The Good, the Bad, and the Ambiguous: The Aggregate Stock Market Dynamics around Macroeconomic News

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Abstract

Using a representative agent model in which the investor is averse to ambiguity (Knightian uncertainty) and sees an ambiguous piece of news about the fundamental value of a risky asset, I show a number of predictions for the dynamics of stocks around news: Stocks respond more strongly to bad news than to good news, respond positively to neutral news, and increase on average through news. In times of high ambiguity, the magnitudes of each effect is larger, and the volatility of stocks around news changes in a predictable manner as well. I provide empirical evidence consistent with the model by analyzing the high-frequency behavior of the aggregate stock market around macroeconomic news announcements from November, 1997 to March, 2014. The model helps to understand features of the data that challenge existing frameworks; e.g., the findings that the stock market reacts especially strongly to bad news versus good news during crisis periods and that about 1/3 of equity returns in the 17 year sample accrues in the 10 minutes around the release of macroeconomic data. In addition to providing evidence for the role of ambiguity in financial markets generally and in how financial assets reflect macroeconomic shocks specifically, the empirical results also have implications for the behavior of investors. Investors treat bad news as more relevant in bad times than in good times but treat good news the same in good and bad times.

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1 Introduction

Uncertainty plays a central role in determining asset prices. How investors interpret news and impound that information into financial assets is a likewise important topic in asset pricing. These two themes are very much related, for investors are routinely exposed to news of uncertain value and must pass judgement on the relevance of said news for financial markets. The first focus of this paper is the use of a representative agent model based off Epstein and Schneider (2008) to investigate how investors process news that has a specific type of uncertainty, Knightian uncertainty or ambiguity, and the resulting implications for asset pricing. In the model, the investor sees a piece of news about the fundamental value of a risky asset, but this news is ambiguous in the sense that the investor knows the variance of the noise component only within a range. If the investor believes that the variance is low, the news is precise or relevant; otherwise, the news is imprecise or irrelevant. The investor is furthermore ambiguity-averse and picks the worst-case belief for the noise variance that minimizes expected utility. This setup yields four predictions for the behavior of stocks around ambiguous news, the first three of which are (i) the asymmetry effect or asymmetrically strong response of stocks to bad news versus good news, (ii) the no news is good news effect or the positive response of stocks to no (neutral) news, and (iii) the ambiguity premium or the average positive return of stocks around news. As the amount of ambiguity, equivalent to the range of the noise variance, increases, the model further conjectures that the magnitude of each of these three phenomenon increases. There is an additional (iv) risky asset volatility effect or corresponding increase or decrease in the volatility of stocks around news depending on the source of the increase in ambiguity.

Much of the work involving Knightian uncertainty is theoretical in nature. The second focus of this paper is thus empirical and shows that the aforementioned model with ambiguity accurately captures the real-world behavior of stocks in a way that existing frameworks in the literature cannot. To arrive at this conclusion, I investigate the behavior of the aggregate stock market around macroeconomic news announcements (MNAs) concerning inflation, output, and the labor market. The results demonstrate that ambiguity can contribute to our understanding of how asset markets price macroeconomic shocks. Using high-frequency intraday data on the S&P 500 futures contract in the ±5 minutes around a comprehensive sample of macroeconomic data releases from November, 1997 to March, 2014, I show whole sample evidence consistent with the asymmetry effect, the no news is good news effect, and the ambiguity premium. In the 10-minute window around MNAs, stocks increase 2.416 bps

1It is not without reason that another name for Knightian uncertainty or ambiguity is unmeasurable uncertainty.
to a unit of good news but decrease 8.557 bps to a unit of bad news, which results in a meaningful 6.141 bps asymmetry effect.\footnote{News is a standardized variable such that good news corresponds to “better”-than-expected data; i.e., higher-than-expected inflation or output and lower-than-expected unemployment. See Section 3.1 for details.} At the same time, stocks increase 3.204 bps to no (neutral) news. All of the referenced numbers are statistically significant. Strikingly, the stock market increases a significant 1 bp on average through the 3,194 10-minute return intervals that contain macroeconomic news releases yet only an insignificant 0.014 bps on average through the other 588,671 10-minute return intervals during the sample period. In other words, stocks compounded 36.250\% around MNAs and 66.267\% otherwise such that about 1/3 of the stock market return over 17 years accrues in that tiny fraction of time around macroeconomic news releases. The standard deviation of returns is, however, only modestly higher in intervals containing MNAs relative to all other intervals, so this set of empirical observations is hard to reconcile with standard risk-based stories. The ambiguity premium provides an explanation for this puzzle.

The model makes several sharper predictions for how the aggregate stock market dynamics around macroeconomic data releases depends on the amount of ambiguity. Motivated by earlier academic studies such as Drechsler (2013), I use the variance risk premium, the difference between risk-neutral and physical expectations of stock market return variance, as a state variable for ambiguity in empirical tests. Existing measures of the variance risk premium, however, are problematic as proxies for ambiguity. To overcome these issues, I construct my own time series which behaves as a more reasonable proxy. The variance risk premium is elevated during well-known times of market stress such as the 2008 financial crisis when investors are plausibly less sure about the relevance of a piece of macroeconomic news for the fundamental value of the stock market; i.e., ambiguity is high. In less turbulent times, such as the mid-2000s, the variance risk premium is lower, consistent with the intuition that investors are more certain about the salience of macroeconomic data for stocks; i.e., ambiguity is low. As a consequence of how the variable is constructed, the variance risk premium predicts stock returns at long horizons but not short horizons in contrast to results in the literature.

Using the variance risk premium time series as a proxy for ambiguity, I find that, consistent with the model, the stock market reacts most asymmetrically to bad news versus good news during times of high ambiguity and progressively less so during times of lower ambiguity. The reaction of stocks to signed news is essentially symmetric when ambiguity is at its lowest. Intriguingly, the stronger reaction of stocks to bad news relative to good news in times of high ambiguity comes from the increased sensitivity of stocks to bad news and not from the decreased sensitivity of stocks to good news. This result, interpreted through
the model, says that ambiguity, defined as the range of news noise variance, changes due to changes in the lower bound of the range instead of the upper bound of the range. The real-world implication for the behavior of investors is that during times of high ambiguity, which also tend to be times of panic in financial markets, investors think that bad macroeconomic news is more relevant for the stock market but good macroeconomic news is not any less relevant for the stock market. Phrased simply, investors focus more on bad news in bad times than in good times but treat good news the same in good and bad times.

The data also corroborate the no news is good news effect: Stocks react more strongly to neutral MNAs during times of high ambiguity than during times of low ambiguity. The evidence for the ambiguity premium is less clear-cut. True to the model, stocks earn a positive average return around macroeconomic data releases, but this average return is not increasing in ambiguity. Indeed, there is little time-variation in the average return of stocks around MNAs. The implication is that the ambiguity premium exists but is not time-varying. Based on the asymmetry effect, we know that changes in ambiguity occur in a specific way, and how ambiguity changes helps to reconcile the lack of time-variation in the ambiguity premium with the model. Moreover, the way in which ambiguity changes implies, though the risky asset volatility effect, that the volatility of stocks around MNAs should be higher in times of high ambiguity. This result shows up in the data.

How does the model generate the predictions that it does? When the investor sees a piece of news with noise variance known only within a range, ambiguity aversion dictates that the investor believes the actual noise variance is the one that minimizes his expected utility. If the news is positive for the fundamental value of the risky asset, the investor believes that the noise variance is high; hence, the news has low relevance and the risky asset responds weakly. If the news is negative, the investor believes that the noise variance is low; hence, the news has high relevance and the risky asset responds strongly. This is the asymmetry effect. Prior to the arrival of news, the investor knows that ambiguous news is coming. Because the investor dislikes ambiguity, he must be compensated for holding the risky asset. Neutral news provides no information on the value of the risky asset but does resolve the ambiguity, so the rise of the risky asset in response to no news measures this compensation. This is the no news is good news effect. The average change in the price of the risky asset around news is equal to the sum of the no news is good news and asymmetry effects. This sum is positive and is equal to the ambiguity premium. Finally, if ambiguity or the range of news noise variance increases because the lower (upper) bound of the range decreases (increases), the risky asset responds more (less) strongly to negative (positive) news. As such, the volatility of the risky asset around news increases (decreases). This is the risky asset volatility effect.

While we must always exercise caution in interpreting the implications of a representative
agent model for the real-world, there are several reasons why the behavior of the aggregate stock market (the risky asset) around news about macroeconomic conditions (the news) is an appropriate environment to test the model. Investors care about the fundamental value of the stock market, which is ultimately a stream of dividends, but can only infer future dividends from various news reports. One important type of news is that concerning the macroeconomy, for it is well-established that market participants pay close attention to and actively trade such reports. As a result, the aggregate stock market reacts in a systematic manner to MNAs: Stocks react positively to news of higher-than-expected inflation or output and lower-than-expected unemployment. MNAs are not, however, precise pieces of news about stock market fundamentals. A piece of news about macroeconomic conditions does not lay out the future stream of dividends with certainty, and there is considerable freedom in interpreting the relevance of such news. In other words, MNAs are ambiguous pieces of news about the stock market. Taking the model literally, investors have a set of beliefs encoded in the set of precisions of a given macroeconomic news release and its relevance for the fundamental value of the stock market. The amount of ambiguity can vary over time with high levels of ambiguity corresponding to environments in which investors have a great deal of uncertainty in interpreting the salience of macroeconomic news for stocks; that is, the precision of the news in investors’ minds could be anywhere from very low to very high. When ambiguity is low, however, investors are more sure of how informative macroeconomic news is for the stock market, so investors have a narrower range of precisions in mind. Ex ante, we might expect that ambiguity is highest at identifiable times such as during the 2008 financial crisis or the 2011 height of the European sovereign-debt crisis and concurrent U.S. debt-ceiling crisis. At other times, such as the few years before the financial crisis when economic and financial conditions were relatively stable, we might expect lower levels of ambiguity. Introspection suggests that such a narrative is reasonable.

This paper builds on the literature at the intersection of ambiguity and finance. In particular, the model with ambiguity follows from Epstein and Schneider (2008) who use the max-min expected utility theory of Gilboa and Schmeidler (1989) to capture the idea of ambiguity aversion. Hansen and Sargent (2010) among other papers by the two co-authors represents an alternative but related way to formulate aversion to ambiguity using robust control theory. A few studies have looked at how ambiguity can aid in explaining various phenomena in financial markets. For example, Illeditsch (2011) shows that ambiguity can account for portfolio inertia and excess volatility, Boyarchenko (2012) attributes spikes in CDS spreads during the 2008 financial crisis to increases in ambiguity, and Drechsler (2013) calibrates a model with ambiguity that matches the variance risk premium and implied volatility surface of stock index options as well as other properties of stocks. Related to my
findings, Williams (2014) provides empirical evidence that individual stocks respond more strongly to bad earnings news than to good earnings news and especially so when the VIX, used as a proxy for ambiguity, is elevated. To my knowledge, however, no existing research explores the broad set of equity characteristics addressed in this paper and how these features in the data provide evidence for a model with ambiguity.

The behavior of the aggregate stock market around macroeconomic data releases is a novel setting in which to evaluate the impact of ambiguity. Many papers in the literature have used this setting to explore topics related to how financial assets reflect macroeconomic risk; e.g., Jones, Lamont, and Lumsdaine (1998), Andersen, Bollerslev, Diebold, and Vega (2003, 2007), Boyd, Hu, and Jagannathan (2005), Faust, Rogers, Wang, and Wright (2007), Faust and Wright (2012), and Savor and Wilson (2013, 2014). These studies have investigated an assortment of assets (e.g., stocks, bonds, and currencies) in various sample periods (e.g., expansionary and contractionary states). How asset prices vary in response to macroeconomic news can give insight into other areas of economics as well. Swanson and Williams (2013, 2014) and Zhou (2014), for example, show that the Federal Reserve’s zero lower bound attenuates interest rate sensitivity to news about the macroeconomy.

An integral part of my research is the construction of an appropriate proxy for ambiguity. The state variable for ambiguity that I choose, the variance risk premium, has been analyzed from a number of different angles. Evidence from Bollerslev, Tauchen, and Zhou (2009), Faust and Wright (2012), Drechsler (2013), and Bekaert and Hoerova (2014) shows that the variance risk premium is a significant predictor of stock returns in the time series. Bekaert, Hoerova, and Lo Duca (2013) also find interesting lead-lag relationships between the variance risk premium and the stance of monetary policy. Importantly, academic work such as Bekaert, Hoerova, and Lo Duca (2013) and, especially, Drechsler (2013), have discussed and provided justification for the variance risk premium as a measure of ambiguity. There is no data series in the literature that serves as the gold standard for the variance risk premium, however, so much work on the subject is necessarily methodological in nature; e.g., Carr and Wu (2009) in addition to some of the aforementioned studies. One of the contributions of my paper is the construction of a variance risk premium series that behaves as a more reasonable metric of ambiguity in the time series. This data series differs meaningfully from those in the literature in other ways, for example in the predictive power for stock returns.

The predictions that the model with ambiguity makes and that I subsequently verify empirically are related to several strands of research. Consistent with the asymmetry effect, Barberis, Shleifer, and Vishny (1998) and Veronesi (1999) have models that imply that stocks react more strongly to bad news than to good news. In their models, however,
the asymmetry occurs in good times and decreases (or even flips) in bad times. Conrad, Cornell, and Landsman (2002) find that individual stocks do indeed react asymmetrically stronger to bad earnings announcements versus good earnings announcements in good times, as measured by the equity market valuation, but not in bad times. Brown, Harlow, and Tinic (1988) and Campbell and Hentschel (1992) are alternative explanations for the asymmetric response of stocks to signed news. None of these frameworks involve ambiguity, however, and I show in Section 7 of this paper that the behavior of stocks around macroeconomic news supports an ambiguity-based explanation for the asymmetry effect over some of these existing explanations. Note that, as mentioned previously, Williams (2014) shows additional evidence that ambiguity drives the asymmetry effect using the response of individual stocks to earnings announcements.

My finding of a large, positive average return of stocks around MNAs is most closely related to work by Savor and Wilson (2013) who show a similar result using daily data instead of intraday data. Instead of interpreting this positive return as evidence of an ambiguity premium, the co-authors construct a model in which macroeconomic data releases reveal important information about the state of the economy. Stocks do poorly if the state of the economy is bad, which creates a large risk premium on days with MNAs. Faust and Wright (2012) find that standard return predictability regressions cannot predict the amount stocks earn around MNAs, which suggests that the premium earned is not time-varying. The increase of the aggregate stock market around macroeconomic announcements also parallels the earnings announcement premium for individual stocks for which there are various explanations. Frazzini and Lamont (2007), for example, reason that earnings announcements grab the attention of investors who are short-sale constrained or otherwise have a predisposition to be long.

Finally, the risky asset volatility effect is related to the well-documented time-variation of stock return volatility. Campbell and Hentschel (1992) and Veronesi (1999) are two of the papers that propose mechanisms generating the volatility fluctuations seen in the data.

The organization of this paper is as follows. Section 2 introduces the representative agent model with ambiguity and highlights the predictions for the behavior of the risky asset around ambiguous news. Section 3 describes the data on macroeconomic news releases and high-frequency stock prices used to empirically evaluate the model. Through analysis of the aggregate stock market around MNAs, Section 4 presents whole sample evidence supportive of the asymmetry effect, no news is good news effect, and ambiguity premium. Section 5 discusses the variance risk premium, its properties, and its suitability as a state variable for ambiguity. Using the variance risk premium to proxy for ambiguity, Section 6 shows how the asymmetry effect, no news is good news effect, ambiguity premium, and risky
asset volatility effect vary with ambiguity. Section 7 address alternative explanations for the model predictions. Section 8 concludes.

2 Model with Ambiguity

2.1 Utility Function

To illustrate the impact of ambiguity on financial markets, I consider a model with a representative agent based off Epstein and Schneider (2008). The agent is ambiguity-averse in the sense of having recursive multiple-priors utility with utility function $U$ at time $t$:

$$U_t = \min_{m_t \in M_t} \mathbb{E}_{m_t} [u(C_t) + \beta U_{t+1}].$$

(1)

$u(\cdot)$, $C_t$, and $\beta$ are the familiar notations for the Bernoulli utility function, consumption at time $t$, and the discount factor, respectively. I introduce the notation $M_t$ and $m_t$ to denote the set of models considered by the investor at time $t$ and a specific model within that set, respectively. Finally, $\mathbb{E}_{m_t} [\cdot]$ is the expectation given the beliefs generated by model $m_t$.

The utility function in Eq. (1) captures both risk-aversion and ambiguity-aversion. The former shows up through the Bernoulli utility function $u(\cdot)$. To see the latter, note that if $M_t$ consists of a single model, we are back in a standard framework, and hence there is no ambiguity-aversion. As the size of $M_t$ increases, ambiguity-aversion plays an increasingly important role. The reason is that the investor contemplates a range of models within $M_t$ and picks the model $m_t$ that generates worst-case beliefs and leads to the lowest expected utility.

2.2 Three Period Model

The stylized model has three dates: $t = 0$, $1$, and $2$. The investor can invest in either a risky asset, the aggregate stock market, or a risk-free asset. The risky asset is a claim on a dividend $d$ that is revealed at $t = 2$, while the risk-free rate is zero by assumption. As such, wealth at $t = 2$ is $W_2 = W_0 + (d - p) \theta$, in which $W_0$ is starting wealth at $t = 0$, $p$ is the price of the risky asset, and $\theta$ is the amount invested in the risky asset. The investor cares only about consumption at $t = 2$ and consumes all of his wealth $C_2 = W_2$. I assume that there is no time discounting and that period utility is exponential; that is, $\beta = 1$, and $u(C_t) = -\exp(-AC_t)$, with $A$ the coefficient of absolute risk aversion.
Working backward in time, at \( t = 2 \), the dividend
\[
d = \overline{d} + \epsilon_d
\]
is revealed. \( \overline{d} \) is the mean dividend, and \( \epsilon_d \sim \mathcal{N}(0, \sigma_d^2) \) is a normal, mean-zero shock.

