return around earnings announcements are the non-dividend paying stocks, stocks of large firms, stocks of firms with high leverage, and stocks with low MTB ratio.

[Insert Table 1 about here]

[Insert Table 2 about here]

Next, we try to capture the information asymmetry associated to different categories of stocks. In this sense, Table 3 reports the mean of the standard deviation of analysts' forecasts (a proxy of information asymmetry) for different categories of stocks. As noticed, the stocks with greater information asymmetry are in general non-dividend paying stocks, stocks of low MTB, smaller size, and low leverage. Put in a different light, dividend stocks, high MTB stocks, large stocks, and highly leveraged stocks have on average lower level of firm specific information asymmetry.

[Insert Table 3 about here]

Ambiguity affects investors' expectations and their trading behavior, and can consequently impact the stock price. When facing high ambiguity, the ambiguity-averse investors would be mainly interested in protecting themselves against bad earnings surprises. We investigate whether the firm specific information asymmetry can offer such protection in the presence of high macro level ambiguity. That is, we posit and test whether firms with smaller information asymmetry can help mitigate the reaction of stock market to bad earnings surprises. We proxy the information asymmetry by the standard deviation of analysts' earnings forecast. Such variable is a firm-specific measure and can change over time.

[Insert Figure 4 about here]

When comparing the average abnormal return around earnings announcements for firms with high vs. low information asymmetry (high values of information asymmetry are those above the sample median, and low values are those below the sample median), we notice that firms with smaller information asymmetry tend to have indeed a weaker reaction to both positive and negative earnings surprises (Figure 4).

Our goal is to test whether stocks with lower information asymmetry can act as a natural hedge against the high ambiguity scenarios. In reality, most of the investors do not have a direct measure of firm specific information asymmetry (such as the standard deviation of analysts' forecasts) in real time. We investigate whether investors can use firm specific 'signals' to alleviate the firm's information asymmetry, and consequently mitigate the stock reaction to bad earnings news in the presence of high ambiguity.

4. Methodology and Selected Empirical Results

We expect that stocks of firms with greater information asymmetry experience a greater reaction to the unexpected component of corporate news. We divide the sample into firms with high and low information asymmetry (i.e. above and below the sample median for the earnings dispersion of analysts' forecast). Then, we look at the impact of positive and negative earnings surprises on the abnormal return of stocks around the earnings announcement. As captured in Figure 4 (Panels A and B), positive and negative earnings surprises are associated with changes in the abnormal return in the same direction. Positive earnings surprises are accompanied by an increase in the average abnormal return across stocks, and also by an increase in the standard deviation of the abnormal return. As noticed, stocks of firms with greater information asymmetry exhibit on average greater reaction to earnings releases. Conversely, negative earnings surprises intuitively have a negative impact on the abnormal return of stocks, and hence are associated with smaller average abnormal return relative to non-announcement periods. Overall, the stocks with greater information asymmetry seem to experience a greater response to earnings releases.

To conduct the analysis, we first investigate the impact of positive and negative earnings surprises on the cumulative abnormal return (CAR) across the three day interval (t-1, to t+1), around the earnings announcement. The CAR is the sum of the daily abnormal returns from one day before, until one day after the earnings announcement release. The abnormal return for a particular day is the difference between the actual return and the predicted return according to the one factor model. That is, for each individual stock, we estimate the one factor model over the period (-61,-11) days before earnings announcements. We use the estimated coefficients from the one factor model to predict the 'normal' values of the return for each day in the window (-1, +1) days around the earnings release. We then compute the abnormal return over the (-1, +1) window as the difference between the actual return and the 'normal return', as predicted by the one factor model. We perform this analysis across pairs of stocks that can potentially be regarded as facing low vs. high information asymmetry, namely dividend payers vs. non-payers, high vs. low MTB stocks, stocks of firms with high vs. low leverage, and stocks of large firms vs. the stocks of small firms. We then run the regression in (3), where we differentiate between bad and good earnings news by following the method in Conrad, Cornell, and Landsman (2002) and Williams (2015):

$$\begin{aligned} CAR_{it} &= \alpha_0 + \alpha_1 GoodNews_{it} + \alpha_2 BadNews_{it} \\ &\quad + \alpha_3 GoodNews_{it} * Alternative_{it} + \alpha_4 BadNews_{it} * Alternative_{it} \\ &\quad + Controls_{it} + \varepsilon_{it} \qquad (3) \end{aligned}$$

CAR_{it} is the three day (t-1, t+1) cumulative abnormal return for firm i over the quarterly earnings announcement date t. $GoodNews$ and $BadNews$ refer to the positive and negative earnings surprises. More precisely, $GoodNews$ ($BadNews$) takes the value of the earnings surprise if the surprise is positive (negative), and zero otherwise. The variable $Alternative$ is a dummy variable that will help us differentiate between different types of stocks. For instance, when comparing the impact of earnings surprises on dividend vs. non-dividend paying stocks, the variable $Alternative$ is replaced by a dummy variable ($D\_Dividend$) with values of 1 if the analyzed stock pays dividends, and 0 otherwise. In this case, the coefficient α_1 would indicate the impact of a positive surprise on non-dividend paying stocks, while the coefficient α_2 would capture the impact of a negative surprise on such stocks. In addition, the coefficients α_3 (coefficient α_4) would indicate whether the impact of positive (negative) earnings surprises is significantly different for dividend paying stocks relative to non-dividend paying stocks. In a similar fashion, we replace the $Alternative$ variable with $D\_highMTB$ which takes values of 1 for high MTB ratio (i.e. above the sample median), and zero otherwise; with $D\_highLEVERAGE$, which equals 1 if the leverage of the analyzed firm is above the sample median, and zero otherwise; and with a $D\_LargeSize$ dummy, with values of 1 if the firm has a greater size than the sample median, and 0 otherwise. We use as control variables (alternatively, adjusted to the use of '*Alternative*') the market-to-book ratio (MTB), the size of the firm (Size), the leverage of the firm (Leverage), the standard deviation of analysts' earnings forecast (Analyst Dispersion), and the market return (Mret).

[Insert Table 6 about here]

We report the results of expression (3) in Table 6. The findings suggest that (in general) the stocks with smaller information asymmetry tend to have a weaker reaction to earnings surprises. For instance, dividend stocks, high MTB stocks, and large stocks experience a weaker reaction to good news relative to their counterparts, i.e. respectively non-dividend paying stocks, low MTB stocks, and small stocks. In addition, large stocks and stocks of highly leveraged firms experience a significantly weaker reaction to bad earnings surprises relative to their counterparts (small stocks and stocks of firms with low leverage).

In the next step of the analysis, we investigate the role played by ambiguity in shaping the stock market participants' responses to corporate news. Ambiguity affects investors' expectations and their trading behavior, and can consequently impact the stock price. It has been documented that when facing high ambiguity, investors tend to make irrational decisions that they would not make otherwise. In periods of high ambiguity, the ambiguity-averse investors would most probably be mainly concerned about bad earnings news due to their negative impact on the stock return. We investigate whether the firm specific information asymmetry can offer some protection against bad earnings news in the presence of high ambiguity. We posit and test whether there are some idiosyncratic factors that can mitigate the stock market reaction to unfavorable corporate news in the presence of high Knightian uncertainty. We focus on four characteristics of stocks that provide signals of future expected cash flows, and can thereby help resolve uncertainty, i.e. dividend policy, capital structure, market-to-book ratio, and the size of the firm.

4.1. *Dividend vs. Non-Dividend Stocks*

The results reported in Table 6 emphasize that for both dividend and non-dividend stocks, there is a positive relationship between the cumulative abnormal return around earnings announcements (from day -1 to day +1) and the earnings surprise itself (either good or bad). Non-dividend paying stocks are on average associated with greater information asymmetry (Table 3), and have (as expected) a stronger reaction to good earnings surprises relative to dividend stocks. However, their response to bad earnings surprises is similar to the response of dividend stocks. These findings are somehow consistent with our expectations based on the information asymmetry story. Investors trading stocks have imperfect information about the firm's profitability, less accurate information compared to the firm's management for instance. Thus, investors might want to use the dividends as signals of future expected cash flows and future earnings (in line with Bhattacharya (1979), Miller and Rock (1985)). In presence of positive earnings surprises, the reaction of dividend stocks would be weaker than for non-dividend payers, because part of the news was anticipated from the dividend.

Table 6 also reports the results from the Wald test investigating whether there is an asymmetry in the response of different stocks to good vs. bad earnings surprises. The results are reported at the bottom of the table, and suggest that dividend paying stocks have a stronger reaction to good earnings news than to bad earnings news.

In order to test whether paying dividends helps alleviate or amplify the reaction of stocks to bad earnings news in the presence of high ambiguity, we run the same regression as in (3) (the variable $Alternative$ being replaced by the dummy $D\_Dividend$) for different quintiles of ambiguity (ie. The 22 days moving average VRP). The results are summarized in Table 7.

[Insert Table 7 about here]

For low and medium levels of ambiguity, dividend stocks have a weaker reaction to good earnings news and a similar reaction to bad news, relative to non-dividend paying stocks. However, for large levels of ambiguity (the fifth quintile) that we are mostly interested in, the dividend stocks seem to have a significantly weaker effect to both good and bad news relative to non-dividend paying stocks (consistent with our first hypothesis). That is, in the presence of extreme ambiguity, stocks with lower information asymmetry such as dividend stocks in this case, provide a natural hedge against bad earnings news.

4.2. *High vs. Low MTB Stocks*

For studying the reaction of high vs. low MTB stocks to earnings surprises, we run the regression in (3), where the $Alternative$ variable is replaced by $D\_highMTB$. This is a dummy variable taking values of 1 for stocks with the MTB ratio above the sample median, and 0 otherwise. The results are reported in the second column of Table 6, and indicate that low MTB stocks react stronger to good earnings news and similarly to bad earnings news relative to high MTB stocks. This indicates that firms with smaller information asymmetry (high MTB) have a weaker reaction to earnings news relative to the reaction of firms with greater information asymmetry (low MTB). The results are not consistent with the 'Torpedo' effect identified by Lakonishok, Schleifer, and Vishny (1994), according to which high MTB stocks have a stronger reaction to bad earnings news than low MTB stocks.

We also investigate whether this difference in the response of high vs. low MTB stocks to earnings news still holds for periods of high vs. low ambiguity. More precisely, we test whether the high MTB stocks (low information asymmetry) can be perceived as a natural hedge against high ambiguity scenarios. To do so, we run a similar model as in relation (3) per quintiles of ambiguity, and we report the results in Table 8.

[Insert table 8 about here]

The high MTB stocks experience indeed a weaker reaction to good earnings news, as expected. However, the reaction of high MTB stocks to bad earnings surprises differs based on the level of ambiguity. We notice a significantly weaker reaction (second quintile of ambiguity) of high MTB stocks to bad earnings news in the presence of relatively low ambiguity. However, high MTB stocks react stronger than low MTB stocks to bad earnings news in the presence of moderate towards high ambiguity levels (fourth quintile of ambiguity). We reject our second hypothesis. The 'Torpedo effect' previously found in literature seems to be characteristic of relatively moderate (towards high) levels of ambiguity only, while periods of low ambiguity are characterized by a phenomenon opposite to the 'torpedo effect'.

4.3.Stocks of Small vs. Large Firms

Large firms generally reveal more information than small firms, are followed more intensively by security analysts because investors pay more attention to their stocks. The results from Table 3 indicate that large firms have on average lower information asymmetry than small firms. Hence, we expect to find a weaker reaction of large firms to firm specific earnings news than in the case of small firms. For testing this, we run the regression in (3) and replace the $Alternative$ variable with the dummy variable $D\_largeSize$ taking values of 1 for firms with the size above the sample median, and 0 otherwise. The results are summarized in the third column of Table 6. Large firms experience indeed a weaker reaction to good and bad earnings surprises, relative to small firms. We then run the same regression per quintiles of ambiguity and report the results in Table 9. The results indicate that large firms experience weaker reactions (than small firms) to both good and bad earnings news in the presence of high and low ambiguity (consistent with our third hypothesis). Therefore, stocks of firms with smaller information asymmetry (such as the stocks of large firms in this case) can be perceived as a natural hedge against bad earnings news during high ambiguity periods.

[Insert table 9 about here]

4.4. Stocks of Firms with High vs. Low Leverage

Highly leveraged firms experience lower information asymmetry relative to firms with low leverage (Table 3). This can potentially happen because highly leveraged firms need to reveal more firm specific information when borrowing, and are subject to greater monitoring from the creditors. The high leverage can also be perceived as restricting the rent seeking behavior of the management (the 'control role of debt' as in Jensen (1986)). We would hence expect that highly leveraged firms (lower information asymmetry) experience a weaker reaction to earnings surprises than firms with low leverage. For testing this, we run the regression in (3) and replace the $Alternative$ variable with the dummy $D\_highLeverage$. The dummy has values of 1 for high leverage firms (i.e. leverage is above the sample median), and 0 otherwise. The results are reported in Table 6, and show that indeed highly leveraged firms experience a weaker reaction to bad earnings surprises (similar reaction to good news) relative to low leveraged firms.

However, one can potentially argue that a high level of leverage might not necessarily be perceived as a good ’signal’. Some highly leveraged firms can be firms in financial distress, close to bankruptcy. In the presence of high macro ambiguity, investors follow a conservative approach and focus on the worst-case scenario. Thus, it is possible that when facing high ambiguity, investors perceive extreme high leverage as a negative signal, rather than an indicator that solves information asymmetry. One can also argue that the macro ambiguity itself can increase the firm specific information asymmetry. However, the results in Table 5 reveal that in general there is a weak and insignificant correlation between the firm specific information asymmetry and the level of macro ambiguity for highly leveraged firms. In other words, the information asymmetry of these highly leveraged firms is not quite sensitive to the level of macro ambiguity.