At \( t = 1 \), a piece of news arrives about the dividend:
\[
n = \alpha \epsilon_d + \epsilon_n. \tag{2}
\]
\( \alpha \in [0, 1] \) measures the relevance of the news. For example, if \( \alpha = 1 \), the news is just a noisy estimate of \( \epsilon_d \). On the other hand, if \( \alpha = 0 \), the news provides no information on the dividend to be paid in one period. \( \epsilon_n \sim \mathcal{N}(0, \sigma_n^2) \) is a normal, mean-zero shock that is independent from \( \epsilon_d \). The news is ambiguous in the sense that the agent only knows that the variance of \( \epsilon_n \) is within an interval: \( \sigma_n^2 \in [\sigma_n^2, \overline{\sigma_n^2}] \). As the range \( \sigma_n^2 - \overline{\sigma_n^2} \) of this interval increases, there is a greater amount of ambiguity and the agent is less confident about the news’ precision. Referring to prior notation, \( [\sigma_n^2, \overline{\sigma_n^2}] \) maps to \( \mathcal{M}_1 \), and \( \sigma_n^2 \) maps to \( m_1 \). From Eq. (1), the utility function at \( t = 1 \) is
\[
U_1 = \min_{\sigma_n^2 \in [\sigma_n^2, \overline{\sigma_n^2}]} \mathbb{E}_{\sigma_n^2} \left[ - \exp \left( -A \left( W_0 + (d - p) \theta \right) \right) \right]. \tag{3}
\]
I ignore the \( u(C_1) \) term because the investor only cares about consumption at \( t = 2 \), and I substitute \( U_2 = - \exp \left( -A \left( W_0 + (d - p) \theta \right) \right) \) to reflect that final period utility is simply the utility from consuming all available wealth \( W_2 \). Finally, the utility function in Eq. (3) is conditional on observing the news \( n \) in Eq. (2).

At \( t = 0 \), the agent knows that ambiguous news will arrive in one period. His utility function at \( t = 0 \) is thus
\[
U_0 = \min_{\sigma_n^2 \in [\sigma_n^2, \overline{\sigma_n^2}]} \mathbb{E}_{\sigma_n^2} \left[ \min_{\sigma_n^2 \in [\sigma_n^2, \overline{\sigma_n^2}]} \mathbb{E}_{\sigma_n^2} \left[ - \exp \left( -A \left( W_0 + (d - p) \theta \right) \right) \right] \right]. \tag{4}
\]
This expression comes from straightforward substitution of Eq. (3) into Eq. (1). \( \mathcal{M}_0 = [\sigma_n^2, \overline{\sigma_n^2}] \) is the range of the noise variance from the first period perspective and is equal to \( \mathcal{M}_1 \). From \( \mathcal{M}_0 \), the agent at \( t = 0 \) selects the \( \sigma_n^2 \) that results in the worst-case expected utility.
2.3 Equilibrium Prices at $t = 0$ and $t = 1$ with Ambiguity-Aversion

We are interested in finding the price of the risky asset at $t = 0$, before the arrival of the news, and at $t = 1$, after the arrival of the news, in the case when the news is ambiguous, as well as in the case when the news is not ambiguous. To focus on the effect of ambiguity in the model, I assume that the investor is risk-neutral ($A = 0$). Consider the case of ambiguous news first, with $\sigma_n^2 > \sigma^2$.

2.3.1 Price at $t = 1$ with Ambiguity-Aversion

At $t = 1$, the investor’s optimization problem based on Eq. (3) is

$$
\max_\theta U_1 = \max_\theta \min_{\sigma^2_n \in [\sigma_n^2, \sigma^2]} \mathbb{E}_{\sigma^2_n} [- \exp (-A (W_0 + (d - p) \theta)) | n] \\
= \max_\theta \min_{\sigma^2_n \in [\sigma_n^2, \sigma^2]} - \log (\mathbb{E}_{\sigma^2_n} [\exp (-A (W_0 + (d - p) \theta)) | n]) .
$$

(5)

The second equality comes from the fact that the log ($\cdot$) function is monotonic. Since the joint distribution of $d$ and $n$ is given by

$$
\begin{pmatrix} n \\ d \end{pmatrix} = \begin{pmatrix} \alpha \epsilon_d + \epsilon_n \\ \frac{d}{d} + \epsilon_d \end{pmatrix} \sim \mathcal{N} \left( \begin{pmatrix} 0 \\ \frac{d}{d} \end{pmatrix}, \begin{pmatrix} \alpha^2 \sigma_d^2 + \sigma_n^2 \alpha \sigma_d^2 \\ \alpha \sigma_d^2 \sigma_d^2 \end{pmatrix} \right),
$$

(6)

following the formula in Appendix A.1 gives the result that dividend $d$ given news $n$ is conditionally normally distributed:

$$
d | n \sim \mathcal{N} \left( \overline{d} + \phi n, \sigma_d^2 (1 - \alpha \phi) \right),
$$

(7)

with

$$
\phi = \frac{\alpha \sigma_d^2}{\alpha^2 \sigma_d^2 + \sigma_n^2}.
$$

(8)

Note that the conditional distribution in Eq. (7) depends on $\sigma_n^2$ through $\phi$. In particular, $\phi \in [\phi, \overline{\phi}] \subset [0, 1]$, with

$$
\phi = \frac{\alpha \sigma_d^2}{\alpha^2 \sigma_d^2 + \sigma_n^2}, \text{ and }
$$

\overline{\phi} = \frac{\alpha \sigma_d^2}{\alpha^2 \sigma_d^2 + \sigma_n^2}.

(9)
Since I assume that $\sigma_n^2 > \sigma_n^2$, $\bar{\phi} > \underline{\phi}$. Using Eq. (7), I rewrite the optimization problem in Eq. (5):

$$\begin{align*}
\max_\theta U_1 &= \max_\theta \min_{\phi \in [\underline{\phi}, \bar{\phi}]} \mathbb{E}_\phi \left[-A (W_0 + (d - p) \theta) | n \right] - \frac{1}{2} \mathbb{V}_\phi \left[-A (W_0 + (d - p) \theta) | n \right] \\
&= \max_\theta \min_{\phi \in [\underline{\phi}, \bar{\phi}]} \theta \mathbb{E}_\phi \left[d - p | n \right] - \frac{1}{2} A \theta^2 \mathbb{V}_\phi \left[d - p | n \right] \\
&= \max_\theta \min_{\phi \in [\underline{\phi}, \bar{\phi}]} \theta \mathbb{E}_\phi \left[d - p | n \right].
\end{align*}$$

(11)

The first equality uses the fact that for a log-normal variable $z$, $\log (\mathbb{E} [z]) = \mathbb{E} [\log (z)] + \frac{1}{2} \mathbb{V} [\log (z)]$. I also replace $\sigma_n^2$ with $\phi$ and $[\sigma_n^2, \sigma_n^2]$ with $[\underline{\phi}, \bar{\phi}]$ due to the one-to-one mapping between the variables in Eqs. (8), (9), and (10). $\bar{\phi} - \underline{\phi}$ thus proxies for the amount of ambiguity in the same way that $\sigma_n^2 - \sigma_n^2$ does. The second step simplifies the optimization problem by dropping additive and multiplicative constants. The final step sets $A = 0$ to reflect that the agent is risk-neutral.

Solving Eq. (11) for the equilibrium price at $t = 1$ yields

$$p_1(n) = \min_{\phi \in [\underline{\phi}, \bar{\phi}]} \mathbb{E}_\phi \left[d | n \right] = \min_{\phi \in [\underline{\phi}, \bar{\phi}]} \bar{d} + \phi \bar{n} = \begin{cases} \\
\bar{d} + \phi \bar{n} & \text{if } n > 0 \\
\bar{d} + \underline{\phi} \bar{n} & \text{if } n \leq 0
\end{cases}. \quad (12)$$

Since the investor evaluates actions under the worst-case scenario, the price at $t = 1$ minimizes the conditional mean dividend and depends on the news value. Because $\underline{\phi} < \bar{\phi}$, the result is that the price of the risky asset is asymmetric in the value of the news. Moreover, the extent of this asymmetry is larger as the difference between $\bar{\phi}$ and $\underline{\phi}$ grows and there is greater ambiguity. If the news is good and $n > 0$, $p_1(n)$ has sensitivity $\underline{\phi}$ to $n$. On the other hand, if the news is bad and $n \leq 0$, $p_1(n)$ has sensitivity $\bar{\phi}$ to $n$. When the investor sees positive news, he thinks that it has high variance $\sigma_n^2$ (which corresponds to $\underline{\phi}$) and is therefore not particularly informative about the dividend in the next period. Upon seeing a negative piece of news, however, the investor thinks that it has low variance $\sigma_n^2$ (which corresponds to $\bar{\phi}$) and contains precise information about the dividend.

While Eq. (12) gives the price conditional on the news value, we are also interested in the average price of the risky asset after the investor sees the news. To derive this quantity, I use the distribution of $n$ from Eq. (6), and make the key assumption that the true variance of $\epsilon_n$ is $\sigma_n^2 \in [\underline{\sigma}_n^2, \bar{\sigma}_n^2]$. The average price $\bar{p}_1$ is then
\[ p_1 = \mathbb{E}_{\tilde{\sigma}_n^2} [\bar{d} + \phi n | n > 0] \times \mathbb{P}_{\tilde{\sigma}_n^2} [n > 0] + \mathbb{E}_{\tilde{\sigma}_n^2} [\bar{d} + \bar{\phi} n | n \leq 0] \times \mathbb{P}_{\tilde{\sigma}_n^2} [n \leq 0] \]
\[ = \bar{d} + \frac{1}{2} \phi \mathbb{E}_{\tilde{\sigma}_n^2} [n | n > 0] + \frac{1}{2} \phi \mathbb{E}_{\tilde{\sigma}_n^2} [n | n \leq 0] \]
\[ = \bar{d} - \frac{1}{2} (\bar{\phi} - \phi) \mathbb{E}_{\tilde{\sigma}_n^2} [n | n > 0] \]
\[ = \bar{d} - \frac{1}{\sqrt{2\pi}} (\bar{\phi} - \phi) \sqrt{\alpha^2 \sigma_d^2 + \tilde{\sigma}_n^2}. \quad (13) \]

The second and third steps use the fact that the news is symmetric around zero, and the last step uses the property of the normal distribution shown in Appendix A.2 that for \( z \sim N(0, \sigma_z^2) \), \( \mathbb{E}[z | z > 0] = \sigma_z \sqrt{2} / \sqrt{\pi} \). If the news value equals zero, the price at \( t = 1 \) equals \( p_1(0) = \bar{d} \) from Eq. (12). The average price, however, is below \( \bar{d} \) due to the asymmetric reaction of the price to the news. A visual way to see this result is that the price is concave in the news, so averaging over the price creates a Jensen’s inequality effect. With greater ambiguity and a larger magnitude of \( \bar{\phi} - \phi \), the average price is discounted more relative to \( \bar{d} \) due to the stronger price reaction to a negative piece of news versus a positive piece of news. The size of this asymmetry discount is
\[ p_1 - p_1(0) = -\frac{1}{\sqrt{2\pi}} (\bar{\phi} - \phi) \sqrt{\alpha^2 \sigma_d^2 + \tilde{\sigma}_n^2}. \quad (14) \]

### 2.3.2 Price at \( t = 0 \) with Ambiguity-Aversion

Moving back to \( t = 0 \), the agent’s optimization problem based on Eq. (4) is
\[
\max_{\theta} U_0 = \max_{\theta} \min_{\sigma^2_n \in [\sigma_n^2, \tilde{\sigma}_n^2]} \mathbb{E}_{\sigma^2_n} \left[ \min_{\sigma^2_n \in [\sigma_n^2, \tilde{\sigma}_n^2]} \mathbb{E}_{\sigma^2_n} [\exp (-A (W_0 + (d - p) \theta)) | n] \right] 
\]
\[
= \max_{\theta} \min_{\sigma^2_n \in [\sigma_n^2, \tilde{\sigma}_n^2]} \mathbb{E}_{\sigma^2_n} \left[ \min_{\sigma^2_n \in [\sigma_n^2, \tilde{\sigma}_n^2]} -\log \mathbb{E}_{\sigma^2_n} [\exp (-A (W_0 + (d - p) \theta)) | n] \right]. \quad (15) 
\]

I once again utilize the fact that the \( \log (\cdot) \) function is monotonic. Parallel to Eq. (11), the steps below simplify the optimization problem in Eq. (15) using the property of the log-normal distribution and the assumed risk-neutral nature of the investor:
max \( U_0 = \max_\theta \min_{\sigma_n^2 \in [\sigma_n^2, \sigma_n^2]} \mathbb{E}_{\sigma_n^2} \left[ \min_{\phi \in [\phi, \bar{\phi}]} -\mathbb{E}_\phi [-A (W_0 + (d - p) \theta) | n] - \frac{1}{2} \nabla_\phi [-A (W_0 + (d - p) \theta) | n] \right] \)

\[= \max_\theta \min_{\sigma_n^2 \in [\sigma_n^2, \sigma_n^2]} \mathbb{E}_{\sigma_n^2} \left[ \min_{\phi \in [\phi, \bar{\phi}]} \theta \mathbb{E}_\phi [d - p | n] - \frac{1}{2} A \theta^2 \nabla_\phi [d - p | n] \right] \]

\[= \max_\theta \min_{\sigma_n^2 \in [\sigma_n^2, \sigma_n^2]} \mathbb{E}_{\sigma_n^2} \left[ \min_{\phi \in [\phi, \bar{\phi}]} \theta \mathbb{E}_\phi [d - p | n] \right]. \tag{16} \]

For notational purposes, I replace the \( \sigma_n^2 \) variables with the \( \phi \) counterparts only in the inner minimization procedure. Solving Eq. (16) for the price at \( t = 0 \), we see that

\[ p_0 = \min_{\sigma_n^2 \in [\sigma_n^2, \sigma_n^2]} \mathbb{E}_{\sigma_n^2} \left[ \min_{\phi \in [\phi, \bar{\phi}]} \mathbb{E}_\phi [d | n] \right] \]

\[= \min_{\sigma_n^2 \in [\sigma_n^2, \sigma_n^2]} \mathbb{E}_{\sigma_n^2} \left[ \mathbb{P}_{\sigma_n^2} \left( n > 0 \right) \right] \]

\[= \min_{\sigma_n^2 \in [\sigma_n^2, \sigma_n^2]} \left[ \bar{d} + \frac{1}{2} \mathbb{E}_{\sigma_n^2} [n | n > 0] + \frac{1}{2} \tilde{\phi} \mathbb{E}_{\sigma_n^2} [n | n \leq 0] \right] \]

\[= \min_{\sigma_n^2 \in [\sigma_n^2, \sigma_n^2]} \bar{d} - \frac{1}{2} \tilde{\phi} \mathbb{E}_{\sigma_n^2} [n | n > 0] \]

\[= \min_{\sigma_n^2 \in [\sigma_n^2, \sigma_n^2]} \bar{d} - \frac{1}{\sqrt{2\pi}} \left( \tilde{\phi} - \tilde{\phi} \right) \sqrt{\sigma_n^2} \]

\[= \bar{d} - \frac{1}{\sqrt{2\pi}} \left( \tilde{\phi} - \tilde{\phi} \right) \sqrt{\alpha^2 \sigma_n^2 + \sigma_n^2} \]. \tag{17} \]

The first four steps in the derivation correspond exactly the four steps leading to the derivation of \( p_1 \) in Eq. (13), with the only difference the \( \min_{\sigma_n^2 \in [\sigma_n^2, \sigma_n^2]} \) operation. The final step substitutes in \( \sigma_n^2 \) as the \( \epsilon_n \) variance that minimizes the expression.

\( p_0 \) is equal to the mean dividend \( \bar{d} \) less a positive term that represents a no news is good news effect. The investor earns exactly this term from before the arrival of the news to after the arrival of the news when the news is equal to zero, or there is no news. In other words, this term measures the compensation that the investor receives for weathering ambiguity.
in the case when the news itself is not informative for the fundamental value of the risky asset. More precisely, the $t = 0$ investor knows that an ambiguous piece of news will arrive in one period and that he will interpret the news in an asymmetric fashion. As noted, this asymmetry implies that the price of the risky asset at $t = 1$ is a concave function of the news. By Jensen’s inequality, the worst-case belief for the investor at $t = 0$ that minimizes the expected price of the risky asset at $t = 1$ is that the news yet to arrive has high variance. That is, the variance of $\epsilon_n$ is at the upper end of the range $\sigma_n^2$. As the amount of ambiguity or $\phi - \bar{\phi}$ increases, the no news is good news effect increases, and $p_0$ correspondingly decreases.