Next, we test whether the capital structure of a firm can amplify or diminish the reaction of stocks to bad earnings announcement in the presence of high ambiguity. We run the same regression as in (3) per quintiles of ambiguity, and report the results in Table 10. As noticed, highly leveraged firms experience a weaker reaction to bad earnings surprises in the presence of high ambiguity (consistent with the fourth hypothesis).

In conclusion, the high leverage can be an indicator of lower information asymmetry (relative to low leverage). Stocks of highly leveraged firms can be seen as natural hedge against bad earnings news in the presence of high ambiguity. However, when deciding to invest in such stocks, an investor should also pay attention to other firm characteristics, to ensure that the leverage is indeed a good signal, and the firm is not in a financial distress, for example.

[Insert table 10 about here]

5. Conclusion

In this essay we investigate whether there are idiosyncratic factors that can reduce the response of the stock market to firm-specific earnings news in the presence of high ambiguity. Based on the previous literature, the stock market reacts asymmetrically to earnings news in the presence of high ambiguity because investors follow a conservative approach and choose the worst-case scenario. However, when ambiguity is low, bad and good earnings news are weighted similarly.

We investigate whether certain types of stocks can be perceived as ‘natural hedge’ during periods of high ambiguity. More precisely, we focus on four characteristics of stocks that can be perceived as signals/indicators of future expected cash flows, and may thereby help resolve uncertainty, i.e. the dividend policy, the capital structure, the market-to-book ratio and the size of the firm.

Our main findings indicate that the firm’s dividend policy can help reduce the reaction of stocks to bad earnings surprises, in the presence of high ambiguity. We also find that the ‘torpedo effect’ previously found in literature is only characteristic to periods of high ambiguity. Large size firms and firms with high leverage provide a natural hedge for bad earnings surprises, under the high ambiguity scenario. Large firms have lower information asymmetry (on average) relative to small firms, since they reveal more information, are followed more intensively by security analysts. Similarly, highly leveraged firms have a lower information asymmetry (on average), relative to low leveraged firms.

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Appendix

Description of Variables

Tobin's Q=Market value of assets/Book Value of assets= (ATQ-EQQ+CSHOQ*PRCCQ)/ATQ

Leverage= (DLTTQ+DLCQ)/(ATQ-CEQQ+CSHOQ*PRCCQ)

Size=PRCCQ*CSHOQ

Table 1 – Descriptive Statistics of Main Variables

This table reports the summary statistics of the main variables used in the analysis: the cumulative abnormal return (CAR) computed over a window of 3 days (-1, 0, and 1) around each earning announcements, the negative and positive earnings surprises, the 22 days moving average variance risk premium (VRP) (winsorized at the 5% and 95% percentiles), the size of the firm, the leverage, the market-to-book (MTB) ratio, and the value weighted market return (mret). The summary statistics are provided for both periods of low and high ambiguity. High (Low) ambiguity is defined as the period when the 22 days moving average variance risk premium is above (below) its sample median. The sample period covered is 03/06/2000 to 08/15/2015.

Panel A: Full Sample

	Mean	Median	STDDEV	Min	Max	Skewness	Kurtosis
CAR (-1, +1)	0.0019	0.0010	0.0870	-0.8579	1.7077	0.2418	9.7937
Negative Surprise	-0.3103	0.0000	0.6949	-35.3553	0.0000	-6.4573	169.0333
Positive Surprise	0.4294	0.1041	0.6990	0.0000	17.8794	3.0110	18.4061
VRP	15.4646	11.6268	13.9466	-1.4738	55.9156	1.6399	2.2638
Size	6719.3718	1136.4203	23601.5362	0.0181	717000.2515	9.6664	134.1830
Leverage	0.1406	0.1007	0.1480	0.0000	0.9791	1.3735	1.9720
MTB	2.2207	1.5466	23.8599	0.2814	6402.1179	238.4434	59613.9410
Mret	0.0003	0.0008	0.0132	-0.0898	0.1149	-0.0070	7.9702

Panel B: Low Ambiguity

	Mean	Median	STDEV	Min	Max	Skewness	Kurtosis
CAR (-1, +1)	0.0012	0.0001	0.0807	-0.8579	1.4142	0.2303	9.7103
Negative Surprise	-0.3099	0.0000	0.6745	-32.5269	0.0000	-5.3714	116.5157
Positive Surprise	0.4191	0.0967	0.6892	0.0000	17.8794	3.3195	27.0885
VRP	6.0800	6.4522	3.5421	-1.4738	11.6871	-0.5587	-0.4521
Size	7083.1888	1208.2605	24365.6976	0.0181	717000.2515	9.1061	117.4666
Leverage	0.1356	0.0969	0.1440	0.0000	0.9738	1.4341	2.2804
MTB	2.3937	1.6171	32.6132	0.3056	6402.1179	174.8520	31982.1661
Mret	0.0004	0.0007	0.0081	-0.0457	0.0411	-0.1257	2.1760

Table 1 contd.

Panel C: High Ambiguity

	Mean	Median	STDEV	Min	Max	Skewness	Kurtosis
CAR (-1, +1)	0.0024	0.0926	0.0019	-0.8308	1.7077	0.3314	10.8742
Negative Surprise	-0.3141	0.7376	0.0000	-35.3553	0.0000	-8.8849	281.5858
Positive Surprise	0.4383	0.7093	0.1086	0.0000	9.8995	2.7858	12.1878
VRP	24.8569	14.1227	18.4527	11.6904	55.9156	1.2886	0.3122
Size	6365.2910	23290.3757	1046.9212	0.0195	643120.1292	10.2953	152.5387
Leverage	0.1464	0.1516	0.1063	0.0000	0.9791	1.3127	1.7151
MTB	2.0294	1.7592	1.4736	0.2814	69.8963	6.8212	123.1371
Mret	0.0002	0.0173	0.0011	-0.0898	0.1149	-0.0355	4.2730

Table 2 - Descriptive Statistics of CAR (-1, 1) for different types of stocks

This table reports the summary statistics (per categories of stocks) of the cumulative abnormal return (CAR) computed over a window of 3 days (-1, 0, and 1) around each earning announcements. The abnormal return on each day is computed as difference between the actual return and the predicted return (for that particular day) according to the one factor model. That is, for each individual stock, we estimate the one factor model over the period (-61,-11) days before earnings announcements. We use the estimated coefficients from the one factor model to predict the 'normal' values of the return over the window (-1, +1) days around the earnings release. We then compute the abnormal return over the (-1, +1) window as the difference between the actual return and the 'normal return', as predicted by the one factor model. The sample period covered is 03/06/2000 to 08/15/2015.

	Dividend Payers	Non-Dividend Payers	Low MTB	High MTB	Small Size	Large Size	Low Leverage	High Leverage
Mean	-0.0003	0.0032	0.0032	0.0003	0.0011	0.0024	0.0008	0.0029
Median	-0.0009	0.0017	0.0010	0.0007	0.0000	0.0016	0.0008	0.0009
STDEV	0.1054	0.0723	0.0843	0.0894	0.1011	0.0695	0.0906	0.0826
Min	-0.7911	-0.8579	-0.8579	-0.7911	-0.7911	-0.8579	-0.8579	-0.8308
Max	1.7077	1.4497	1.4497	1.7077	1.4497	1.7077	1.2461	1.7077
Skewness	0.2514	0.4070	0.6672	-0.0153	0.3349	0.1514	-0.0240	0.7637
Kurtosis	7.9984	11.8690	13.0614	8.6992	8.1728	13.6396	6.5310	16.9781

Table 3 - Information Asymmetry across Different Groups of Stocks

This table reports the mean and the standard deviation for the information asymmetry proxy across different categories of stocks: non-dividend payers vs. dividend payers, low Market-to-Book (MTB) vs. high MTB stocks, stocks of small vs. large firms, stocks of firms with low vs. high leverage. A variable is considered to have high values if its value is above the sample median. Information asymmetry is proxied by the standard deviation of analysis forecasts of earnings. The table provides also a test for the difference in the mean (t-test) and in the standard deviation (F test) of information asymmetry across different categories of stocks. The sample period covered is 03/06/2000 to 08/15/2015. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively.

	Mean	**STDEV**
Non-Dividend Payers	3.2632	290.5282
Dividend Payers	0.0438	0.2662
Test of Difference	*3.2194****	*290.2621****
Low MTB	1.9630	247.0233
High MTB	0.6662	74.6334
Test of Difference	*1.2968**	*172.3899****
Small Size	2.4862	257.9046
Large Size	0.1417	8.9208
Test of Difference	*2.3445****	*248.9837****
Low Leverage	1.9620	249.5354
High Leverage	0.6038	38.4375
Test of Difference	*1.3582***	*211.0978****

Table 4 - Frequency of Good and Bad Earnings Surprises

This table reports the number of good and bad earnings surprises for different types of stocks, under low and high ambiguity scenarios. A variable is considered to have high (low) values if its value is above (below) the sample median. The sample period covered is 03/06/2000 to 08/15/2015.

	Low Ambiguity					**High Ambiguity**				
	Good News		**Bad News**		**Total**	**Good News**		**Bad News**		**Total**
Non-Dividend Payers	10680	(52.89%)	9512	(48.58%)	20192	10528	(52.14%)	9053	(46.23%)	19581
Dividend Payers	19059	(62.80%)	11291	(36.35%)	30350	19755	(65.09%)	11305	(36.40%)	31060
Low MTB	13805	(58.04%)	9979	(36.67%)	23784	16038	(67.43%)	11177	(41.07%)	27215
High MTB	15934	(59.55%)	10824	(46.21%)	26758	14245	(53.24%)	9181	(39.19%)	23426
Small Size	13085	(53.68%)	11290	(43.06%)	24375	14466	(59.35%)	11754	(44.83%)	26220
Large Size	16654	(63.65%)	9513	(38.95%)	26167	15817	(60.45%)	8604	(35.23%)	24421
Low Leverage	15667	(58.05%)	11320	(43.90%)	26987	15138	(56.09%)	10646	(41.29%)	25784
High Leverage	14072	(59.74%)	9483	(38.15%)	23555	15145	(64.30%)	9712	(39.07%)	24857

Table 5 - Correlation between Information Asymmetry and Ambiguity

This table reports the average Pearson Correlation coefficients between the firm specific information asymmetry proxies and the macro-level ambiguity. The firm specific information asymmetry is proxied by the standard deviation of earnings analysts' forecasts, while the ambiguity is measured by the 22 days moving average variance risk premium. The table also reports the p-values associated with each correlation coefficient. The sample period covered is 03/06/2000 to 08/15/2015. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively.

	Correlation Coeff.	**P-value**
Non-Dividend Payers	0.0159***	0.0013
Dividend Payers	0.0120***	0.0027
Low MTB	0.0104**	0.0181
High MTB	0.0096**	0.0295
Small Size	0.0130***	0.0032
Large Size	-0.0059	0.1791
Low Leverage	0.0147***	0.0006
High Leverage	-0.0028	0.5303

Table 6 – Baseline Regression

The table reports the estimates for the following model: $CAR_{it} = \alpha_0 + \alpha_1 GoodNews_{it} + \alpha_2 BadNews_{it} + \alpha_3 GoodNews_{it} * Alternative_{it} + +\alpha_4 BadNews_{it} * Alternative_{it} + Controls_{it} + \varepsilon_{it}$, where CAR_{it} is the cumulative abnormal return (CAR) computed over a window of 3 days (-1, 0, and 1) around each earning announcements. $GoodNews_{it}$ ($BadNews_{it}$) refers to positive (negative) earnings standardized surprises, taking values of the earnings surprise if the surprise is positive (negative), and 0 otherwise. $Alternative_{it}$ is a dummy variable. It can be replaced by a dummy variable *Dividend* (column 2) with values of 1 if the analyzed stock pays dividends, and 0 otherwise. It can be replaced by other dummy variables, such as *D_highMTB* (values of 1 if the stock has a MTB above the sample median, and 0 otherwise), D_largeSize (values of 1 if the stock belongs to a firm with the size above the sample median, and 0 otherwise), or D_highLeverage (values of 1 if the stock belongs to a firm with the level of leverage above the sample median, and 0 otherwise). The regression uses as control variables (alternatively, adjusted to each model) ('$Controls$'): the market-to-book ratio (MTB), the size of the firm (Size), the leverage of the firm (Leverage), the standard deviation of analysts' earnings forecast (Analyst Dispersion) and the market return (Mret). We also provide a test of asymmetry that examines whether the response of stocks to good and bad earnings surprises is asymmetric. The sample period covered is from 03/06/2000 to 08/15/2015. The regressions include year-fixed effects. T-stats are reported in parentheses, close to the coefficients. Errors are clustered along firm and time. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively.