Having established the price $p_0$ before the news and the average price $\bar{p}_1$ after the news, I show that the price of the risky asset increases on average through the news; that is, the ambiguity premium $\bar{p}_1 - p_0 > 0$. The result is immediate from Eqs. (13) and (17):

$$\bar{p}_1 - p_0 = \left(\bar{d} - \frac{1}{\sqrt{2\pi}}(\bar{\phi} - \phi)\sqrt{\alpha^2 \sigma_d^2 + \bar{\sigma}_n^2}\right) - \left(\bar{d} - \frac{1}{\sqrt{2\pi}}(\bar{\phi} - \phi)\sqrt{\alpha^2 \sigma_d^2 + \sigma_n^2}\right)$$

$$= \frac{1}{\sqrt{2\pi}}(\bar{\phi} - \phi)\left(\sqrt{\alpha^2 \sigma_d^2 + \bar{\sigma}_n^2} - \sqrt{\alpha^2 \sigma_d^2 + \sigma_n^2}\right).$$

(18)

Since I have already assumed that $\bar{\phi} - \phi > 0$, $\bar{p}_1 - p_0 > 0$ as long as $\bar{\sigma}_n^2 > \sigma_n^2$; that is, the true variance of $\epsilon_n$ is less than the upper range of the variance considered by the investor. The ambiguity premium depends on $\bar{\phi} - \phi$ and is consequently increasing in the amount of ambiguity. There are two competing effects at work in $\bar{p}_1 - p_0$: the no news is good news effect and the asymmetry effect. As we have seen, the no news is good news effect decreases $p_0$ to compensate the investor for the news ambiguity. Upon the arrival of the news, however, the price of the risky asset decreases more for a negative piece of news than the price increases for a positive piece of news, and this asymmetric reaction has a negative effect on $\bar{p}_1$. It turns out that the impact of the no news is good news effect is greater (in an absolute sense) than that of the asymmetry effect, so the price of the risky asset rises on net through the arrival of the news. The reason is that the magnitude of the asymmetry effect is related to a Jensen’s inequality effect for the average price of the risky asset at $t = 1$ using $\bar{\sigma}_n^2$ as the actual variance of $\epsilon_n$. The magnitude of the no news is good news effect, however, is related to a Jensen’s inequality effect using $\sigma_n^2$ as the investor’s belief for the variance of $\epsilon_n$. Since $\sigma_n^2 > \bar{\sigma}_n^2$ by assumption, Jensen’s inequality has a stronger influence on the no news is good news effect than on the asymmetry effect, so the ambiguity premium is positive.
2.3.3 Volatility of the Risky Asset with Ambiguity-Aversion

Using the expressions for the equilibrium prices of the risky asset, I show that the volatility of the change in the price of the risky asset through the news is increasing or decreasing in news ambiguity depending on the driver of the change in the amount of ambiguity. The variance of the change in the risky asset price from $t = 0$ to $t = 1$ is

$$\mathbb{V}_{\tilde{\sigma}^2_{n}} [p_1(n) - p_0] = \mathbb{E}_{\tilde{\sigma}^2_{n}} [p_1^2(n)] - \bar{p}_1^2. \quad (19)$$

The first component of Eq. (19) is

$$\mathbb{E}_{\tilde{\sigma}^2_{n}} [p_1^2(n)] = \mathbb{E}_{\tilde{\sigma}^2_{n}} \left[ (\bar{d} + \phi n)^2 | n > 0 \right] \times \mathbb{P}_{\tilde{\sigma}^2_{n}} [n > 0] + \mathbb{E}_{\tilde{\sigma}^2_{n}} \left[ (\bar{d} + \phi n)^2 | n \leq 0 \right] \times \mathbb{P}_{\tilde{\sigma}^2_{n}} [n \leq 0]
= \frac{1}{2} \times \mathbb{E}_{\tilde{\sigma}^2_{n}} \left[ \bar{d}^2 + \phi^2 n^2 + 2 \bar{d} \phi n | n > 0 \right] + \frac{1}{2} \times \mathbb{E}_{\tilde{\sigma}^2_{n}} \left[ \bar{d}^2 + \phi^2 n^2 + 2 \bar{d} \phi n | n \leq 0 \right]
= \bar{d}^2 + \frac{1}{2} \left( \phi^2 + \phi^2 \right) \times \mathbb{E}_{\tilde{\sigma}^2_{n}} [n^2 | n > 0] - \bar{d} (\bar{\phi} - \bar{\phi}) \times \mathbb{E}_{\tilde{\sigma}^2_{n}} [n | n > 0]
= \bar{d}^2 + \frac{1}{2} \left( \phi^2 + \phi^2 \right) \left( \alpha^2 \sigma_d^2 + \tilde{\sigma}_n^2 \right) - \bar{d} (\bar{\phi} - \bar{\phi}) \frac{\sqrt{2}}{\sqrt{\pi}} \sqrt{\alpha^2 \sigma_d^2 + \tilde{\sigma}_n^2}.$$

The first equality substitutes in for $p_1(n)$ from Eq. (12), and the final equality uses the math formulas in Appendix A.2 that, for $z \sim N(0, \sigma_z^2)$, $\mathbb{E}[z | z > 0] = \sigma_z \sqrt{\frac{2}{\pi}}$ and $\mathbb{E}[z^2 | z > 0] = \sigma_z^2$. The second component of Eq. (19) simply squares $\bar{p}_1$, which we already know from Eq. (13):

$$\bar{p}_1^2 = \left( \bar{d} - \frac{1}{\sqrt{2\pi}} (\bar{\phi} - \bar{\phi}) \sqrt{\alpha^2 \sigma_d^2 + \tilde{\sigma}_n^2} \right)^2
= \bar{d}^2 + \frac{1}{2\pi} (\bar{\phi} - \bar{\phi})^2 \left( \alpha^2 \sigma_d^2 + \tilde{\sigma}_n^2 \right) - \bar{d} \frac{\sqrt{2}}{\sqrt{\pi}} (\bar{\phi} - \bar{\phi}) \sqrt{\alpha^2 \sigma_d^2 + \tilde{\sigma}_n^2}.$$

The variance of the risky asset price change is thus

$$\mathbb{V}_{\tilde{\sigma}^2_{n}} [p_1(n) - p_0] = \mathbb{E}_{\tilde{\sigma}^2_{n}} [p_1^2(n)] - \bar{p}_1^2
= \frac{1}{2} \left( \alpha^2 \sigma_d^2 + \tilde{\sigma}_n^2 \right) \left( \bar{\phi}^2 + \phi^2 - \frac{1}{\pi} (\bar{\phi} - \bar{\phi})^2 \right)
= \frac{1}{2} \left( \alpha^2 \sigma_d^2 + \tilde{\sigma}_n^2 \right) \left( 1 - \frac{1}{\pi} \right) \bar{\phi}^2 + \left( 1 - \frac{1}{\pi} \right) \phi^2 + \frac{2\bar{\phi} \phi}{\pi \bar{\phi} \phi}. \quad (20)$$

Simple comparative statics on the variance show that the risky asset volatility is increasing.
If, on the one hand, an increase in \( \phi \) (decrease in \( \sigma_n^2 \)) drives an increase in ambiguity, the volatility of the risky asset increases. If, on the other hand, a decrease in \( \phi \) (increase in \( \sigma_n^2 \)) drives an increase in ambiguity, the volatility of the risky asset decreases. The reason for this result is that the volatility of the risky asset depends on how the risky asset responds to the news, and \( \phi \) and \( \phi \) control the sensitivity of the risky asset price to negative and positive news, respectively. A larger \( \phi \) means the asset responds more strongly to bad news, which increases volatility, whereas a smaller \( \phi \) means the asset responds less strongly to good news, which decreases volatility. Note that the variance in Eq. (20) is more sensitive to \( \phi \) than \( \phi \):

\[
\frac{\partial}{\partial \phi} V_{a_\phi} [p_1 (n) - p_0] = \frac{1}{2} \left( \alpha^2 \sigma_d^2 + \bar{\sigma}_n^2 \right) \left( 2 \left( 1 - \frac{1}{\pi} \right) \bar{\phi} + \frac{2}{\pi} \phi \right) > 0
\]

\[
\frac{\partial}{\partial \phi} V_{a_\phi} [p_1 (n) - p_0] = \frac{1}{2} \left( \alpha^2 \sigma_d^2 + \bar{\sigma}_n^2 \right) \left( 2 \left( 1 - \frac{1}{\pi} \right) \phi + \frac{2}{\pi} \overline{\phi} \right) > 0
\]

To see this, I simplify the left- and right-hand sides in the following steps and arrive at an obviously true inequality:

\[
2 \left( 1 - \frac{1}{\pi} \right) \bar{\phi} + \frac{2}{\pi} \phi > 2 \left( 1 - \frac{1}{\pi} \right) \phi + \frac{2}{\pi} \phi
\]

\[
\iff \bar{\phi} - \frac{1}{\pi} (\phi - \phi) > \phi - \frac{1}{\pi} (\phi - \overline{\phi})
\]

\[
\iff \bar{\phi} - \phi > \frac{2}{\pi} (\overline{\phi} - \phi).
\]

Thus, even if an increase in ambiguity, as proxied by \( \overline{\phi} - \phi \), is driven equally by increases in \( \phi \) and decreases in \( \phi \), the volatility of the risky asset still increases.

### 2.4 Equilibrium Prices at \( t = 1 \) and \( t = 0 \) under an Unambiguous Benchmark

To arrive at the unambiguous benchmark, all we have to consider is the case of \( \sigma_n^2 = \overline{\sigma}_n^2 = \bar{\sigma}_n^2 \); or, equivalently, \( \phi = \overline{\phi} = \bar{\phi} \). With an unambiguous piece of news, the investor has only one model in mind with which to interpret any given piece of news. Based on Eq. (12), the price
at $t = 1$ in response to a piece of news $n$ is

$$p_t(n) = \overline{d} + \phi n.$$  

There is no more asymmetry in the reaction of the risky asset to the news: The price increases as much for a positive piece of news as it decreases for a negative piece of news. It follows that the average price of the risky asset after the news arrival is just the mean of the dividend:

$$\overline{p}_1 = \overline{d}.$$  

From Eq. (17), we see that the price at $t = 0$ before the news arrival is also equal to the mean of the dividend:

$$p_0 = \overline{d}.$$  

There is no longer a no news is good news effect, because the investor at $t = 0$ knows that the news to arrive in one period is unambiguous. Finally, it is obvious that the risky asset price on average does not change in response to the news, so there is no ambiguity premium:

$$\overline{p}_1 - p_0 = 0.$$  

2.5 Summary of Model Predictions

To summarize, the model leads to the following four propositions, three of which are illustrated in Figure 1.

**Proposition 1: The asymmetry effect** The price of the risky asset reacts asymmetrically to a piece of news about asset fundamentals (dividend payment). That is, the price decreases more for a given negative piece of news than the price increases for a positive piece of news of the same magnitude. Time-variation in the amount of news ambiguity drives time-variation in the extent of this asymmetry, with times of high ambiguity corresponding to times of large asymmetry.

The investor is uncertain of how to interpret the news; in particular, how precise the news is about the fundamental value of the asset. Since the investor conducts worst-case scenario evaluation, he views positive news as being imprecise and negative news as being precise, which leads to the asymmetry effect. News ambiguity is defined as the range of
precisions about the news that the investor considers, so greater ambiguity is equivalent to a greater range of precisions and a more pronounced asymmetry effect. Note that greater asymmetry could be due to either positive news being viewed as less relevant, negative news being viewed as more relevant, or both.

Figure 1 illustrates the asymmetry effect. Under ambiguity in Panel B, the solid blue line $p_1(n) - p_0$ has a gentler slope $\phi < \bar{\phi}$ to the right of the y-axis (corresponding to positive news) and a steeper slope $\bar{\phi} > \phi$ to the left of the y-axis (corresponding to negative news). The point of intersection of the solid blue line and the y-axis is equal to $p_1(0) - p_0$, the price change of the risky asset for a neutral piece of news. Due to the concavity of the solid blue line, the dashed blue line, which connects the ends of the solid blue lines at symmetric points around the y-axis, intersects the y-axis at a lower value equal to $\bar{p}_1 - p_0$, the average price change of the risky asset through a piece of news. The gap between the two points of intersection is thus equal to $p_1(0) - p_1(0)$, the asymmetry discount from Eq. (14). As a result of the risky asset reacting more strongly to negative pieces of news than positive ones, the average price of the risky asset decreases below the price obtained under neutral news. In contrast, Panel A of Figure 1 shows the unambiguous benchmark in which the solid blue line has equal slopes $\phi = \bar{\phi}$ to the left and right of the y-axis. Without asymmetry, a dashed blue line (not shown) that connects the ends of the solid blue lines at symmetric points around the y-axis must intersect the y-axis at the same point as the solid blue line. There is thus no asymmetry discount.

Proposition 2: The no news is good news effect The investor in the risky asset earns a positive return when no news (neutral or value zero) is released. This no news is good news effect is exactly equal to the increase in the price of the risky asset in response to a neutral piece of news. Time-variation in the amount of news ambiguity drives time-variation in the magnitude of the no news is good news effect, with times of high ambiguity corresponding to times of a large no news is good news effect.

Before the arrival of the news, the investor knows that ambiguous information about the risky asset will arrive in the future. The arrival of a neutral piece of news contains no information for inferring the fundamental value of the asset but does resolve the ambiguity associated with the news. As a result, the price of the risky asset still rises in response to a neutral piece of news and rises more when there is more ambiguity.

Turning to Figure 1, each solid blue line intersects the y-axis at $p_1(0) - p_0$, which is the change in the price of the risky asset if the news is neutral. The distance between the point of intersection and the origin thus measures the size of the no news is good news effect. In
the case of ambiguity in Panel B, \( p_1(0) - p_0 > 0 \), so the no news is good news effect is positive, whereas with no ambiguity in Panel A, \( p_1(0) - p_0 = 0 \), and there is no no news is good news effect.

Proposition 3: The ambiguity premium

On average, the price of the risky asset increases from before the arrival of the news to after the arrival of the news. That is, the ambiguity premium is positive.

The ambiguity premium has two components: the no news is good news effect and the asymmetry effect. The former leads to an increase in the price of the risky asset with the arrival of the news, but the latter on average leads to a decrease in the price of the asset after the news is revealed. On balance, the magnitude of the asymmetry effect is larger than that of the no news is good news effect, which leads to a positive ambiguity premium.

In Panel B of Figure 1, we have already graphically identified the no news is good news effect as the distance between the intersection of the solid blue line and the origin (equal to \( p_1(0) - p_0 \)) and the asymmetry effect as the distance between the intersections of the solid and dashed blue lines (equal to \( \bar{p}_1 - p_1(0) \)). The ambiguity premium should then just be the distance between the intersection of the dashed blue line and and the origin: \( (p_1(0) - p_0) + (\bar{p}_1 - p_1(0)) = \bar{p}_1 - p_0 \), the average price of the risky asset after the arrival of the news less the price before the arrival of the news. In the unambiguous benchmark of Panel A, the ambiguity premium is necessarily zero because the no news is good news effect and asymmetry effect are both zero.

Proposition 4: The risky asset volatility effect

The volatility of the change in the price of the risky asset from before the news to after the news is increasing in news ambiguity if the increase in ambiguity is due to the investor allowing for a smaller lower bound for the variance of the news noise. The volatility is decreasing in news ambiguity if the increase in ambiguity is due to the investor allowing for a larger upper bound for the variance of the news noise.

A smaller lower bound for the variance of the news noise leads to a stronger reaction of the asset to bad news (since a smaller \( \sigma_s^2 \) leads to a larger \( \bar{\phi} \), which determines the sensitivity of the risky asset to negative news). A larger upper bound for the variance of the news noise leads to a weaker reaction of the asset to good news (since a larger \( \overline{\sigma_s^2} \) leads to a smaller \( \underline{\phi} \), which determines the sensitivity of the risky asset to positive news).
3 The Stock Market Response to Macroeconomic News

To demonstrate how the model with ambiguity-aversion can accurately describe real-world financial markets, I explore the dynamics of the aggregate stock market around macroeconomic news releases; i.e., news about inflation, output, or the labor market. The first section below introduces the sample of MNAs, and the second section discusses the data on the aggregate stock market.

3.1 Data on MNAs

Table 1 shows the full sample of MNAs considered in this paper. For each data release, the table presents the name, units, number of observations, start date, end date, frequency, government agency or private-sector firm responsible, and intraday announcement timestamp. In all, I analyze 18 economic announcements, which cover the lion’s share of important MNAs. Data for the majority of the announcements begin in late-1997 and extend to early-2014, with the primary exceptions being Existing Home Sales and Pending Home Sales, which start in 2005. All of the announcements occur once a month excluding Initial Jobless Claims, which is a weekly data release. The data in my sample are released at either 8:30 AM, 9:15 AM, or 10:00 AM ET.

While the macroeconomic announcements are officially produced and released by various government agencies (e.g., the Bureau of Labor Statistics), and private-sector firms (e.g., the National Association of Realtors), I collect the data from Bloomberg. Specifically, for each event, I download both the actual data release and the expected data release, the latter of which comes from a survey of economists. The difference between the actual number and the expected number constitutes the news that impacts the stock market.

The metric of the news surprise that I use in this paper is the conventional standardized news variable employed by Balduzzi, Elton, and Green (2001) as well as many subsequent papers in the literature of asset price reactions to MNAs. For a given economic indicator, the standardized news variable at time \( t \) is

\[
S_t = \frac{A_t - \hat{E}_t - [A_t]}{\hat{\sigma}}.
\]

(21)

\( A_t \) is the actual data, \( \hat{E}_t - [A_t] \) is the expectation of the data from the Bloomberg survey, and \( \hat{\sigma} \) is the sample standard deviation of \( A_t - \hat{E}_t - [A_t] \). Consistent with the model, I define the variable such that a positive value corresponds to “better”-than-expected data; i.e., higher-than-expected inflation or output and lower-than-expected unemployment. For this reason,
I multiply the Initial Jobless Claims and the Unemployment Rate data by $-1$ while keeping the sign of the other data unchanged, as shown by the sign column of Table 1. As the name suggests, the standardized news variable provides a single metric that is standardized across different types of news about macroeconomic fundamentals and allows for comparability. This is important because different types of news are released with different units.

The standardized news variable $S_t$ in Eq. (21) is the empirical counterpart to the theoretical news $n$ in Eq. (2) of the model. A positive (negative) news surprise with $S_t > 0$ ($S_t < 0$), like positive (negative) news $n > 0$ ($n < 0$), suggests a higher (lower) fundamental value of the stock market in the form of higher (lower) dividends. A neutral news release with $S_t = 0$, like neutral news $n = 0$, provides no new information on stock market fundamentals, since investors’ expectations are exactly met.

The use of the standardized news variable in conjunction with data from Bloomberg is common in testing the effect of macroeconomic news surprises on asset prices. Many financial market participants use Bloomberg to get a sense of the consensus forecast for any given MNA and to see how the actual data compares to the forecasted data at the time of the release. The survey expectation is furthermore unbiased and unlikely to be stale, since economists can adjust their forecasts until the very last moment.