Dependent Variable: Cumulative Abnormal Return (-1, 1)

Variables	**Dividend**	**D_highMTB**	**D_largeSize**	**D_highLeverage**
GoodNews	0.0209***	0.0203***	0.0250***	0.0174***
	(22.52)	(30.07)	(29.62)	(28.26)
BadNews	0.0144***	0.0138***	0.0155***	0.0159***
	(10.35)	(10.96)	(11.46)	(22.78)
GoodNews*Alternative	-0.0041***	-0.0041***	-0.0113***	0.0012
	(-4.35)	(-5.23)	(-13.3)	(1.65)
BadNews*Alternative	-0.0007	0.0007	-0.0041***	-0.0030***
	(-0.47)	(0.56)	(-3.10)	(-2.30)
Controls	yes***	yes***	yes***	yes***
Test of Asymmetry				
*GoodNews+(GoodNews*Alternative)*	0.0168	0.0162	0.0137	0.0186
*BadNews+(BadNews*Alternative)*	0.0137	0.0145	0.0113	0.0129
Difference	0.0031***	0.0017	0.0024**	0.0057***

Table 7 - The Response of Dividend and Non-Dividend Stocks to Earnings Surprises - Per Quintiles of Ambiguity

The table reports the estimates for the following model:
$CAR_{it} = \alpha_0 + \alpha_1 GoodNews_{it} + \alpha_2 BadNews_{it} + \alpha_3 GoodNews_{it} * Dividend_{it} + +\alpha_4 BadNews_{it} * Dividend_{it} + Controls_{it} + \varepsilon_{it}$, where CAR_{it} is the cumulative abnormal return (CAR) computed over a window of 3 days (-1, 0, and 1) around each earning announcements. $GoodNews_{it}$ ($BadNews_{it}$) refers to positive (negative) earnings standardized surprises, taking values of the earnings surprise if the surprise is positive (negative), and 0 otherwise. $Dividend_{it}$ is a dummy variable, taking values of 1 if the stock i pays dividends, and 0 otherwise. The regression uses as control variables ('$Control_{it}$'): the market-to-book ratio (MTB), the size of the firm (Size), the leverage of the firm (Leverage), the standard deviation of analysts' earnings forecast (Analyst Dispersion) and the market return (Mret). The table also reports a test of asymmetry that examines whether the response of stocks to good and bad earnings surprises is asymmetric. The sample period covered is from 03/06/2000 to 08/15/2015. The regressions include year-fixed effects. Errors are clustered along firm and time. T-stats are reported in parentheses, close to the coefficients. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively.

	Dependent Variable: Cumulative Abnormal Return (-1, 1)				
Variables	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
GoodNews	0.0197***	0.0186***	0.0235***	0.0227***	0.0213***
	(11.64)	(19.82)	(23.05)	(23.47)	(16.82)
BadNews	0.0169***	0.0138***	0.0133***	0.0115***	0.0239***
	(15.38)	(17.27)	(7.02)	(6.81)	(15.00)
GoodNews*Dividend	-0.0023	-0.0037***	-0.0078***	-0.0047***	-0.0047***
	(-1.41)	(-3.79)	(-7.58)	(-4.48)	(-3.37)
BadNews*Dividend	-0.0010	-0.0004	0.0009	0.0004	-0.0076***
	(-0.78)	(-0.38)	(0.48)	(0.25)	(-4.00)
MTB	-0.0014***	-0.0000***	-0.0019***	-0.0007***	-0.0027***
	(-6.71)	(-3.35)	(-7.16)	(-2.96)	(-7.23)
Size	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(-5.36)	(-3.67)	(-6.48)	(-7.02)	(-2.32)
Leverage	0.0087***	0.0053***	-0.0049*	0.0109***	0.0055
	(2.73)	(2.17)	(-1.83)	(4.12)	(1.4)
Analyst Dispersion	-0.0000***	-0.0000***	-0.0000***	0.0000	0.0000
	(-2.42)	(-2.39)	(-2.74)	(-0.42)	(0.87)
Mret	0.0655	0.0859***	-0.1029***	0.1101***	0.0819***
	(1.21)	(2.13)	(-2.66)	(3.87)	(3.32)
Test of Asymmetry					
*GoodNews+(GoodNews*Dividend)*	0.0174	0.0149	0.0157	0.0181	0.0167
*BadNews+(BadNews*Dividend)*	0.0159	0.0134	0.0142	0.0119	0.0163
Difference	0.0015***	0.0015***	0.0015***	0.0062***	0.0004

Table 8 - The Response of High vs. Low Market-to Book Stocks to Earnings Surprises- Per Quintiles of Ambiguity

This table reports the estimates for the following model: $CAR_{it} = \alpha_0 + \alpha_1 GoodNews_{it} + \alpha_2 BadNews_{it} + \alpha_3 GoodNews_{it} * D\_highMTB_{it} + +\alpha_4 BadNews_{it} * D\_highMTB_{it} + Controls_{it} + \varepsilon_{it}$, where CAR_{it} is the cumulative abnormal return (CAR) computed over a window of 3 days (-1, 0, and 1) around each earning announcements. $GoodNews_{it}$ ($BadNews_{it}$) refers to positive (negative) earnings standardized surprises, taking values of the earnings surprise if the surprise is positive (negative), and 0 otherwise. $D\_highMTB_{it}$ is a dummy variable, taking values of 1 if the Market-to-Book (MTB) ratio of stock i is above the sample median, and 0 otherwise. The regression uses as control variables ('$Control_{it}$'): a dummy for identifying whether a stock pays dividend or not (Dividend), the size of the firm (Size), the leverage of the firm (Leverage), the standard deviation of analysts' earnings forecast (Analyst Dispersion) and the market return (Mret). The table also reports a test of asymmetry that examines whether the response of stocks to good and bad earnings surprises is asymmetric. The sample period covered is from 03/06/2000 to 08/15/2015. The regressions include year-fixed effects. Errors are clustered along firm and time. T-stats are reported in parentheses, close to the coefficients. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively.

	Dependent Variable: Cumulative Abnormal Return (-1, 1)				
Variables	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
GoodNews	0.0214***	0.0188***	0.0202***	0.0216***	0.0193***
	(20.47)	(23.93)	(27.36)	(24.6)	(20.04)
BadNews	0.0161***	0.0163***	0.0138***	0.0103***	0.0182***
	(15.41)	(19.45)	(6.90)	(7.26)	(14.57)
GoodNews*D_highMTB	-0.0054***	-0.0045***	-0.0037***	-0.0042***	-0.0026***
	(-3.98)	(-5.24)	(-4.29)	(-4.37)	(-2.10)
BadNews*D_highMTB	0.0003	-0.0047***	0.0000	0.0037***	0.0019
	(0.24)	(-4.53)	(-0.02)	(2.39)	(1.05)
Dividend	0.0006	-0.0002	0.0003	-0.0008	0.0017
	(0.73)	(-0.31)	(0.38)	(-1.11)	(1.54)
Size	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(-6.23)	(-4.39)	(-8.24)	(-7.53)	(-3.82)
Leverage	0.0107***	0.0044*	-0.0005	0.0093***	0.0123***
	(3.30)	(1.75)	(-0.19)	(3.64)	(3.26)
Analyst Dispersion	-0.0000***	-0.0000***	-0.0000***	0.0000	0.0000
	(-2.31)	(-2.32)	(-2.30)	(-0.43)	(0.05)
Mret	0.0638	0.0859***	-0.0987***	0.1077***	0.0827***
	(1.17)	(2.13)	(-2.55)	(3.77)	(3.35)
Test of Asymmetry					
*GoodNews+(GoodNews*D_highMTB)*	0.0159	0.0143	0.0165	0.0174	0.0167
*BadNews+(BadNews*D_highMTB)*	0.0164	0.0116	0.0138	0.0140	0.0201
Difference	-0.0005***	0.0027***	0.0027**	0.0034***	-0.0033*