### 3.2 Data on High-Frequency Stock Prices

I use the front E-mini S&P 500 (ES) futures contract as the primary source for stock market price data and obtain intraday tick data from Tick Data, a data vendor. The data are available from late-1997 to mid-2014. High-frequency data are important because they allow me to consider the reaction of the stock market in a narrow window (±5 minutes) around each macroeconomic news event. Stocks likely vary over the window only due to any surprise embedded in the news announcement. By extension, lower frequency data can be problematic because events unrelated to MNAs are more likely to influence prices. As an example of the importance of high-frequency data, the scatterplot in Figure 2 compares the 10-minute return of the stock market around a MNA (based on ES data) and the daily return of the stock market for the day of the MNA (based on S&P 500 index data). The correlation between the intraday return and the daily return is a positive 0.159, which suggests that the intraday response of stocks to macroeconomic news tends to influence the daily return of stocks in the expected manner. That is, when stocks do well (poorly) intraday in response to good (bad) news, the daily return also tends to be higher (lower). Nonetheless, the correlation is far from one, and the scatterplot clearly shows many instances in the 2nd and 4th quadrants in
which stocks react positively (negatively) to macroeconomic news in the short interval around the news release but fall (rise) for the day. The annotated arrow in Figure 2 points to the example of the 10/16/2008 9:15 AM ET release of industrial production data. A worse-than-expected industrial production data release led to a $-1.024\%$ return of ES between 9:10 AM ET and 9:20 AM ET. For the day, however, the S&P 500 rallied 4.251\% as a bounceback from the pummeling that stocks had taken earlier in the month as the 2008 financial crisis spread. The use of daily data in this instance and many others would lead to the erroneous observation that good (bad) macroeconomic news counterintuitively results in negative (positive) stock performance. I show in unreported robustness tests that the use of daily price data on the stock market in the form of the S&P 500 index weakens the empirical results in this paper due to the lower resolution of the data.

While high-frequency data are available for instruments aside from futures, the use of futures data is important because many MNAs are released early in the morning before equity markets officially open at 9:30 AM ET. Whereas some markets (most relevantly, the traditional stock market) are less liquid at that early hour, futures markets are already active. Not surprisingly, financial market participants also tend to react to data surprises by trading in these futures directly.

4 Empirical Results: Whole Sample

The following two sections present empirical results in support of Propositions 1-3 using the whole sample. That is, I show that the asymmetry effect, no news is good news effect, and ambiguity premium exist using the entire sample period from November, 1997 to March, 2014.

4.1 The Asymmetry Effect and No News is Good News Effect

To assess the reaction of the stock market to macroeconomic news, I rely on the regression specification below:

$$R_t = \alpha + \beta^+ D^+ S_t + \beta^- (1 - D^+) S_t + \epsilon_t,$$

in which $R_t$ is the % change in the price level (measured in bps) associated with the front ES futures contract in a $\pm 5$ minute window around a given MNA, $S_t$ is the standardized
news for that data release defined in Eq. (21), and $D_t$ is a dummy variable equal to one if $S_t > 0$ and zero otherwise. $\beta^+$ measures the reaction of the stock market to positive news surprises, $\beta^-$ measures the reaction of the stock market to negative news surprises, and $\alpha$ measures the reaction of the stock market in the case of neutral news.

Table 2 shows the results from running Eq. (22) over the whole sample as defined in Table 1. Each row of Table 2 corresponds to a different regression with the specified event, and the last row aggregates all the MNAs together. If there is news ambiguity and investors are averse to this ambiguity, Propositions 1 and 2 imply the existence of the asymmetry effect and the no news is good news effect.

The asymmetry effect is that $\hat{\beta}^+ - \hat{\beta}^- < 0$, so that a unit of bad macroeconomic news lowers the stock market more than a unit of good macroeconomic news increases the stock market. We see from the last column of Table 3 that most of the $\hat{\beta}^+ - \hat{\beta}^-$ are negative, and of the numbers that are significantly different from zero based on a Wald test, all are negative. The last row says that $\hat{\beta}^+ - \hat{\beta}^- = -6.141$ bps, which has the economic interpretation that a one unit positive MNA surprise increases the stock market by 6.141 bps less than a one unit negative MNA surprise decreases the stock market. In particular, the positive surprise increases stocks by $\hat{\beta}^+ = 2.416$ bps, but the negative surprise decreases stocks by a larger $\hat{\beta}^- = 8.557$ bps.

The no news is good news effect is that $\hat{\alpha} > 0$, so that the stock market rises in response to neutral news as the arrival of the news resolves ambiguity. We see that most of the $\hat{\alpha}$ in the corresponding column of Table 2 are greater than zero, and all of the significant parameter estimates are greater than zero, with the exception of the weakly significant $\hat{\alpha}$ corresponding to Leading Index data releases. From the last row, $\hat{\alpha} = 3.204$ bps, so on average the stock market increases by 3.204 bps due to the resolution of ambiguous but neutral macroeconomic news.

To ensure that the covariate $S_t$ used in the regressions is well-behaved, I plot the time series of standardized news in Figure 3 and calculate accompanying summary statistics in Panel A of Table 3. $S_t$ behaves in the manner one would expect a news variable to behave in that it is unbiased and symmetric. In fact, MNA surprises look like normal shocks. Importantly, Figure 3 shows visual evidence that the distribution of standardized news is stable in the time series.
4.2 The Ambiguity Premium

Moving on to Proposition 3, I evaluate whether there is an ambiguity premium over the whole sample from November, 1997 to March, 2014. Under risk-neutrality, the model defines the ambiguity premium as the average return of the stock market around news. In reality, this average return also reflects various types of risk premia. Since I do not focus on these risk premia, I equate the ambiguity premium with the average return of the stock market around news and show that this quantity is positive and too large to be explained by conventional stories.

Panel A of Table 4 calculates the arithmetic sum of returns in the 10-minute window around MNAs in the first row (expressed in %) and the mean of returns in the bottom row (expressed in bps). Stocks increase a cumulative sum of 43.903% around MNAs or 1.102 bps on average per macroeconomic news release, which is suggestive evidence for a positive ambiguity premium. Panel A of Table 4 further decomposes the ambiguity premium into two components using the estimated $\hat{\alpha}$, $\hat{\beta}^+$, and $\hat{\beta}^-$ from the last row of Table 2: the positive no news is good news effect and the negative asymmetry effect. The “No News” column is that portion of the ambiguity premium attributed to the no news is good news effect and is equal to $\hat{\alpha} \times N$ for the top row, in which $N$ is the number of MNAs, and just $\hat{\alpha}$ for the bottom row. The “+ News” column is that portion of the ambiguity premium attributed to the reaction of the stock market to positive news and is equal to the sum of $\hat{\beta}^+ \times S_t$ for $S_t > 0$ for the top row and the same quantity divided by $N$ for the bottom row. The “- News” column is that portion of the ambiguity premium attributed to the reaction of the stock market to negative news and is equal to the sum of $\hat{\beta}^- \times S_t$ for $S_t < 0$ for the top row and the same quantity divided by $N$ for the bottom row. The “Asymm.” column is that portion of the ambiguity premium attributed to the asymmetric reaction of the stock market to positive news versus negative news and simply sums the “+ News” and “- News” columns. As would be expected in a decomposition, the “Return” column is equal to the “No News” column plus the “Asymm.” column. In sum (on average), the 43.903% (1.102 bps) ambiguity premium can be attributed to a positive no news is good news effect of 127.688% (3.204 bps) which is greater in magnitude than the $-83.784\%$ ($-2.102$ bps) asymmetry effect.

While Panel A of Table 4 is useful for understanding how the ambiguity premium can be decomposed into its two components, the results double count some return intervals when multiple MNAs occur at the exact same time. I address this issue by presenting additional evidence for the ambiguity premium in Table 5, which calculates unique return intervals that include MNAs.$^3$ In particular, I compute 10-minute return intervals for the whole

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$^3$All results in the paper are robust to dropping MNA observations that occur at the exact same time.
November, 1997 to March, 2014 sample and split these intervals into those that contain MNAs ("MNA") and those that do not ("nMNA"). The table presents summary statistics on the 3,194 “MNA” return intervals, 588,671 “nMNA” return intervals, and the difference between these two types of intervals.

Methodology-wise, returns are calculated as the % change in the price level (measured in bps) associated with the front ES futures contract. I calculate return intervals only for those days that the S&P 500 was open as well as on the following dates on which the S&P 500 was closed but futures markets were open: 4/2/1999, 4/6/2007, 4/2/2010, and 4/6/2012 (all corresponding to Good Friday); and 10/29/2012 (corresponding to Hurricane Sandy). For each day, I forward fill in price data for all 1440 minutes and attempt to split the day into 144 10-minute increments. For any MNA, I ensure that there is a corresponding 10-minute interval formed from the ±5 window around the MNA, consistent with the event window used elsewhere in the paper. If doing so prevents the formation of 144 evenly spaced 10-minute intervals for that day, I allow the intervals surrounding the interval containing the MNA to be slightly longer. For example, if the MNA occurs at 8:30 AM, the interval that contains the MNA is from 8:25 AM to 8:35 AM. The preceding interval is from 8:10 AM to 8:25 AM, and the following interval is from 8:35 AM to 8:50 AM; both surrounding intervals cover 15 minutes instead of 10 minutes. The rest of the intervals for that day are then exactly 10 minutes.

Focusing on the first three columns of Table 5 and the “Mean” row, we see that the stock market rises on average a statistically significant 1 bp in the 10-minute window around MNAs, which is consistent with Proposition 3. Interestingly, however, the stock market, rises a statistically insignificant 0.014 bps in all other 10-minute windows. The difference in means of 0.986 bps is statistically significant. The “Total” row shows returns compounded over all intervals, expressed in bps. Over the whole sample period, the stock market rises a compounded 36.250% over the 10-minute windows containing MNAs and 66.267% in all other 10-minute windows.⁴ That is, approximately 1/3 of the stock market return from November, 1997 to March, 2014 accrues in the tiny fraction of time around macroeconomic news releases. Despite the much higher mean of “MNA” return intervals versus “nMNA” return intervals, the standard deviation is only about 2.5 times greater in the former (25.179 bps) than the latter (10.460 bps). The Sharpe ratio of “MNA” intervals is consequently much higher than that of “nMNA” intervals. As the rightmost three columns demonstrate, the results are robust to winsorizing “MNA” and “nMNA” return intervals separately at the

⁴This total return differs from that reported in Panel A of Table 4 for two reasons. First, as already noted, Panel A of Table 4 double counts some return intervals. Second, Panel A of Table 4 presents the arithmetic sum of returns as opposed to the compounded total return.
1% and 99%.

Note that the above methodology ignores certain days in which there are ES futures price data (for example, Sundays) and thus understates the number of “nMNA” return intervals. Since these days tend to have more stale prices, forward filling the price data to compute return intervals would create additional “nMNA” return intervals with zero returns. Including these extra days would thus lower both the mean return and standard deviation of “nMNA” intervals. The impact on results, however, is unlikely to be significant.

5 State Variable for Ambiguity

Aside from stating the existence of the asymmetry effect, no news is good news effect, and ambiguity premium, Propositions 1-3 have the more nuanced prediction that the magnitudes of these behaviors should be larger at times of greater ambiguity. Similarly, Proposition 4 predicts that the volatility of the stock market around MNAs depends on the amount of ambiguity. It is consequently vital to have a state variable for ambiguity in order to fully test the model. Below, I construct such a proxy for ambiguity, the variance risk premium, explore some of its properties for the predictability of stock returns, and discuss alternate state variables for ambiguity.

5.1 Variance Risk Premium

The variance risk premium $VRP_{t,T}$ is the difference between risk-neutral ($Q$-measure) and physical ($P$-measure) expectations of stock market return variance over a given horizon $RV_{t+1,T}$:

$$VRP_{t,T} = \mathbb{E}_t^Q[RV_{t+1,T}] - \mathbb{E}_t^P[RV_{t+1,T}].$$

Expectations are taken at time $t$ for realized variance from the period $t + 1$ to $T$.

One way to interpret the variance risk premium is that it measures the premium embedded in an option on the equity market. The premium exists because investors not only care about uncertainty of the stock market return, as embodied by the return variance, but also uncertainty about the return variance itself. An option on the stock market hedges against high realized variance and thus demands a positive variance risk premium for this insurance.

Alternatively, consider a variance swap, an over-the-counter derivative. An investor who
is long the swap receives the realized variance over the maturity of the swap less a fixed quantity, the variance swap rate. It is costless to enter such a swap, so by no arbitrage, the variance swap rate has to equal \( \mathbb{E}_{t}^{Q}[RV_{t+1,T}] \), the first component of the variance risk premium. By being long the variance swap, an investor protects himself against high realized variance. The price of this protection is simply the variance swap rate less the true/statistical expectation of variance or the variance risk premium.

As previewed, I use the variance risk premium as a proxy for ambiguity. The motivation for this choice of state variable is Drechsler (2013). In that paper, a representative investor has a range of models in mind about the dynamics of economic fundamentals (e.g., the frequency and magnitude of jump shocks to expected growth and growth volatility processes for consumption and dividends). That is, the investor is uncertain about the true model governing economic fundamentals. Because the investor is ambiguity-averse, he evaluates decisions under the worst-case model, a model in which realized variance is high and thus options have high payoffs. Options hedge the investor’s model uncertainty, which results in a price premium, the variance risk premium. Drechsler (2013) shows that the size of the variance risk premium is directly linked to ambiguity in the model.

I construct a daily empirical measure of the variance risk premium in the time series for a one-month horizon (the interval between \( t + 1 \) and \( T \) is one month). For the sake of notation, I set \( T = t + 22 \) and assume that there are 22 trading days in a month. Britten-Jones and Neuberger (2000) and Carr and Wu (2009), among others, have shown that, in continuous time, the risk-neutral expectation of stock market realized variance is equal to the value of a portfolio of European options on the stock market. A natural proxy for \( \mathbb{E}_{t}^{Q}[RV_{t+1,T+22}] \) is then the daily Chicago Board Options Exchange (CBOE) VIX index which is a risk-neutral expectation of S&P 500 variance over 30 calendar days or about 22 trading days, consistent with my assumption. The VIX produces this measure of implied volatility in a model-free manner (without relying on an option-pricing model) by calculating a weighted average of a portfolio of S&P 500 calls and puts. Since the VIX is quoted as an annual volatility variable, I create a squared VIX variable \( VIX_{t}^{2}/12 \) that simply squares the day-end VIX and divides by 12. This squared VIX quantity is a monthly variance variable that I use to proxy for \( \mathbb{E}_{t}^{Q}[RV_{t+1,T+22}] \).

To create a daily series for \( \mathbb{E}_{t}^{P}[RV_{t+1,T+22}] \), I first calculate a daily time series of monthly realized variances \( RV_{t+1,T+22} \). For a given \( t \), \( RV_{t+1,T+22} \) is the sum of the 22 daily realized variances between the two dates (inclusive). Daily realized variance is the sum of squared five-minute log returns on ES futures from 9:30 AM ET to 4:00 PM ET and the squared close-to-open log return. Calculating realized variance by summing high-frequency squared returns is a well-established procedure. Papers as early as French, Schwert, and Stambaugh (1987)
and Schwert (1989) estimate monthly realized variance by summing daily squared returns. The literature has subsequently provided formal justification for this practice; e.g., Andersen, Bollerslev, Diebold, and Ebens (2001). Sampling returns at a higher frequency increases the accuracy of estimated realized variance at a lower frequency. Sampling returns at too-high of a frequency, however, can be problematic due to market microstructure issues such as the presence of the bid-ask spread, so a five-minute frequency is a reasonable compromise.

With a daily series for $RV_{t+1,t+22}$ in hand, I construct $E_t^P[RV_{t+1,t+22}]$ using the standard variance forecasting technique of projecting realized variance onto variables in a lagged information set. That is, I run a daily time series regression of $RV_{t+1,t+22}$ on one-month lagged realized variance $R_{t-21,t}$ and one-month lagged squared VIX, $VIX_t^2/12$. The regression covers the period from late-1997 (when my sample of intraday ES futures data for constructing $RV_{t+1,t+22}$ begins) to mid-2014. The regression with heteroskedasticity-consistent standard errors is below:

$$RV_{t+1,t+22} = 2.130 + 0.310 \times R_{t-21,t} + 0.464 \times VIX_t^2/12 + e_t.$$ (24)

I subsequently construct $E_t^P[RV_{t+1,t+22}]$ from the one-step-ahead forecasts of this regression. Several considerations motivate the specification of Eq. (24). First, the use of $R_{t-21,t}$ and $VIX_t^2/12$ as covariates stems from the persistence of realized variance and evidence in the literature that implied volatility has bearing on future stock market variance. These covariates do a good job of forecasting future realized variance as evidenced by the high adjusted $R^2 = 0.519$. Second, Bekaert, Hoerova, and Lo Duca (2013) and Bekaert and Hoerova (2014) have tested a number of different regression specifications for forecasting realized variance. They find that the simple model in Eq. (24) does well on a number of criteria such as subsample coefficient stability and out-of-sample root-mean-squared error.

Differencing $VIX_t^2/12$ and $E_t^P[RV_{t+1,t+22}]$ yields a daily time series for the variance risk premium $VRP_{t,t+22}$. The first set of rows indexed by “Daily” in Table 6 and Panel A of Figure 4 show summary statistics and plot the three series, respectively, from November, 1997 to March, 2014. $VRP_{t,t+22}$ is generally positive, persistent, right-skewed, and has significant excess kurtosis. We expect the variance risk premium to be positive because it represents a premium paid to hedge realized variance, and it appears that approximately a quarter of the risk-neutral expectation of realized variance is attributed to the premium. Panel A of Figure 4 provides more color on the non-normality of the variance risk premium as well as that of the squared VIX and the physical expectation of realized variance. We see that all three time series spike dramatically at events such as the 2008 financial crisis.

The daily time series of the variance risk premium has two drawbacks as a proxy for
ambiguity. First, while the variance risk premium is mostly positive, it clearly goes negative at times; e.g., the premium obtains a minimum value of -64.363 on 11/4/2008. These negative values violate the intuition and theoretical restriction that the premium should be positive. Relatedly, while the time series fluctuates in a well-behaved manner most of the time, the variance risk premium can fluctuate wildly at times; e.g., just a few days after hitting its minimum value, the premium obtains a maximum value of 179.842 on 11/20/2008. It is unreasonable to infer that, during a period of high ambiguity such as the 2008 financial crisis, investors faced the lowest amount of ambiguity on record on 11/4/2008 and subsequently faced the highest amount of ambiguity on record just two weeks later on 11/20/2008. Instead, the fact that both drawbacks of the daily time series present themselves at times when the variance risk premium is elevated suggests a more straightforward explanation. As surmised by Bekaert and Hoerova (2014), crisis periods lead to spikes in realized variance which in turn affect the physical expectation of realized variance through Eq. (24). Fluctuations in the physical expectation then drive fluctuations in the variance risk premium and result in the premium sometimes turning negative. The time series model for forecasting variance in Eq. (24) is likely too simple to capture the reality that realized variance has different components, some of which should be allowed to mean-revert more quickly and therefore not affect the physical expectation of realized variance as much. To my knowledge, the literature has not established more sophisticated econometric models that adequately address the aforementioned drawbacks.

Instead of attempting to fix the daily time series, I instead construct monthly time series for the variance risk premium as well as its two components by taking a simple average of corresponding daily data in each month. Smoothing the data in this manner results in a well-behaved estimate of the variance risk premium at the monthly frequency. The “Monthly Averages” index in Table 6 and Panel B of Figure 4 show summary statistics and plot the three series, respectively, from November, 1997 to March, 2014. The monthly \( VRP_{t,t+22} \) has similar properties to the daily \( VRP_{t,t+22} \), as both are persistent and display non-normal properties due to large moves during times of crisis. The key difference and major improvement is that the monthly variance risk premium series is never negative and fluctuates in a reasonable manner; that is, the two drawbacks associated with the daily series no longer present problems. As such, I use this monthly time series of the variance risk premium as my main proxy for ambiguity.

Figure 5 magnifies the monthly variance risk premium series from Panel B of Figure 4 and annotates the plot based on identifiable events. Peaks in the time series correspond to various crises: LTCM/Russian financial crisis, September 11, the corporate scandals of 2002, the 2008 financial crisis, and the European sovereign debt and U.S. debt ceiling crises.
Troughs correspond to times of relative economic and financial stability such as during the mid-2000s. This time series behavior of the variance risk premium suggests that the premium is an appropriate proxy for ambiguity. That is, it is reasonable to think that during crisis periods, investors are highly unsure of how informative macroeconomic news is for the stock market; the news could be very relevant, very irrelevant, or somewhere in the middle. On the flipside, during placid times, investors are more certain of how to interpret the significance of macroeconomic news for stocks.

My monthly variance risk premium series is a more reasonable proxy for ambiguity than estimates of the premium on the stock market in the literature; e.g., Carr and Wu (2009), Bollerslev, Tauchen, and Zhou (2009), Drechsler (2013), and Bekaert and Hoerova (2014). The reason is that the estimates in the literature suffer from the drawbacks of my daily variance risk premium metric discussed above: The premium is at times highly volatile and liable to turn negative, especially during crisis periods. Consider the following result representative of variance risk premium estimates in the literature. I directly estimate a monthly time series by first using end-of-month squared VIX $VIX_t^2$ to proxy for $E^p_t [RV_{t+1,t+22}]$, with $t$ the last trading day of a given month. Note that I keep all notation the same as before, but obviously some months have more trading days than other months. Monthly realized variance $RV_{t+1,t+22}$ is the sum of daily realized variances for the month that includes days $t+1$ to $t+22$. Analogous to Eq. (24), I estimate $E^p_t [RV_{t+1,t+22}]$ from one-step-ahead forecasts of the monthly regression of realized variance on one-month lagged realized variance and one-month lagged squared VIX:

$$RV_{t+1,t+22} = 0.195 + 0.282 \times R_{t-21,t} + 0.511 \times VIX_{t-22}^2/12 + e_t$$ (25)

Though the adjusted $R^2 = 0.437$ of Eq. (25) is high, it is substantially lower than that of the daily regression in Eq. (24), which suggests that the daily regression provides substantially more statistical power than the monthly regression. The monthly variance risk premium $VRP_{t,t+22}$, for the month with $t$ as its last trading day, is still $VIX_t^2/12 - E^p_t [RV_{t+1,t+22}]$. The third set of rows indexed by “Monthly End-of-Month” in Table 6 and Panel C of Figure 4 show summary statistics and plot the three series, respectively, from November, 1997 to March, 2014. We see that the variance risk premium once again obtains a negative value some of the time; e.g., the premium is at its lowest value of -5.235 for 10/2008. The monthly estimate is also unreasonably volatile: Just one month later, the the premium is near its maximum value at 48.858 for 11/2008. As a proxy for ambiguity, this time series says that ambiguity was at an all-time low in one month of the 2008 financial crisis and at an all-time high in the next month of the crisis. This behavior is problematic and justifies my
construction of a different monthly series for the variance risk premium.

5.2 Does the Variance Risk Premium Predict Stock Returns?

To illustrate the impact of methodology choice in constructing the variance risk premium, I explore how the premium predicts stock returns in the time series. A number of papers in the literature including Bollerslev, Tauchen, and Zhou (2009), Faust and Wright (2012), Drechsler (2013), and Bekaert and Hoerova (2014) have found evidence suggesting that the variance risk premium predicts stock returns even when controlling for traditional predictor variables such as the price-to-earnings or dividend-to-price ratios. Does the “Monthly Averages” variance risk premium that I construct and argue is a better proxy for ambiguity than existing variance risk premium measures in the literature also predict stock returns? To address this question, I run basic predictability regressions using the “Monthly Averages” variance risk premium as a predictor variable and compare the results to the same regressions using the “Monthly End-of-Month” variance risk premium, which suffers similar drawbacks to extant series in the literature.

The return predictability regressions, using monthly data from November, 1997 to March, 2014, are of the form

\[ r_{t,t+h} = a + bX_t + \epsilon_{t,t+h}, \]  

in which \( r_{t,t+h} \) is the continuously compounded return of the stock market over a \( h \)-month horizon from the end of month \( t \) to the end of month \( t + h \), and \( X_t \) is the set of predictor covariates known at month \( t \). I calculate \( r_{t,t+h} \) as the annualized log return of the front ES futures contract from 4:00 PM ET of the last trading day (in which the S&P 500 is open) of month \( t \) to the same time of the last trading day of month \( t + h \). Most predictability regressions in the literature use excess returns of spot stock prices over a measure of the risk-free rate on the left-hand-side of Eq. (26). Assuming no-arbitrage between spot and future prices and ignoring the distinction between futures and forwards, the return calculated using futures data is equivalent to the excess return calculated using spot data.\(^5\) To adjust for serial correlation from overlapping stock returns, I use \( \max \{3, 2h\} \) Newey-West lags as in Bekaert and Hoerova (2014).

Table 7 shows \( \hat{b} \), associated \( t \)-statistics, and adjusted \( R^2 \) for varying horizons \( h \) and 5 different combinations of covariates \( X_t \). The first set of rows corresponds to \( X_t = \{\log (P/E)\} \),

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\(^5\)Suppose the stock market is worth \( S_t \) at \( t \) and \( S_{t+h} \) at \( t + h \), and \( r \) is the continuously compounded risk-free rate. Assuming no dividends, the respective forward prices to be paid at time \( T \) are \( S_t e^{r(T-t)} \) and \( S_{t+h} e^{r(T-t-h)} \). The log return calculated from the two forward prices is \( \ln (S_{t+h} e^{r(T-t-h)}/S_t e^{r(T-t)}) = \ln (S_{t+h}/S_t) - rh \), which is identical to the excess return.

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the log of the cyclically adjusted price-to-earnings ratio obtained from Robert Shiller’s website. In this benchmark regression, the price-to-earnings ratio negatively predicts stock returns, though only starting at $h = 12$ months are the coefficient estimates statistically significant. Note that the adjusted $R^2$ and magnitude of the parameter estimate increase with $h$. Boudoukh, Richardson, and Whitelaw (2008) point out that in return predictability regressions with persistent regressors and overlapping returns, even under the null hypothesis of no predictability, it is possible to observe this increasing pattern for the adjusted $R^2$ and magnitude of the parameter estimate. Thus it is important to be careful in interpreting the results of these and subsequent predictability regressions.

In the second set of rows, I set $X_t = \{VRP_t\}$, the “Monthly Averages” variance risk premium. From $h = 6$ on, the “Monthly Averages” variance risk premium is significant in positively predicting stock returns. In the third set of rows, I include both the “Monthly Averages” variance risk premium and the price-to-earnings ratio; $X_t = \{\log (P/E)_t, VRP_t\}$. Neither variable is significant at short horizons, with $\log (P/E)_t$ first significant at $h = 18$ and $VRP_t$ first significant at $h = 24$. Comparing the adjusted $R^2$ of the regression with both predictors to those with an individual predictor, we see that there are significant improvements in the adjusted $R^2$ for nearly all horizons. For example, at $h = 6$, the regression with $X_t = \{\log (P/E)_t, VRP_t\}$ has an adjusted $R^2$ of 5.453 versus an adjusted $R^2$ of 3.572 for $X_t = \{\log (P/E)_t\}$ and 3.736 for $X_t = \{VRP_t\}$. The “Monthly Averages” variance risk premium that I argue is a state variable for ambiguity thus has some predictive power for stock returns, especially at longer horizons.

How does the “Monthly End-of-Month” variance risk premium compare in predicting stock returns? The fourth and fifth set of rows in Table 7 are analogous to the second and third set of rows, respectively, with the exception of using the “Monthly End-of-Month” variance risk premium instead of the “Monthly Averages” one. With only $X_t = \{VRP_t\}$ in the fourth set of rows, we see that the “Monthly End-of-Month” variance risk premium is a strong predictor of stock returns at all horizons. The fifth set of rows includes the price-to-earnings ratio for the regression with $X_t = \{\log (P/E)_t, VRP_t\}$. $\log (P/E)_t$ is significant only at long horizons, but $VRP_t$ is highly significant at short horizons, less significant at intermediate horizons, and significant again at long horizons. From an adjusted $R^2$ perspective, the regressions with both covariates are significantly better than the corresponding regressions with only one of the covariates.

The strong predictive power of the “Monthly End-of-Month” variance risk premium at short horizons is consistent with findings in the literature; e.g., Bollerslev, Tauchen, and Zhou (2009), Faust and Wright (2012), and Drechsler (2013). This is unsurprising given that I construct the “Monthly End-of-Month” variance risk premium to mimic the properties of the
series in the literature. Why is it that the “Monthly End-of-Month” variance risk premium predicts returns so well at short horizons, but the “Monthly Averages” variance risk premium does not? The reason is that the former series is volatile and sometimes negative during crisis periods, the two justifications I gave for ruling the series out as a proxy for ambiguity. For example, as discussed, the “Monthly End-of-Month” variance risk premium is at its lowest value of -5.235 for 10/2008. Stocks dropped for the remainder of 2008 and the early part of 2009, which leads to a high degree of short-run predictability. In contrast, the “Monthly Averages” variance risk premium is near its highest value for 10/2008, which, while sensible for the interpretation of the variable as a metric of ambiguity, reduces the short-run predictive power for stock returns.

5.3 Alternate State Variables for Ambiguity

I consider several alternate state variables for ambiguity but ultimately reject these proxies in favor of the “Monthly Averages” variance risk premium. From an empirical perspective, both the squared VIX and the physical expectation of realized variance constructed in the previous section seem like plausible proxies for ambiguity. Williams (2014), for example, explicitly uses the VIX to measure ambiguity. Based on Figure 4, the time series of these two variables spike at the “right” times; that is, during crisis episodes when the variance risk premium also spikes. Whereas there is theoretical justification for why the variance risk premium measures ambiguity, however, there is no such justification for the true/statistical expectation of variance. By extension, the VIX, which incorporates the physical expectation of realized variance as one of its two components, is a less-ideal metric of ambiguity than the variance risk premium.

Another measure of ambiguity that feels plausible is the dispersion of forecasts about macroeconomic conditions. This intuition seems especially relevant since this paper assesses how the stock market responds to news about macroeconomic conditions. To explore this idea further, I obtain dispersion data from Bloomberg on the standard deviation and the range (maximum minus minimum) of the professional forecasts for each of the MNAs in the sample. In order to allow for comparison across different events with different units, I separately standardize the two types of dispersion data for each event to have standard deviations equal to one over the entire sample. A daily simple moving average of the standardized dispersion data for all MNAs in a one year window yields the two candidate daily time series in Panel A of Figure 6: one based on the standard deviation of forecasts (“stdev”) and one based on the range of forecasts (“range”). As evident from the figure, the dispersion series
behave quite differently from the variance risk premium series and do not seem to be good empirical proxies for ambiguity. On the one hand, the dispersion series increase significantly during the 2008 financial crisis consistent with the rise of the variance risk premium during a time of heightened stress. On the other hand, the dispersion series also spike in the fall of 2005 (due to Hurricane Katrina), whereas the variance risk premium remains low, and the dispersion series remain low in the fall of 2011, whereas the variance risk premium spikes. Patton and Timmermann (2010) provide some intuition for why the dispersion series do not proxy for ambiguity. They suggest that at short forecast horizons, dispersion in forecasts about some macroeconomic fundamental is driven primarily by heterogeneity in private information related to that fundamental as opposed to heterogeneity in models about the evolution of that fundamental, the latter of which corresponds more closely with the idea of ambiguity. At long horizons, however, the opposite is true. The rationale is that forecasters have access to and use different information to form short-horizon forecasts. At longer horizons, these informational differences are likely to be less important. More important are modeling differences such as the econometric structure or the choice of sample period for model estimation. Since my entire sample of MNAs concerns forecasts at very short horizons (on the order of one week to one month), the resulting dispersion series may reflect forecasters’ different information signals instead of any notion of ambiguity. That the dispersion series diverge from the variance risk premium series in the fall of 2005 is evidence in support of short-horizon forecast dispersion representing informational differences instead of ambiguity. As a result of Hurricane Katrina, forecasters may have disagreed on an informational basis such as whether unemployment insurance initial claims would be filed in a timely manner. It is less likely that a one-off event could significantly increase modeling disagreement among forecasters.

The Patton and Timmermann (2010) reasoning implies that dispersion in longer-horizon forecasts on macroeconomic conditions do represent model uncertainty and hence could better serve as a proxy for ambiguity. To explore this implication, I look at the dispersion (75th percentile minus 25th percentile) in forecasts of a number of macroeconomic variables from the Federal Reserve Bank of Philadelphia’s Survey of Professional Forecasters (SPF). In particular, I look at the quarterly time series of dispersion for q/q real GDP growth for forecast horizons ranging from 1 quarter to 4 quarters. Panel B of Figure 6 plots this series for all four forecast horizons from 1997Q1 to 2014Q3. We see that the series spike during the 2008 financial crisis, consistent with the time series behavior of short-horizon forecast dispersions and the variance risk premium. Moreover, in line with the Patton and Timmermann (2010) intuition, the long-horizon forecast dispersions appear to proxy for model uncertainty better than the short-horizon series; e.g., the former do not increase in the fall of 2005 as a result
of Hurricane Katrina. Other papers in the literature also interpret long-horizon dispersions as proxying for model uncertainty. Drechsler (2013), for example, shows that the 1-quarter forecast dispersion for q/q real GDP growth from the SPF correlates well with his measure of the variance risk premium.

Nonetheless, I find the long-horizon forecast dispersions in Panel B of Figure 6 to be lacking as measures of ambiguity. Take the European sovereign debt and U.S. debt ceiling crises episode during the later part of 2011. As noted, the variance risk premium rose significantly during that period, consistent with the intuition that ambiguity must also have been high at that time. It is clear, however, that the long-horizon forecast dispersions do not rise during that time (neither do the short-horizon dispersions). I find broadly similar results when plotting (unreported) q/q growth time series of the GDP price index and nominal GDP from the SPF. Note that Drechsler (2013) does not address this divergence between the long-horizon dispersions and his variance risk premium because his time series end in 2009.

What explains this divergence? While long-horizon forecast dispersions capture model uncertainty, the uncertainty is that experienced by economic forecasters who do not know the right model for predicting the evolution of macroeconomic conditions. In contrast, I focus on the model uncertainty that investors experience when interpreting news about macroeconomic conditions for the fundamental value of the stock market. These two types of ambiguity, while plausibly correlated, do not have to move in lockstep. In 2011, the European sovereign debt and U.S. debt ceiling crises may have led investors to become less sure of their interpretation of macroeconomic news for stocks without forcing forecasters to become less sure of how macroeconomic variables would evolve in the short- and long-horizons.

The final proxy for ambiguity that I consider is the Baker, Bloom, and Davis (2013) index for economic policy uncertainty. Their monthly index has three underlying components: newspaper article mentions of words related to economic policy uncertainty, upcoming expirations of federal tax code provisions, and dispersion of macroeconomic forecasts based on the SPF. In unreported results, I look at the time series behavior of the overall index as well as its components. Though the empirical behavior of the various series suggest some ability to track ambiguity (e.g., increases during the 2008 financial crisis), two concerns prevent serious consideration of the series. First, the overall index includes dispersion of macroeconomic forecasts, which, as discussed, is a problematic proxy for the ambiguity that I model. Second, there is no good theoretical justification for why newspaper references to economic policy uncertainty or expirations of federal tax code provisions should measure investors’ uncertainty about the impact of macroeconomic news on the stock market. As such, I stick
with the variance risk premium as my measure of ambiguity.

6 Empirical Results: Time-Varying Ambiguity

Using the “Monthly Averages” variance risk premium as a state variable for ambiguity, I test the sharper predictions of the model that the behavior of stocks in response to macroeconomic news depends on the amount of news ambiguity. The first section shows that the asymmetry effect and the no news is good news effect are greater in magnitude when there is greater ambiguity. The increased strength of the asymmetry effect is due to a stronger response of the stock market to bad news as opposed to a weaker response to good news. When viewed through the lens of the model, this finding implies that increases in ambiguity come from investors thinking that the lower bound for the noise of macroeconomic news in determining the fundamental value of the stock market is smaller as opposed to the upper bound being larger. In the second section, I show that the ambiguity premium exists independent of the amount of ambiguity, a result which can be reconciled with the model. Finally, the third section finds that the volatility of stocks around MNAs is greater in times of higher ambiguity.