Table 9 - The Response of Stocks of Small vs. Large Firms to Earnings Surprises- Per Quintiles of Ambiguity

This table reports the estimates for the following model: $CAR_{it} = \alpha_0 + \alpha_1 GoodNews_{it} + \alpha_2 BadNews_{it} + \alpha_3 GoodNews_{it} * D\_LargeSize_{it} + +\alpha_4 BadNews_{it} * D\_LargeSize_{it} + Controls_{it} + \varepsilon_{it}$, where CAR_{it} is the cumulative abnormal return (CAR) computed over a window of 3 days (-1, 0, and 1) around each earning announcements. $GoodNews_{it}$ ($BadNews_{it}$) refers to positive (negative) earnings standardized surprises, taking values of the earnings surprise if the surprise is positive (negative), and 0 otherwise. $D\_LargeSize_{it}$ is a dummy variable, taking values of 1 if the size of firm i is above the sample median, and 0 otherwise. The regression uses as control variables ('$Control_{it}$'): a dummy for identifying whether a stock pays dividend or not (Dividend), the market-to-book (MTB) ratio, the leverage of the firm (Leverage), the standard deviation of analysts' earnings forecast (Analyst Dispersion) and the market return (Mret). The table also reports a test of asymmetry that examines whether the response of stocks to good and bad earnings surprises is asymmetric. The sample period covered is from 03/06/2000 to 08/15/2015. The regressions include year-fixed effects. Errors are clustered along firm and time. T-stats are reported in parentheses, close to the coefficients. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively.

	Dependent Variable: Cumulative Abnormal Return (-1, 1)				
Variables	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
GoodNews	0.0273***	0.0200***	0.0233***	0.0280***	0.0249***
	(22.02)	(19.67)	(23.38)	(25.79)	(21.85)
BadNews	0.0182***	0.0185***	0.0159***	0.0124***	0.0202***
	(17.23)	(21.00)	(7.31)	(7.77)	(14.48)
GoodNews*D_LargeSize	-0.0141***	-0.0060***	-0.0080***	-0.0142***	-0.0125***
	(-10.36)	(-5.97)	(-8.19)	(-13.34)	(-10.08)
BadNews*D_LargeSize	-0.0057***	-0.0095***	-0.0057***	-0.0025	-0.0039***
	(-4.47)	(-9.51)	(-2.77)	(-1.55)	(-2.17)
Dividend	0.0010	-0.0005	-0.0007	0.0004	0.0018*
	(1.15)	(-0.72)	(-0.89)	(0.56)	(1.69)
MTB	-0.0013***	-0.0000***	-0.0018***	-0.0006***	-0.0025***
	(-6.14)	(-3.20)	(-6.50)	(-2.27)	(-6.82)
Leverage	0.0084***	0.0055***	-0.0051*	0.0111***	0.0061
	(2.66)	(2.22)	(-1.88)	(4.21)	(1.55)
Analyst Dispersion	-0.0000***	-0.0000***	0.0000	0.0000	0.0000
	(-2.57)	(-2.35)	(-1.63)	(-0.39)	(0.32)
Mret	0.0628	0.0855***	-0.1058***	0.1094***	0.0819***
	(1.16)	(2.12)	(-2.74)	(3.84)	(3.32)
Test of Asymmetry					
*GoodNews+(GoodNews*D_LargeSize)*	0.0132	0.0140	0.0153	0.0138	0.0124
*BadNews+(BadNews*D_LargeSize)*	0.0125	0.0090	0.0102	0.0099	0.0163
Difference	0.0007	0.0050***	0.0050***	0.0039***	-0.0039**

Table 10 - The Response of Stocks of High vs. Low Leverage Firms Earnings Surprises- Per Quintiles of Ambiguity

The table reports the estimates for the following model: $CAR_{it} = \alpha_0 + \alpha_1 GoodNews_{it} + \alpha_2 BadNews_{it} + \alpha_3 GoodNews_{it} * D\_HighLeverage_{it} + +\alpha_4 BadNews_{it} * D\_HighLeverage_{it} + Controls_{it} + \varepsilon_{it}$, where CAR_{it} is the cumulative abnormal return (CAR) computed over a window of 3 days (-1, 0, and 1) around each earning announcements. $GoodNews_{it}$ ($BadNews_{it}$) refers to positive (negative) earnings standardized surprises, taking values of the earnings surprise if the surprise is positive (negative), and 0 otherwise. $D\_highLeverage$ is a dummy variable, taking values of 1 if the leverage of firm i is above the sample median, and 0 otherwise. The regression uses as control variables ('$Control_{it}$'): a dummy for identifying whether a stock pays dividend or not (Dividend), the size of the firm (Size), the market-to-book ratio (MTB), the standard deviation of analysts' earnings forecast (Analyst Dispersion) and the market return (Mret). The table also reports a test of asymmetry that examines whether the response of stocks to good and bad earnings surprises is asymmetric. The sample period covered is from 03/06/2000 to 08/15/2015. The regressions include year-fixed effects. Errors are clustered along firm and time. T-stats are reported in parentheses, close to the coefficients. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively

	Dependent Variable: Cumulative Abnormal Return (-1, 1)				
Variables	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
GoodNews	0.0176***	0.0151***	0.0187***	0.0194***	0.0181***
	(14.61)	(24.72)	(27.24)	(28.18)	(19.03)
BadNews	0.0163***	0.0121***	0.0141***	0.0158***	0.0216***
	(15.41)	(17.31)	(16.30)	(17.30)	(18.66)
GoodNews*D_HighLeverage	0.0016	0.0020***	-0.0014	-0.0004	-0.0005
	(1.24)	(2.55)	(-1.63)	(-0.43)	(-0.38)
BadNews*D_HighLeverage	0.0017	0.0034***	-0.0007	-0.0067***	-0.0041***
	(1.26)	(3.42)	(-0.36)	(-4.47)	(-2.34)
Dividend	-0.0001	-0.0002	-0.0010	-0.0010	0.0003
	(-0.13)	(-0.26)	(-1.34)	(-1.37)	(0.25)
MTB	-0.0015***	-0.0000***	-0.0017***	-0.0009***	-0.0028***
	(-7.24)	(-3.54)	(-6.61)	(-3.53)	(-7.86)
Size	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(-6.16)	(-4.32)	(-7.25)	(-7.66)	(-2.46)
Analyst Dispersion	-0.0000***	-0.0000***	-0.0000***	0.0000	0.0000***
	(-3.56)	(-2.44)	(-5.68)	(-0.45)	(7.27)
Mret	0.0713	0.0797***	-0.0976***	0.0988***	0.0689***
	(1.35)	(2.03)	(-2.59)	(3.55)	(2.87)
Test of Asymmetry					
*GoodNews+(GoodNews*D_HighLeverage)*	0.0193	0.0171	0.0173	0.0190	0.0177
*BadNews+(BadNews*D_HighLeverage)*	0.0179	0.0155	0.0134	0.0092	0.0175
Difference	0.0013	0.0016	0.0039*	0.0098***	0.0002