6.1 The Asymmetry Effect and No News is Good News Effect

If Propositions 1 and 2 are true, the magnitudes of the asymmetry effect and no news is good news effect should be increasing in the amount of ambiguity. Running Eq. (22) over the sample of MNAs that occur at times of high ambiguity should lead to a larger \( \hat{\alpha} \) and a more negative \( \hat{\beta^+} - \hat{\beta^-} \) compared to the same regression over a sample of MNAs that occur at times of lower ambiguity. To this end, I use the variance risk premium time series to proxy for ambiguity and associate each MNA with the corresponding value of the variance risk premium in the month of the data release. I then split the full sample of MNAs into five variance risk premium quintiles, with the first quintile consisting of macroeconomic news announced when the variance risk premium is at its lowest and the fifth quintile consisting of news announced when the premium is at its highest. Panel B of Table 3 provides summary statistics on the standardized news variable \( S_t \) across the quintiles. We see that for each quintile, the distribution of news is unbiased and symmetric. Moreover, the distribution of \( S_t \) is similar across the five quintiles. One might expect that at certain times, such as during the 2008 financial crisis, the frequency or magnitude of negative news about the macroeconomy
should increase. Since the variance risk premium time series also spikes at these times based on Figure 5, the above logic suggests that $S_t$ may be negatively-biased in the higher variance risk premium quintiles. The reason that this effect is not present in Panel B of Table 3 is that $S_t$ is calculated as the actual data release relative to expectations. While times of crisis do result in more negative data releases of macroeconomic variables, economic forecasters correspondingly revise lower expectations for data releases. This downward revision of expectations offsets the poorer data, so $S_t$ is distributed symmetrically in each quintile and comparably across quintiles.

Table 8 shows results from the regression in Eq. (22) for each quintile of the variance risk premium, and Figure 7 plots the regression parameters against the quintiles. Together, Table 8 and Figure 7 provide the main evidence in support of Propositions 1 and 2. Looking at the last column of Table 8 and Panel B of Figure 7, we see that, consistent with Proposition 1, the stock market exhibits little asymmetry to macroeconomic news in times of low ambiguity but large asymmetry in times of high ambiguity. $\hat{\beta}^+ - \hat{\beta}^- = -0.955$ bps is statistically indistinguishable from zero in the first variance risk premium quintile based on a Wald test, so the stock market reacts by a similar amount to a unit of positive surprise versus a unit of negative surprise. Moving to higher variance risk premium quintiles, $\hat{\beta}^+ - \hat{\beta}^-$ decreases consistently and becomes statistically different from zero. In the fifth quintile, $\hat{\beta}^+ - \hat{\beta}^- = -10.618$ bps; that is, the stock market falls 10.618 bps more for a unit of negative macroeconomic news than it rises for a unit of positive news.

The increase in the asymmetry effect comes entirely from the increased sensitivity of the stock market to negative news as opposed to the decreased sensitivity of the stock market to positive news. From the $\hat{\beta}^+$ and $\hat{\beta}^-$ columns of Table 8 and Panel A of Figure 7, we see that $\hat{\beta}^+$ shows no clear pattern across the variance risk premium quintiles, whereas $\hat{\beta}^-$ increases consistently from 1.551 bps in the first quintile to 15.648 bps in the fifth quintile. In the context of the model and Eq. (12), the results imply that while greater news ambiguity increases $\bar{\phi} - \phi$ (equivalently, $\sigma^2_s - \sigma^2_s$), this increase comes primarily through an increase in $\bar{\phi}$ (decrease in $\sigma^2_s$) and not through a decrease in $\phi$ (increase in $\sigma^2_s$). The representative investor has a range of variances in mind for the noisiness of a given piece of news about the fundamental value of the risky asset. With greater ambiguity, this range of variances expands, but it expands in a skewed manner such that the lower end of the range decreases, but the upper end of the range stays approximately the same. When the investor sees a positive piece of news, he believes that the variance of the noise component is at the upper end of the range, which reduces the impact of the good news on the risky asset. Since the upper end of the range is similar for times of low and high ambiguity, the risky asset has a similarly subdued response to good news in both states of the world. When the investor sees
a negative piece of news, he believes that the variance of the noise component is at the lower end of the range, which amplifies the impact of the bad news on the risky asset. The lower end of the range is lower for times of high ambiguity versus low ambiguity, however, so the risky asset responds more strongly to the negative news in the former case versus the latter case. Since ambiguity, as proxied by the variance risk premium in Figure 5, is generally high during times of market stress, another way of stating the above result is that investors believe that good news is equally relevant (or irrelevant) for stocks in good and bad times. Investors believe that bad news, however, is more relevant for stocks in bad states than in good states.

From the $\hat{\alpha}$ column of Table 8 and Panel C of Figure 7, we see that $\hat{\alpha}$ increases from the first variance risk premium quintile to the fifth quintile, which supports Proposition 2. The magnitude of $\hat{\alpha}$ averages to 2.174 bps in the first two quintiles and 4.720 bps in the last two quintiles, an increase of 2.546 bps. That is, in times of high news ambiguity, the stock market increases 2.546 bps more in response to no news than in times of low news ambiguity.

### 6.2 The Ambiguity Premium

Based on the model, the ambiguity premium from Eq. (18) should, all else equal, be increasing in the news ambiguity $\bar{\phi} - \hat{\phi}$, which is the first term in parentheses. Taking the data from Panel A of Table 4, Panel B of the same table breaks the stock market return through MNAs into quintiles by the variance risk premium. The top set of rows presents the arithmetic sum of returns (expressed in %), and the bottom set of rows presents the mean of returns (expressed in bps). Focusing on the “Return” column, which is the actual return of the front ES contract around MNAs, we see that returns are positive in each of the variance risk premium quintiles. The ambiguity premium is thus not only positive over the whole sample, but also when the sample is split in five by the variance risk premium. It is clear from Table 4, however, that there is not much of a pattern in the “Return” column across variance risk premium quintiles. To better understand this result, I decompose the ambiguity premium in each quintile of Panel B into two components, as in Panel A, using the estimated $\hat{\alpha}, \hat{\beta}^+, \hat{\beta}^-$ from Table 8: the positive no news is good news effect and the negative asymmetry effect. Consistent with earlier results, the asymmetry effect exerts a more negative effect on the average return of the stock market around MNAs as ambiguity increases. The no news is good news effect has the counterbalancing role of exerting a more positive effect on the average return of the stock market around MNAs as ambiguity increases. These two results depend on the verification of Propositions 1 and 2 in Table 8.
as well as the similar distribution of MNA surprises across variance risk premium quintiles documented in Table 3. The asymmetry effect and the no news is good news effect both change in such a way across variance risk premium quintiles that their sum, the ambiguity premium, exhibits no discernable pattern across quintiles.

An alternate method to assess whether the ambiguity premium is time-varying is to conduct predictability regressions as in Eq. (26). Instead of forecasting \( r_{t,t+h} \), the stock return from month \( t \) to month \( t+h \), I forecast \( r_{t,t+h}^{MNA} \), that portion of the stock return attributed to the release of macroeconomic news. If the ambiguity premium varies over time, \( r_{t,t+h}^{MNA} \) should be predictable. More specifically, if the ambiguity premium is higher at times of greater ambiguity, the variance risk premium should be a positive, significant predictor of \( r_{t,t+h}^{MNA} \). My regression specification is

\[
r_{t,t+h}^{MNA} = a_{MNA} + b_{MNA}X_t + \epsilon_{t,t+h}^{MNA},
\]

in which \( r_{t,t+h}^{MNA} \) is the annualized sum of the continuously compounded return of the stock market in the ±5 minutes around MNAs from the end of month \( t \) to the end of month \( t+h \). As discussed previously, \( r_{t,t+h}^{MNA} \) can be thought of as an excess return due to the use of futures data in calculating returns. Panel A of Table 9 shows \( \hat{b}_{MNA} \), associated \( t \)-statistics, and adjusted \( R^2 \) for a range of horizons and three sets of covariates \( X_t \). When \( X_t = \{ \log (P/E)_t \} \), there is little evidence of predictability except at the longest horizons. Setting \( X_t = \{ \text{VRP}_t \} \), the “Monthly Averages” variance risk premium, no coefficients are significant. Similarly, incorporating both the price-to-earnings ratio and variance risk premium for \( X_t = \{ \log (P/E)_t, \text{VRP}_t \} \) yields no significant coefficients. There is some suggestive evidence that the variance risk premium positively predicts stock returns at short horizons. For example, at \( h = 3 \) months, the coefficient for the \( X_t = \{ \text{VRP}_t \} \) regression has a \( t \)-statistic of 1.457, which is significant at the 15% level, and an adjusted \( R^2 \) of 1.324. The presence of the variance risk premium also improves the adjusted \( R^2 \) of the \( X_t = \{ \log (P/E)_t, \text{VRP}_t \} \) regression specification to 1.581 versus the -0.326 with only \( X_t = \{ \log (P/E)_t \} \). On the whole, however, the return of stocks around macroeconomic news does not appear to vary much over time, which suggests that the ambiguity premium is not increasing in the amount of ambiguity as measured by the variance risk premium. Since we know from Table 7 and the extensive literature on return predictability that stock returns in general are predictable yet find stock returns around MNAs are not predictable, a natural follow-up is to check if stock returns in times excluding MNAs are predictable. In Panel B of Table 9, I run regressions of the form

\[
r_{t,t+h}^{nMNA} = a_{nMNA} + b_{nMNA}X_t + \epsilon_{t,t+h}^{nMNA},
\]

in which \( r_{t,t+h}^{nMNA} \) is the annualized sum of the continuously compounded return of the stock market in the ±5 minutes around MNAs from the end of month \( t \) to the end of month \( t+h \).
Can the lack of time-variation in the ambiguity premium be reconciled with the model? Consider the expression for the ambiguity premium in Eq. (18), specifically the second term in parentheses \( \left( \sqrt{\alpha^2 \sigma_d^2 + \bar{\sigma}_s^2} - \sqrt{\alpha^2 \sigma_d^2 + \tilde{\sigma}_s^2} \right) \). Based on the fact that the asymmetry effect is due primarily to the increased sensitivity of the stock market to negative news as opposed to the decreased sensitivity of the stock market to positive news, we have inferred in the previous section that increases in \( \phi \) (decreases in \( \sigma_s^2 \)) drive increases in news ambiguity \( \phi - \tilde{\phi} \), not decreases in \( \tilde{\phi} \) (increases in \( \bar{\sigma}_s^2 \)). As such, the second term in parentheses in the expression for the ambiguity premium does not increase with news ambiguity unlike in the case if news ambiguity were driven by decreases in \( \phi \) (increases in \( \bar{\sigma}_s^2 \)). This result dampens the positive relationship between the ambiguity premium and ambiguity. A second explanation for the stability of the ambiguity premium centers on \( \tilde{\sigma}_s^2 \), the true variance of the \( \epsilon_s \) component of the news. If \( \tilde{\sigma}_s^2 \) were close to \( \sigma_s^2 \), the second term in parentheses of the ambiguity premium would be close to zero, which would make it difficult to see an increasing relationship between the ambiguity premium and ambiguity. The investor thinks that the news could be a very noisy indicator of the fundamental value of the risky asset \( \bar{\sigma}_s^2 \), and it turns out that the news is in fact a quite noisy indicator \( \tilde{\sigma}_s^2 \). Alternatively, if \( \tilde{\sigma}_s^2 \) were increasing in news ambiguity for some reason, the second term in parentheses would be decreasing in ambiguity, which would offset the rise in \( \phi - \tilde{\phi} \) and sever the link between the ambiguity premium and ambiguity.

### 6.3 Risky Asset Volatility

The final prediction of the model, Proposition 4, says that the volatility of the stock market around macroeconomic news releases can be either increasing or decreasing in the amount of ambiguity depending on what drives increases in ambiguity. If, as implied by the results corroborating the asymmetry effect, increases in ambiguity in the model are due to investors’ allowing for smaller lower bounds for the variance of the news noise, stock market volatility around MNAs should be increasing in ambiguity. Panel A of Figure 8 plots the time series of the 10-minute return of the stock market in the ±5 minutes around MNAs. We see that this return is heteroscedastic and is highly variable at predictable episodes such as
the 2008 financial crisis. Table 10 splits this return time series into variance risk premium quintiles and calculates the standard deviation of returns in each quintile in the “10-Minute Std.” column. As suggested by Panel A of Figure 8 and consistent with Proposition 4, the standard deviation of stock returns around macroeconomic news increases substantially as the amount of ambiguity increases. This standard deviation is 14.791 bps in the lowest quintile versus 36.587 bps in the highest quintile.

The observation that the volatility of stock returns around MNAs increases with ambiguity is related to the well-studied phenomenon that the volatility of stock returns in general fluctuates substantially in the time series. Panel B of Figure 8 plots the time series of daily stock market returns for days with MNAs. There is substantial heteroscedasticity, and the volatility of daily returns appears to increase at the same time that the volatility of intraday returns increases. The “1-Day Std.” column of Table 10 calculates the standard deviation of daily returns when separated into variance risk premium quintiles. Similar to the result for the volatility of intraday returns, the volatility of daily returns also increases in ambiguity from a low of 64.703 bps in the first quintile to a high of 205.910 bps in the fifth quintile. Together, Figure 8 and Table 10 provide suggestive evidence that some of the time variation in the volatility of stock returns more generally can be attributed to the impact of ambiguity on the volatility of stock returns around MNAs.

7 Alternative Explanations

To my knowledge, no explanation in the literature provides a unified story for the full set of empirical patterns exhibited by the aggregate stock market around MNAs. There are, however, stories not related to ambiguity that could plausibly explain a subset of the findings. In the two sections below, I investigate different narratives that have the prediction that the stock market reacts asymmetrically to good news versus bad news. The data support the model based on ambiguity over these alternative explanations.

7.1 Good Times versus Bad Times

Veronesi (1999) presents a rational, regime-switching framework in which the aggregate stock market can react asymmetrically to news depending on whether the news is good or bad.
In his model, investors are uncertain about the state of the market and must infer whether times are good or bad. During good times, bad news has a large impact on stocks by both decreasing the probability investors place on the state of the world being good and increasing uncertainty about the state of the world. In contrast, good news has a small impact on stocks because investors already place a high probability on being in the good state of the world. During bad times, bad news has a small impact on stocks because investors believe they are already in the bad state of the world. The impact of good news on stocks is also muted, however, because while good news increases the probability investors place on the state of the world being good, good news also increases uncertainty about the state of the world. Altogether, one implication of Veronesi (1999) is that the aggregate stock market reacts more strongly to bad news than to good news during good times, and this asymmetry diminishes or is nonexistent during bad times.

The model based on investor sentiment in Barberis, Shleifer, and Vishny (1998) has a related prediction to that of Veronesi (1999) for the response of individual stocks to earnings news. In their model, investors extrapolate good (bad) times, characterized by strings of good (bad) earnings news, and expect future good (bad) earnings news. During good times, bad earnings news is unexpected and generates a large effect, but good earnings news is expected and generates a small effect. In contrast, during bad times, bad earnings is expected and generates a small effect, but good earnings news is unexpected and generates a large effect. The Barberis, Shleifer, and Vishny (1998) framework thus suggests that individual stocks react more strongly to bad earnings news than to good earnings news during good times, but this asymmetry flips during bad times.

Conrad, Cornell, and Landsman (2002) document empirical evidence in support of Veronesi (1999) and Barberis, Shleifer, and Vishny (1998) through investigating the response of individual stocks to earnings announcements. By using a relative price-to-earnings ratio as a proxy for good times versus bad times, Conrad, Cornell, and Landsman (2002) find that stocks indeed react most strongly to bad earnings news versus good earnings news when the relative value of the market is high (good times), with the asymmetry diminishing in magnitude when the market valuation is lower (bad times).7

The results of the aforementioned three papers suggest that the state variable that drives asymmetry is some measure of how good or bad the state of the world is. I assess whether this alternative explanation can account for the stock market behavior around macroeconomic news releases. To do so, I roughly follow Conrad, Cornell, and Landsman (2002) and use the

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7On a related note, papers such as Boyd, Hu, and Jagannathan (2005) suggest that the relationship between stocks and macroeconomic news depends on the phase of the business cycle; i.e., whether the news arrives during NBER recessions or expansions.
cyclically-adjusted price-to-earnings ratio (\(CAPE_t\)) from Robert Shiller’s website to create a proxy for how good or bad times are. I then replicate my results using this state variable instead of the variance risk premium. Panel A of Figure 9 shows the time series of \(CAPE_t\) from November, 1997 to March, 2014, and Panel A of Table 11 provides summary statistics. Conrad, Cornell, and Landsman (2002) argue that using the absolute price-to-earnings ratio is problematic. People may not care, for example, about how good or bad times are on an absolute scale but relative to recent experience. Moreover, as the figure shows, using \(CAPE_t\) as the state variable is essentially the same as just using a time dummy. The market valuation is highest in the early part of the sample around the dot-com bubble, intermediate during the mid-2000s, and lowest during and subsequent to the 2008 financial crisis. Categorizing the whole sample into good times, mediocore times, and bad times in that chronological order seems both simplistic and inaccurate. Similar to Conrad, Cornell, and Landsman (2002), I address this issue by creating a relative price-to-earnings ratio (\(DCAPE_t\)) in Panel B of Figure 9 by taking \(CAPE_t\) and subtracting its own trailing 12-month average. The time series of \(DCAPE_t\) exhibits more reasonable dispersion that is not solely based on time. Summary statistics for \(DCAPE_t\) appear in Panel A of Table 11.