Figure 1. The True and the Predicted Realized Variance $RV_t^{(22)}$

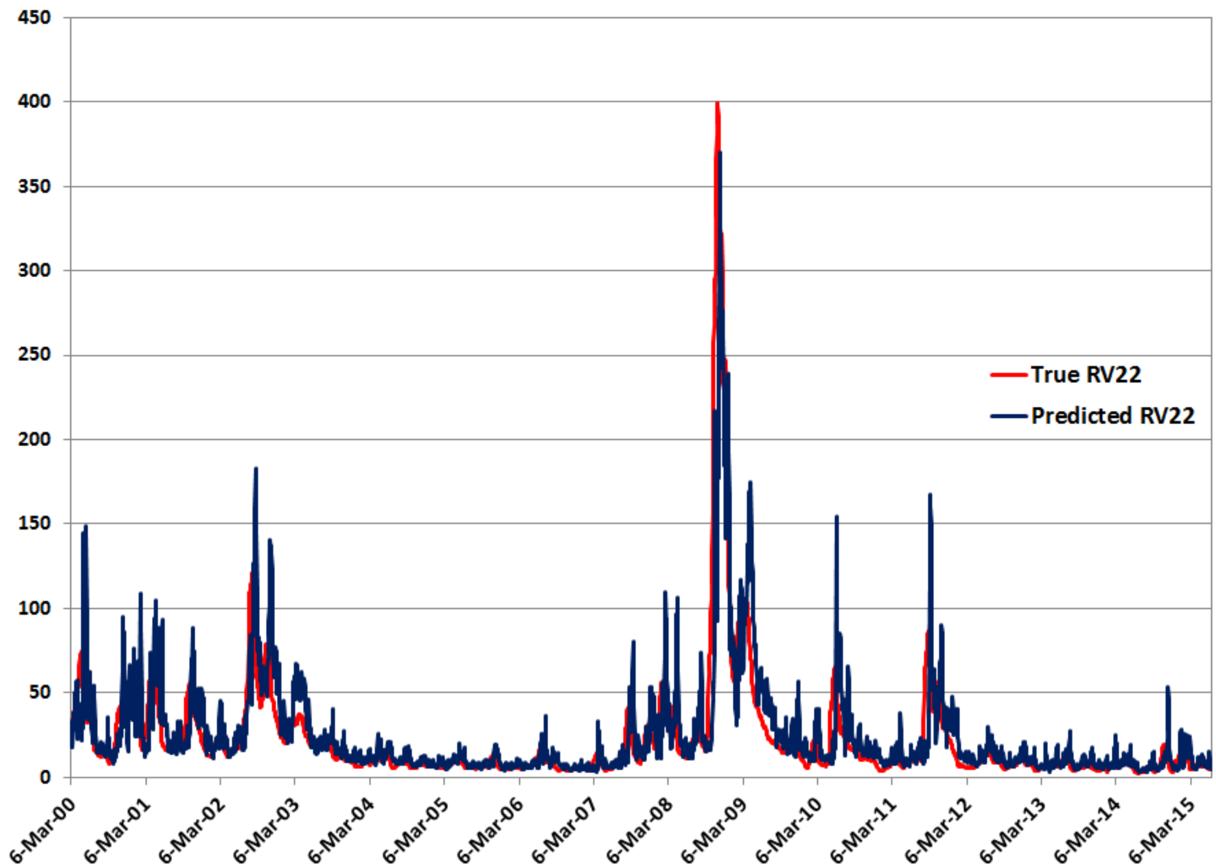


Figure 2. The Predicted Variance Risk Premium and the Predicted Realized Variance RV22