To assess how relative market valuation drives the differential response of the stock market to macroeconomic news, I run regressions as before based on Eq. (22). I use \(DCAPE_t\) to split my sample of MNAs into five quintiles with the first quintile consisting of macroeconomic news occurring when the relative market valuation is lowest and the fifth quintile consisting of macroeconomic news occurring when the relative market valuation is highest. Analogous to Panel B of Table 3, Panel B of Table 11 shows summary statistics for standardized news \(S_t\) across the \(DCAPE_t\) quintiles. \(S_t\) is unbiased and symmetric in each quintile and seems to be distributed similarly across quintiles. Analogous to Table 8, Panel C of Table 11 shows regression results for each quintile. From the rightmost column, \(\hat{\beta}^+ - \hat{\beta}^-\) is most negative in the first quintile at \(-10.317\) bps, statistically indistinguishable from zero in the middle three quintiles, and second-negative in the fifth quintile at \(-8.869\) bps. This pattern is inconsistent with the story that how good or bad the state of the world is, as measured by the relative market valuation, drives the differential response of the stock market to good news versus bad news. If that state variable were the driving force, we would expect \(\hat{\beta}^+ - \hat{\beta}^-\) to be most negative in the fifth quintile and progressively less negative moving down to the first quintile. The response of the aggregate stock market to macroeconomic news provides conflicting evidence for the implications of Veronesi (1999) and Barberis, Shleifer, and Vishny (1998) in contrast with the support that I find in the data for the framework based on ambiguity. This outcome is not particularly surprising given that times of high ambiguity, as measured by the variance risk premium, tend to be bad times, yet these are
also times in which the stock market responds more strongly to bad news than to good news.

There are several reasons why my empirical results differ so significantly from those of Conrad, Cornell, and Landsman (2002). First, I look at the aggregate market response to macroeconomic news instead of the individual stock response to earnings news.\textsuperscript{8} A second explanation for the discrepancy is my use of high-frequency intraday data instead of daily data, which I have stressed makes a significant difference for the empirical results in this paper.

7.2 Volatility Feedback

Volatility feedback can also lead to the asymmetric response of the stock market to good news versus bad news. Campbell and Hentschel (1992) have such a model in which large pieces of news tend to be followed by large pieces of news, which reflects the persistence of volatility. This phenomenon dampens the effect of good news on stocks and amplifies the effect of bad news, thus providing a potential explanation for why the aggregate stock market responds more strongly to bad news than to good news. Volatility feedback is unlikely, however, to explain the asymmetry effect exhibited by stocks around MNAs. The reason is that MNAs are anticipated. If there is a large surprise in a given piece of macroeconomic news, investors take this information into account in forecasting the next piece of macroeconomic news. This self-corrective mechanism means that there is little persistence in the magnitude of the surprise of MNAs. Consistent with this notion, the distribution of MNA surprises is time-invariant as shown in Figure 3, Table 3, and Panel B of Table 11.

8 Conclusion

Using a theoretical framework with ambiguity as its centerpiece, this paper has shown a number of testable predictions for the behavior of stocks around ambiguous news. Stocks react asymmetrically stronger to bad news than to good news, increase in response to neutral news, and have a positive average return through news. Times of higher ambiguity coincide with larger magnitudes for the aforementioned effects and moreover coincide with either higher or lower volatility of stocks around news depending on the driver of the increase in

\textsuperscript{8}Note that the Veronesi (1999) model applies to the aggregate market, the Barberis, Shleifer, and Vishny (1998) model applies to individual stocks, and the model based on ambiguity in my paper can apply to either the stock market as a whole or individual stocks (though I focus on the former).
ambiguity. I find that these predictions receive considerable empirical support based on the
dynamics of the aggregate stock market around news about the macroeconomy. To fully test
the model, I construct a variance risk premium time series that is a more reasonable proxy
for ambiguity than existing data series. Among the observations that corroborate the model
with ambiguity, I find that stocks react more strongly to bad macroeconomic news than
good macroeconomic news and especially so during crisis periods. I also show that about
1/3 of the equity return from 1997 to 2014 accrues in just 10 minutes around MNAs. Viewed
through the model, these results suggest that investors behave in such a way that they treat
bad news as more salient in bad times than in good times but good news as equally salient in
both times. The empirical results are hard to reconcile with existing models and suggest that
ambiguity is an important factor in asset pricing and, in this specific setting, how financial
assets reflect macroeconomic risks. As such, ambiguity warrants further consideration in
finance and macrofinance models.
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### Tables and Figures

**Table 1: Full Sample of MNAs.** Freq. refers to monthly (M) or weekly (W). Source uses the following acronyms: BEA, Bureau of Economic Analysis; BLS, Bureau of Labor Statistics; CB, Conference Board; Census, Census Bureau; ETA, Employment and Training Administration; Fed, Federal Reserve Board of Governors; and ISM, Institute for Supply Management. Table below covers the whole period from November, 1997 to March, 2014.

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<th>Source</th>
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<td>11/04/1997</td>
<td>03/20/2014</td>
<td>M</td>
<td>CB</td>
<td>10:00 AM</td>
<td>1</td>
</tr>
<tr>
<td>New Home Sales</td>
<td>Thousands</td>
<td>195</td>
<td>12/03/1997</td>
<td>03/25/2014</td>
<td>M</td>
<td>Census</td>
<td>10:00 AM</td>
<td>1</td>
</tr>
<tr>
<td>Pending Home Sales</td>
<td>% ch. mom</td>
<td>107</td>
<td>06/01/2005</td>
<td>03/27/2014</td>
<td>M</td>
<td>NAR</td>
<td>10:00 AM</td>
<td>1</td>
</tr>
<tr>
<td>Personal Income</td>
<td>% ch. mom</td>
<td>196</td>
<td>11/03/1997</td>
<td>03/28/2014</td>
<td>M</td>
<td>BEA</td>
<td>8:30 AM</td>
<td>1</td>
</tr>
<tr>
<td>PPI</td>
<td>% ch. mom</td>
<td>193</td>
<td>12/12/1997</td>
<td>03/14/2014</td>
<td>M</td>
<td>BLS</td>
<td>8:30 AM</td>
<td>1</td>
</tr>
<tr>
<td>Retail Sales</td>
<td>% ch. mom</td>
<td>195</td>
<td>11/14/1997</td>
<td>03/13/2014</td>
<td>M</td>
<td>Census</td>
<td>8:30 AM</td>
<td>1</td>
</tr>
<tr>
<td>Unemployment Rate</td>
<td>% rate</td>
<td>196</td>
<td>11/07/1997</td>
<td>03/07/2014</td>
<td>M</td>
<td>BLS</td>
<td>8:30 AM</td>
<td>-1</td>
</tr>
</tbody>
</table>

---

*On 7/31/2001, data was released at 9:36 AM.*

*On 8/1/2000, data was released at 9:26 AM.*
Table 2: The Whole Sample Stock Market Reaction to MNAs. The table shows results from regressions of ES returns on standardized news for each event and then all events (last row): \( R_t = \alpha + \beta^+ D_t^+ S_t + \beta^- (1 - D^+) S_t + \epsilon_t \). The left-hand-side variable \( R_t \) is the % change in the price level (bps) associated with the front ES futures contract in a ±5 minute window around a MNA. The right-hand side variable \( S_t \) for the same MNA is the actual data less the expected data based on a Bloomberg survey of economists, all normalized by the sample standard deviation of the actual less the expected difference for that MNA: \( S_t = (A_t - \bar{E}_t - [A_t]) / \hat{\sigma} \). \( D_t \) is a dummy variable equal to one if \( S_t > 0 \) and zero otherwise. \( t \)-statistics (not shown) are based on heteroscedasticity-consistent standard errors. Rightmost column presents \( \hat{\beta}^+ - \hat{\beta}^- \) and performs a Wald test that the difference is not zero (\( F \)-statistics not shown). *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level. Table below covers the whole period from November, 1997 to March, 2014.

<table>
<thead>
<tr>
<th>Event Name</th>
<th>( \hat{\alpha} ) (bps)</th>
<th>( \hat{\beta}^+ ) (bps)</th>
<th>( \hat{\beta}^- ) (bps)</th>
<th>Adj. ( R^2 )</th>
<th>( N )</th>
<th>( \hat{\beta}^+ - \hat{\beta}^- ) (bps)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change in NFP</td>
<td>10.093**</td>
<td>-7.618</td>
<td>8.079</td>
<td>0.042</td>
<td>196</td>
<td>-15.697</td>
</tr>
<tr>
<td>Consumer Confidence</td>
<td>3.984</td>
<td>7.106*</td>
<td>23.105***</td>
<td>30.727</td>
<td>197</td>
<td>-15.999***</td>
</tr>
<tr>
<td>CPI</td>
<td>3.654</td>
<td>-11.889***</td>
<td>-5.830</td>
<td>11.397</td>
<td>197</td>
<td>-6.059</td>
</tr>
<tr>
<td>Durable Orders</td>
<td>1.475</td>
<td>4.335</td>
<td>10.287***</td>
<td>14.404</td>
<td>197</td>
<td>-5.952</td>
</tr>
<tr>
<td>Existing Home Sales</td>
<td>0.692</td>
<td>14.196**</td>
<td>11.820***</td>
<td>16.529</td>
<td>109</td>
<td>2.376</td>
</tr>
<tr>
<td>Factory Orders</td>
<td>1.294</td>
<td>3.519</td>
<td>5.249**</td>
<td>3.140</td>
<td>196</td>
<td>-1.730</td>
</tr>
<tr>
<td>Housing Starts</td>
<td>1.974</td>
<td>1.401</td>
<td>2.883</td>
<td>0.918</td>
<td>189</td>
<td>-1.481</td>
</tr>
<tr>
<td>Industrial Production</td>
<td>1.774</td>
<td>4.521</td>
<td>7.497*</td>
<td>21.998</td>
<td>194</td>
<td>-2.976</td>
</tr>
<tr>
<td>Initial Jobless Claims</td>
<td>2.487***</td>
<td>2.879***</td>
<td>8.715***</td>
<td>11.101</td>
<td>852</td>
<td>-5.836***</td>
</tr>
<tr>
<td>ISM Manufacturing</td>
<td>5.946*</td>
<td>9.593**</td>
<td>17.262***</td>
<td>15.582</td>
<td>197</td>
<td>-7.670</td>
</tr>
<tr>
<td>ISM Non-Manufacturing</td>
<td>0.379</td>
<td>10.209***</td>
<td>11.388***</td>
<td>14.783</td>
<td>182</td>
<td>-1.179</td>
</tr>
<tr>
<td>Leading Index</td>
<td>-4.025*</td>
<td>7.051*</td>
<td>-0.505</td>
<td>2.337</td>
<td>197</td>
<td>7.556</td>
</tr>
<tr>
<td>New Home Sales</td>
<td>6.783**</td>
<td>0.439</td>
<td>9.555**</td>
<td>3.578</td>
<td>195</td>
<td>-9.116*</td>
</tr>
<tr>
<td>Pending Home Sales</td>
<td>0.664</td>
<td>13.393***</td>
<td>9.535**</td>
<td>19.740</td>
<td>107</td>
<td>3.858</td>
</tr>
<tr>
<td>Personal Income</td>
<td>-0.016</td>
<td>0.955</td>
<td>0.361</td>
<td>-0.641</td>
<td>196</td>
<td>0.594</td>
</tr>
<tr>
<td>PPI</td>
<td>4.093*</td>
<td>-9.431***</td>
<td>5.177</td>
<td>6.463</td>
<td>193</td>
<td>-14.608***</td>
</tr>
<tr>
<td>Retail Sales</td>
<td>9.040***</td>
<td>1.597</td>
<td>18.229***</td>
<td>17.559</td>
<td>195</td>
<td>-16.632***</td>
</tr>
<tr>
<td>Unemployment Rate</td>
<td>5.206</td>
<td>2.767</td>
<td>10.411</td>
<td>0.604</td>
<td>196</td>
<td>-7.644</td>
</tr>
<tr>
<td>All</td>
<td>3.204***</td>
<td>2.416***</td>
<td>8.557***</td>
<td>4.701</td>
<td>3985</td>
<td>-6.141***</td>
</tr>
</tbody>
</table>
Table 3: Summary Statistics of MNA Surprises. Panel A shows summary statistics for the standardized news variable $S_t$ for the whole sample of MNAs. Panel B shows summary statistics for $S_t$ bucketed according to $VRP_t$ quintiles, with the 1st quintile corresponding to the smallest values and the 5th quintile corresponding to the largest values. $S_t$ aggregates the news surprises of all MNAs, as defined in Table 2. $VRP_t$ is the “Monthly Averages” variance risk premium series, which corresponds to the monthly time series in Panel B of Figure 4. Tables below cover the whole period from November, 1997 to March, 2014.

Panel A: Whole Sample

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
<th>Max.</th>
<th>Min.</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Whole Sample</td>
<td>0.030</td>
<td>0.000</td>
<td>1.010</td>
<td>8.018</td>
<td>-5.514</td>
<td>0.181</td>
<td>2.973</td>
<td>3985</td>
</tr>
</tbody>
</table>

Panel B: Sample Bucketed into Variance Risk Premium Quintiles

<table>
<thead>
<tr>
<th>$VRP_t$ Quintile</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
<th>Max.</th>
<th>Min.</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.042</td>
<td>0.000</td>
<td>1.005</td>
<td>6.257</td>
<td>-4.171</td>
<td>0.254</td>
<td>2.786</td>
<td>796</td>
</tr>
<tr>
<td>2</td>
<td>0.003</td>
<td>0.000</td>
<td>0.962</td>
<td>4.866</td>
<td>-3.452</td>
<td>0.042</td>
<td>2.331</td>
<td>780</td>
</tr>
<tr>
<td>3</td>
<td>0.027</td>
<td>0.000</td>
<td>0.920</td>
<td>3.907</td>
<td>-4.315</td>
<td>0.137</td>
<td>1.616</td>
<td>815</td>
</tr>
<tr>
<td>4</td>
<td>0.034</td>
<td>0.000</td>
<td>0.966</td>
<td>5.214</td>
<td>-4.006</td>
<td>-0.113</td>
<td>1.872</td>
<td>781</td>
</tr>
<tr>
<td>5</td>
<td>0.044</td>
<td>0.000</td>
<td>1.176</td>
<td>8.018</td>
<td>-5.514</td>
<td>0.368</td>
<td>3.818</td>
<td>813</td>
</tr>
</tbody>
</table>
Table 4: The Ambiguity Premium and its Decomposition. Panel A considers the whole sample of MNAs, and Panel B buckets the whole sample into variance risk premium quintiles as in Table 3. The “Sum (%)” row(s) of each panel present(s) arithmetic sum of returns in %. The “Mean (bps)” row(s) of each panel present(s) mean of returns in bps. “Return” is the actual return of the front ES contract around MNAs and is equal to the ambiguity premium. Other columns depend on the estimated $\hat{\alpha}$, $\hat{\beta}^+$, and $\hat{\beta}^-$ from Table 2 (Panel A) and Table 8 (Panel B). “No News” is that portion of the ambiguity premium attributed to the no news is good news effect and is equal to $\hat{\alpha} \times N$ for the “Sum (%)” row(s) and just $\hat{\alpha}$ for the “Mean (bps)” row(s). “+ News” is that portion of the ambiguity premium attributed to the reaction of the stock market to positive news and is equal to the sum of $\hat{\beta}^+ \times S_t$ for $S_t > 0$ for the “Sum (%)” row(s) and the same quantity divided by $N$ for the “Mean (bps)” row(s). “- News” is that portion of the ambiguity premium attributed to the reaction of the stock market to negative news and is equal to the sum of $\hat{\beta}^- \times S_t$ for $S_t < 0$ for the “Sum (%)” row(s) and the same quantity divided by $N$ for the “Mean (bps)” row(s). “Asymm.” is that portion of the ambiguity premium attributed to the asymmetric reaction of the stock market to positive news versus negative news and simply sums the “+ News” and “- News” columns. “Return” is equal to “No News” plus “Asymm.” $N$ is the number of MNAs, and $S_t$ aggregates the news surprises of all MNAs, as defined in Table 2. Tables below cover the whole period from November, 1997 to March, 2014.

**Panel A: Whole Sample**

<table>
<thead>
<tr>
<th>Return</th>
<th>No News</th>
<th>+ News</th>
<th>- News</th>
<th>Asymm.</th>
<th>$N$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sum (%)</td>
<td>Whole Sample</td>
<td>43.903</td>
<td>127.688</td>
<td>37.011</td>
<td>-120.795</td>
</tr>
<tr>
<td>Mean (bps)</td>
<td>Whole Sample</td>
<td>1.102</td>
<td>3.204</td>
<td>0.929</td>
<td>-3.031</td>
</tr>
</tbody>
</table>

**Panel B: Sample Bucketed into Variance Risk Premium Quintiles**

<table>
<thead>
<tr>
<th>VRP$_t$ Quintile</th>
<th>Return</th>
<th>No News</th>
<th>+ News</th>
<th>- News</th>
<th>Asymm.</th>
<th>$N$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sum (%)</td>
<td>Whole Sample</td>
<td>20.026</td>
<td>22.516</td>
<td>1.877</td>
<td>-4.368</td>
<td>-2.491</td>
</tr>
<tr>
<td>1</td>
<td>8.237</td>
<td>11.848</td>
<td>12.024</td>
<td>-15.635</td>
<td>-3.612</td>
<td>780</td>
</tr>
<tr>
<td>2</td>
<td>2.695</td>
<td>19.470</td>
<td>5.726</td>
<td>-22.502</td>
<td>-16.776</td>
<td>815</td>
</tr>
<tr>
<td>3</td>
<td>7.256</td>
<td>36.758</td>
<td>-5.389</td>
<td>-24.113</td>
<td>-29.502</td>
<td>781</td>
</tr>
<tr>
<td>4</td>
<td>5.690</td>
<td>38.489</td>
<td>18.186</td>
<td>-50.985</td>
<td>-32.798</td>
<td>813</td>
</tr>
<tr>
<td>Mean (bps)</td>
<td>Whole Sample</td>
<td>2.516</td>
<td>2.829</td>
<td>0.236</td>
<td>-0.549</td>
<td>-0.313</td>
</tr>
<tr>
<td>1</td>
<td>1.056</td>
<td>1.519</td>
<td>1.541</td>
<td>-2.005</td>
<td>-0.463</td>
<td>780</td>
</tr>
<tr>
<td>2</td>
<td>0.331</td>
<td>2.389</td>
<td>0.703</td>
<td>-2.761</td>
<td>-2.058</td>
<td>815</td>
</tr>
<tr>
<td>3</td>
<td>0.929</td>
<td>4.706</td>
<td>-0.690</td>
<td>-3.087</td>
<td>-3.777</td>
<td>781</td>
</tr>
<tr>
<td>4</td>
<td>0.700</td>
<td>4.734</td>
<td>2.237</td>
<td>-6.271</td>
<td>-4.034</td>
<td>813</td>
</tr>
</tbody>
</table>
Table 5: Summary Statistics of 10-minute Stock Market Returns for Periods with and without MNAs. Table splits 10-minute ES return intervals into those that contain MNAs ("MNA") and those that do not ("nMNA") and presents summary statistics. Returns are calculated as the % change in the price level (bps) associated with the front ES futures contract. I calculate ES return intervals only on those days that the S&P 500 was open as well as the following dates on which the S&P 500 was closed but futures markets were open: 4/2/1999, 4/6/2007, 4/2/2010, and 4/6/2012 (all corresponding to Good Friday); and 10/29/2012 (corresponding to Hurricane Sandy). For each day, I forward fill in price data for all 1440 minutes and attempt to split the day into 144 10-minute increments. For any MNA, I ensure that there is a corresponding 10-minute interval formed from the ±5 minutes window around the MNA, consistent with the event window used elsewhere in the paper. If doing so prevents the formation of 144 evenly spaced 10-minute intervals for that day, I allow the intervals surrounding the interval containing the MNA to be slightly longer. For example, if the MNA occurs at 8:30 AM, the interval that contains the MNA is from 8:25 AM to 8:35 AM. The preceding interval is from 8:10 AM to 8:25 AM, and the following interval is from 8:35 AM to 8:50 AM; both surrounding intervals cover 15 minutes instead of 10 minutes. The rest of the intervals for that day are then exactly 10 minutes. The “Total” row shows returns compounded over all intervals, expressed in bps. Leftmost three columns include the whole sample, and rightmost three columns winsorize returns at the 1% and 99%. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level. Table below covers the whole period from November, 1997 to March, 2014.