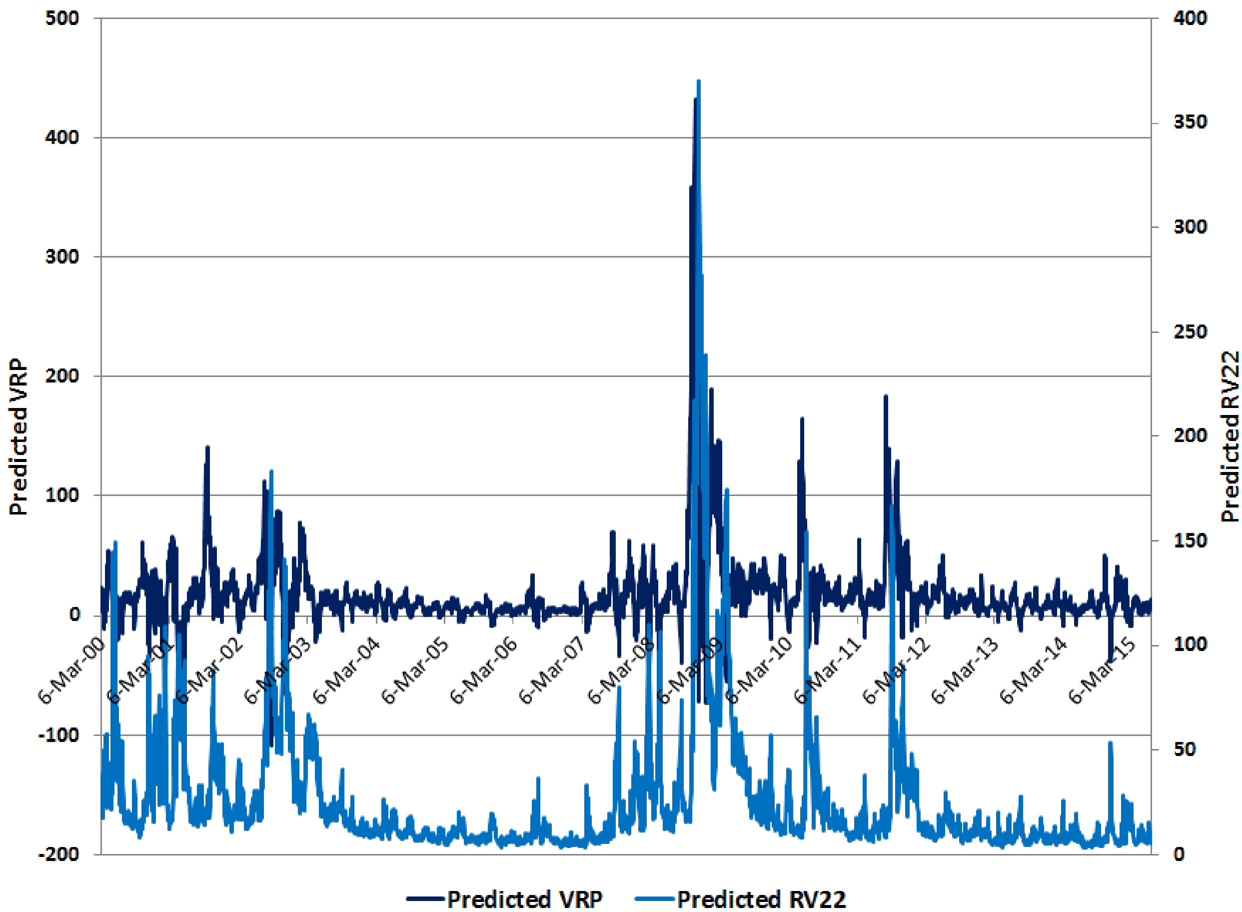


Figure 3. 22 days Moving Average Variance Risk Premium

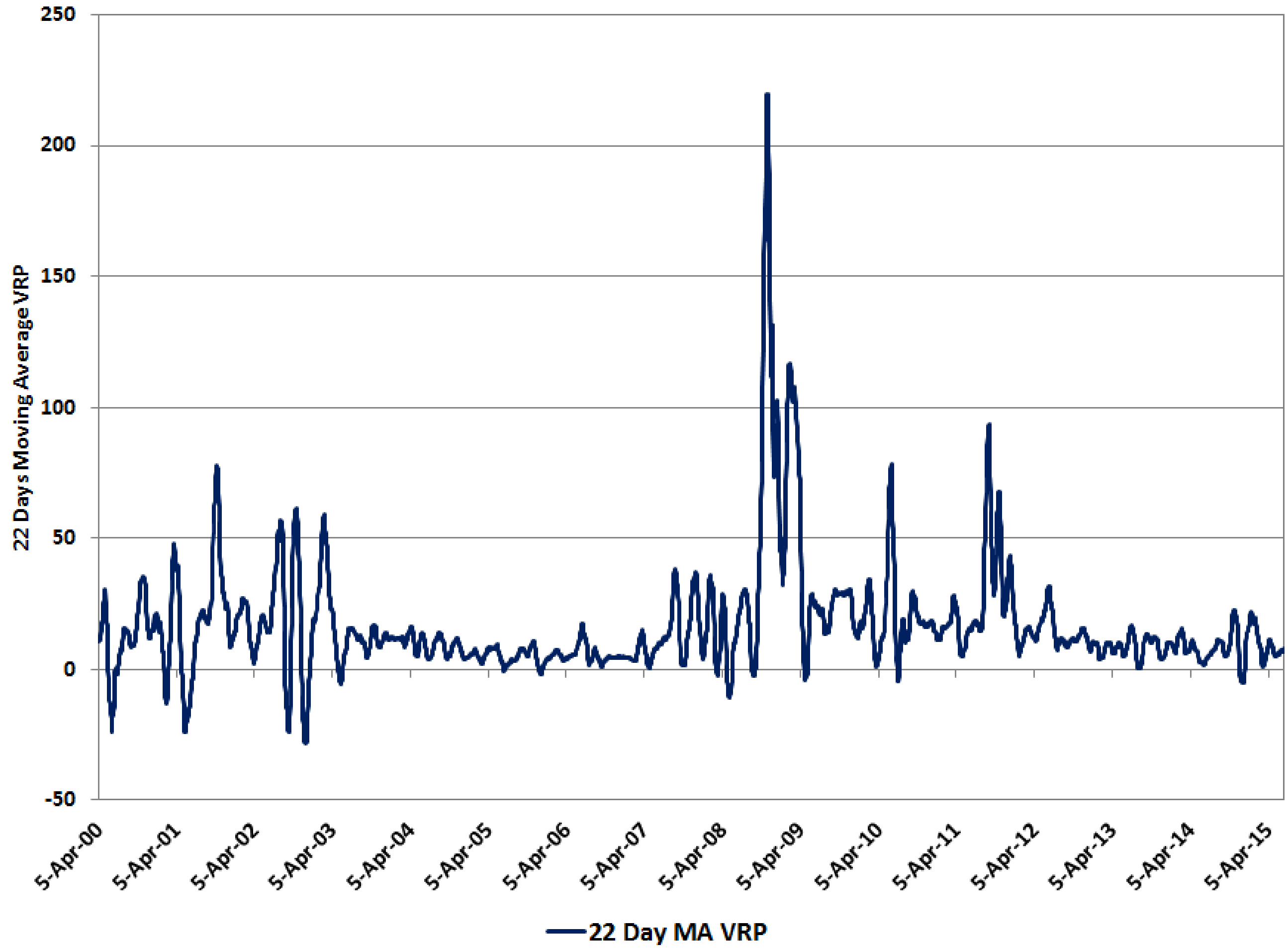
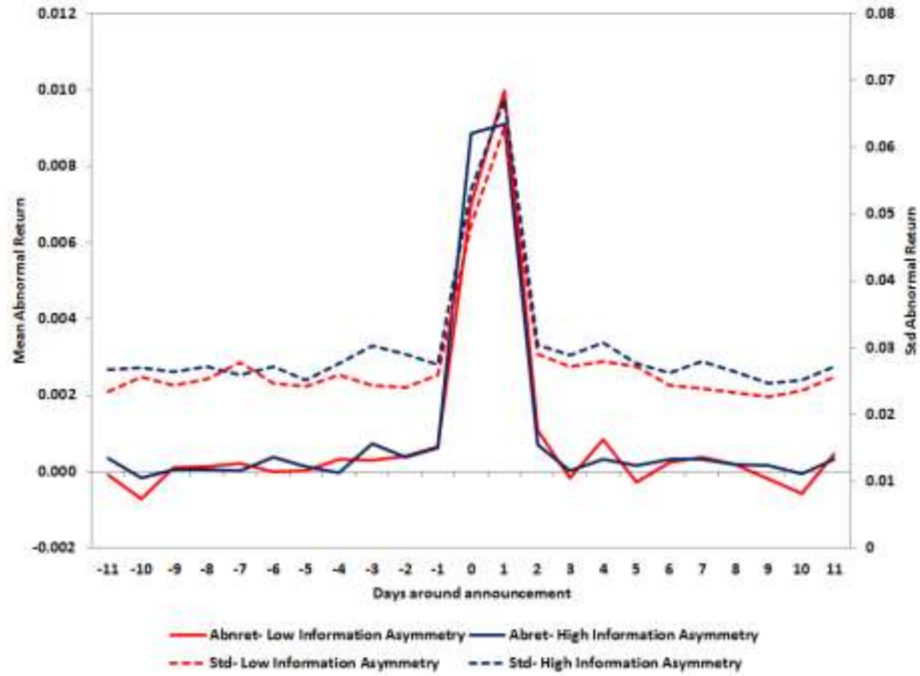


Figure 4. Average and StdDev of Abnormal Return around Earnings Announcements

Panel A. Positive Earnings Surprises



Panel B. Negative Earnings Surprises