<table>
<thead>
<tr>
<th></th>
<th>MNA</th>
<th>nMNA</th>
<th>Diff.</th>
<th></th>
<th>MNA</th>
<th>nMNA</th>
<th>Diff.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All Observations</td>
<td>Winsorized (1% and 99%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>3624.966 6626.671</td>
<td>-3001.705</td>
<td>3510.359 6757.771</td>
<td>-3247.412</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>1.000** 0.014</td>
<td>0.986**</td>
<td>0.983*** 0.012</td>
<td>0.972***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>t-statistic</td>
<td>(2.245) (1.035)</td>
<td>(2.212)</td>
<td>(2.632) (1.208)</td>
<td>(2.600)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1st Percentile</td>
<td>-76.543 -31.627</td>
<td>-44.915</td>
<td>-60.426 -23.354</td>
<td>-37.072</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Median</td>
<td>0.000 0.000</td>
<td>0.000</td>
<td>0.000 0.000</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>75th Percentile</td>
<td>10.549 2.246</td>
<td>8.303</td>
<td>10.271 2.210</td>
<td>8.061</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>99th Percentile</td>
<td>78.233 30.665</td>
<td>47.568</td>
<td>61.183 22.779</td>
<td>38.404</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>25.179 10.460</td>
<td></td>
<td>20.899 7.300</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Skewness</td>
<td>0.143 0.568</td>
<td></td>
<td>0.101 -0.071</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kurtosis</td>
<td>5.826 68.635</td>
<td></td>
<td>2.107 3.625</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>3194 588671</td>
<td></td>
<td>3130 576899</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 6: Summary Statistics of Variance Risk Premium and Components. $VIX_t^2/12$ is the squared VIX, $\mathbb{E}_t^p [RV_{t+1,t+22}]$ is the physical expectation of realized variance, and $VRP_{t+1,t+22}$ is the variance risk premium. The rows indexed by “Daily” correspond to the daily time series in Panel A of Figure 4, the rows indexed by “Monthly Averages” correspond to the monthly time series in Panel B of Figure 4, and the rows indexed by “Monthly End-of-Month” correspond to the monthly time series in Panel C of Figure 4. Refer to the Figure 4 caption for details. Table below covers the whole period from November, 1997 to March, 2014.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
<th>Max.</th>
<th>Min.</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>AC(1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$VIX_t^2/12$</td>
<td>46.163</td>
<td>34.987</td>
<td>45.872</td>
<td>544.862</td>
<td>8.151</td>
<td>4.245</td>
<td>27.277</td>
<td>0.969</td>
</tr>
<tr>
<td>$\mathbb{E}<em>t^p [RV</em>{t+1,t+22}]$</td>
<td>34.261</td>
<td>25.048</td>
<td>35.756</td>
<td>400.182</td>
<td>7.351</td>
<td>4.582</td>
<td>29.392</td>
<td>0.988</td>
</tr>
<tr>
<td>$VRP_{t+1,t+22}$</td>
<td>11.902</td>
<td>8.721</td>
<td>12.665</td>
<td>179.842</td>
<td>-64.363</td>
<td>3.630</td>
<td>24.995</td>
<td>0.883</td>
</tr>
<tr>
<td>Monthly Averages</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$VIX_t^2/12$</td>
<td>46.204</td>
<td>35.780</td>
<td>43.431</td>
<td>332.292</td>
<td>9.781</td>
<td>3.655</td>
<td>18.578</td>
<td>0.838</td>
</tr>
<tr>
<td>$\mathbb{E}<em>t^p [RV</em>{t+1,t+22}]$</td>
<td>34.264</td>
<td>25.248</td>
<td>34.526</td>
<td>281.605</td>
<td>8.474</td>
<td>4.261</td>
<td>24.549</td>
<td>0.822</td>
</tr>
<tr>
<td>$VRP_{t+1,t+22}$</td>
<td>11.941</td>
<td>9.631</td>
<td>10.076</td>
<td>56.722</td>
<td>-5.235</td>
<td>2.105</td>
<td>5.796</td>
<td>0.803</td>
</tr>
<tr>
<td>Monthly End-of-Month</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$VIX_t^2/12$</td>
<td>45.241</td>
<td>37.066</td>
<td>39.436</td>
<td>298.901</td>
<td>9.048</td>
<td>3.069</td>
<td>13.220</td>
<td>0.795</td>
</tr>
<tr>
<td>$\mathbb{E}<em>t^p [RV</em>{t+1,t+22}]$</td>
<td>32.562</td>
<td>24.514</td>
<td>32.931</td>
<td>304.136</td>
<td>6.471</td>
<td>4.243</td>
<td>26.996</td>
<td>0.771</td>
</tr>
<tr>
<td>$VRP_{t+1,t+22}$</td>
<td>12.679</td>
<td>9.740</td>
<td>10.223</td>
<td>59.564</td>
<td>-5.235</td>
<td>2.152</td>
<td>6.145</td>
<td>0.437</td>
</tr>
</tbody>
</table>
Table 7: Predictability of Stock Returns. The table shows results from return predictability regressions using monthly data from November, 1997 to March, 2014: $r_{t,t+h} = a + bX_t + \epsilon_{t,t+h}$. $r_{t,t+h}$ is the annualized log return of the front ES futures contract from 4:00 PM ET of the last trading day (in which the S&P 500 is open) of month $t$ to the same time of the last trading day of month $t+h$. Table displays results for horizons $h = 1, 3, 6, 9, 12, 15, 18, 21, 24$ and five sets of covariates $X_t$ drawn from $\log(P/E)_t$, the log of the cyclically adjusted price-to-earnings ratio from Robert Shiller’s website, the “Monthly Averages” variance risk premium series from Panel B of Figure 4, and the “Monthly End-of-Month” variance risk premium series from Panel C of Figure 4. Table reports estimated parameters $\hat{b}$, associated $t$-statistics, and adjusted $R^2$. $t$-statistics (shown in parentheses) are based on Newey-West standard errors with max{$3, 2h$} lags. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level.

<table>
<thead>
<tr>
<th>Horizon</th>
<th>1</th>
<th>3</th>
<th>6</th>
<th>9</th>
<th>12</th>
<th>15</th>
<th>18</th>
<th>21</th>
<th>24</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adj. $R^2$</td>
<td>-0.156</td>
<td>0.731</td>
<td>3.572</td>
<td>6.783</td>
<td>9.482</td>
<td>13.452</td>
<td>17.953</td>
<td>22.866</td>
<td>27.506</td>
</tr>
<tr>
<td>$VRP_t$</td>
<td>0.183</td>
<td>0.385</td>
<td>0.526**</td>
<td>0.490**</td>
<td>0.440**</td>
<td>0.396**</td>
<td>0.409***</td>
<td>0.450***</td>
<td>0.503***</td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td>-0.404</td>
<td>0.785</td>
<td>3.736</td>
<td>4.807</td>
<td>5.075</td>
<td>5.034</td>
<td>6.530</td>
<td>9.398</td>
<td>13.882</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Monthly Averages</th>
<th>1</th>
<th>3</th>
<th>6</th>
<th>9</th>
<th>12</th>
<th>15</th>
<th>18</th>
<th>21</th>
<th>24</th>
</tr>
</thead>
<tbody>
<tr>
<td>$VRP_t$</td>
<td>0.915**</td>
<td>0.819***</td>
<td>0.701***</td>
<td>0.528**</td>
<td>0.461**</td>
<td>0.406**</td>
<td>0.390***</td>
<td>0.412***</td>
<td>0.440***</td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td>2.266</td>
<td>5.530</td>
<td>7.251</td>
<td>5.880</td>
<td>5.836</td>
<td>5.557</td>
<td>6.162</td>
<td>8.205</td>
<td>11.091</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Monthly End-of-Month</th>
<th>1</th>
<th>3</th>
<th>6</th>
<th>9</th>
<th>12</th>
<th>15</th>
<th>18</th>
<th>21</th>
<th>24</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adj. $R^2$</td>
<td>0.885**</td>
<td>0.778***</td>
<td>0.629***</td>
<td>0.439**</td>
<td>0.365*</td>
<td>0.298</td>
<td>0.269*</td>
<td>0.281**</td>
<td>0.305**</td>
</tr>
<tr>
<td>$VRP_t$</td>
<td>2.278</td>
<td>3.307</td>
<td>2.991</td>
<td>2.016</td>
<td>1.919</td>
<td>1.617</td>
<td>1.762</td>
<td>2.037</td>
<td>2.341</td>
</tr>
</tbody>
</table>
Table 8: Stock Market Reaction to MNAs Bucketed into Variance Risk Premium Quintiles. The table shows results from regressions bucketed by variance risk premium VRP\(_t\) quintiles, with the 1st quintile corresponding to the smallest values and the 5th quintile corresponding to the largest values. The regression in each quintile is of ES returns on standardized news grouping all events together: \( R_t = \alpha + \beta^+ D_t^+ S_t + \beta^- (1 - D_t^+) S_t + \epsilon_t \). \( R_t \) is the stock market return, \( S_t \) aggregates the news surprises of all MNAs, and \( D_t^+ \) is a dummy variable. All regression variables are as defined in Table 2. VRP\(_t\) is the “Monthly Averages” variance risk premium series, which corresponds to the monthly time series in Panel B of Figure 4. \( t \)-statistics (shown in parentheses) are based on heteroskedasticity-consistent standard errors. Rightmost column presents \( \hat{\beta}^+ - \hat{\beta}^- \) and performs a Wald test that the difference is not zero (\( F \)-statistics shown in parentheses). *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level. Table below covers the whole period from November, 1997 to March, 2014.

<table>
<thead>
<tr>
<th>VRP(_t) Quintile</th>
<th>( \hat{\alpha} ) (bps)</th>
<th>( \hat{\beta}^+ ) (bps)</th>
<th>( \hat{\beta}^- ) (bps)</th>
<th>Adj. ( R^2 )</th>
<th>( N )</th>
<th>( \hat{\beta}^+ - \hat{\beta}^- ) (bps)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2.829***</td>
<td>0.596</td>
<td>1.551</td>
<td>0.229</td>
<td>796</td>
<td>-0.955</td>
</tr>
<tr>
<td></td>
<td>(3.748)</td>
<td>(0.589)</td>
<td>(1.614)</td>
<td></td>
<td></td>
<td>(0.322)</td>
</tr>
<tr>
<td>2</td>
<td>1.519</td>
<td>4.407***</td>
<td>5.784***</td>
<td>4.606</td>
<td>780</td>
<td>-1.377</td>
</tr>
<tr>
<td></td>
<td>(1.568)</td>
<td>(3.181)</td>
<td>(2.912)</td>
<td></td>
<td></td>
<td>(0.341)</td>
</tr>
<tr>
<td>3</td>
<td>2.389**</td>
<td>1.980</td>
<td>8.431***</td>
<td>4.188</td>
<td>815</td>
<td>-6.451**</td>
</tr>
<tr>
<td></td>
<td>(2.085)</td>
<td>(0.962)</td>
<td>(4.576)</td>
<td></td>
<td></td>
<td>(5.858)</td>
</tr>
<tr>
<td>4</td>
<td>4.706***</td>
<td>-1.837</td>
<td>9.032***</td>
<td>2.953</td>
<td>781</td>
<td>-10.869***</td>
</tr>
<tr>
<td></td>
<td>(3.418)</td>
<td>(-1.017)</td>
<td>(3.776)</td>
<td></td>
<td></td>
<td>(12.759)</td>
</tr>
<tr>
<td>5</td>
<td>4.734***</td>
<td>5.030***</td>
<td>15.648***</td>
<td>10.497</td>
<td>813</td>
<td>-10.618***</td>
</tr>
<tr>
<td></td>
<td>(2.756)</td>
<td>(2.602)</td>
<td>(7.718)</td>
<td></td>
<td></td>
<td>(11.715)</td>
</tr>
</tbody>
</table>
Table 9: Decomposing the Predictability of Stock Returns. The tables show results from return predictability regressions using monthly data from November, 1997 to March, 2014. Panel A presents results for the specification $r_{t,t+h}^{MNA} = a_{MNA} + b_{MNA}X_t + \epsilon_{t,t+h}^{MNA}$, and Panel B presents results for the specification $r_{t,t+h}^{nMNA} = a_{nMNA} + b_{nMNA}X_t + \epsilon_{t,t+h}^{nMNA}$. $r_{t,t+h}^{MNA}$ is the annualized sum of the continuously compounded return of the stock market in the ±5 minutes around MNAs from the end of month $t$ to the end of month $t+h$. $r_{t,t+h}^{nMNA} = r_{t,t+h} - r_{t,t+h}^{MNA}$, in which $r_{t,t+h}$ is defined in Table 7. Table displays results for horizons $h = 1, 3, 6, 9, 12, 15, 18, 21, 24$ and three sets of covariates $X_t$ drawn from log (P/E)$_t$, the log of the cyclically adjusted price-to-earnings ratio from Robert Shiller’s website, and the “Monthly Averages” variance risk premium series from Panel B of Figure 4. Table reports estimated parameters $\hat{b}$, associated $t$-statistics, and adjusted $R^2$. $t$-statistics (shown in parentheses) are based on Newey-West standard errors with max $\{3, 2h\}$ lags. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level.

Panel A: Predictability of Monthly Stock Returns around MNAs

<table>
<thead>
<tr>
<th>Horizon</th>
<th>1</th>
<th>3</th>
<th>6</th>
<th>9</th>
<th>12</th>
<th>15</th>
<th>18</th>
<th>21</th>
<th>24</th>
</tr>
</thead>
<tbody>
<tr>
<td>log (P/E)$_t$</td>
<td>1.508</td>
<td>1.220</td>
<td>2.020</td>
<td>2.583</td>
<td>3.275</td>
<td>3.420</td>
<td>3.488</td>
<td>3.298*</td>
<td>3.001*</td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td>-0.407</td>
<td>-0.326</td>
<td>0.504</td>
<td>1.806</td>
<td>4.434</td>
<td>6.289</td>
<td>8.390</td>
<td>9.527</td>
<td>10.024</td>
</tr>
<tr>
<td>VRP$_t$</td>
<td>0.043</td>
<td>0.097</td>
<td>0.079</td>
<td>0.046</td>
<td>0.006</td>
<td>0.000</td>
<td>-0.013</td>
<td>-0.017</td>
<td>-0.016</td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td>-0.383</td>
<td>1.324</td>
<td>1.842</td>
<td>0.587</td>
<td>-0.525</td>
<td>-0.556</td>
<td>-0.374</td>
<td>-0.177</td>
<td>-0.139</td>
</tr>
<tr>
<td>VRP$_t$</td>
<td>0.059</td>
<td>0.116</td>
<td>0.104</td>
<td>0.074</td>
<td>0.036</td>
<td>0.032</td>
<td>0.020</td>
<td>0.015</td>
<td>0.013</td>
</tr>
</tbody>
</table>
Panel B: Predictability of Monthly Stock Returns Excluding MNAs

<table>
<thead>
<tr>
<th>Horizon</th>
<th>1</th>
<th>3</th>
<th>6</th>
<th>9</th>
<th>12</th>
<th>15</th>
<th>18</th>
<th>21</th>
<th>24</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(-0.754)</td>
<td>(-0.888)</td>
<td>(-1.490)</td>
<td>(-1.788)</td>
<td>(-2.063)</td>
<td>(-2.540)</td>
<td>(-3.070)</td>
<td>(-3.751)</td>
<td>(-4.596)</td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td>-0.053</td>
<td>0.956</td>
<td>4.286</td>
<td>7.903</td>
<td>11.262</td>
<td>15.768</td>
<td>20.718</td>
<td>25.980</td>
<td>30.591</td>
</tr>
<tr>
<td>$VRP_t$</td>
<td>0.143</td>
<td>0.307</td>
<td>0.468**</td>
<td>0.474**</td>
<td>0.465***</td>
<td>0.432***</td>
<td>0.452 ***</td>
<td>0.495***</td>
<td>0.531***</td>
</tr>
<tr>
<td></td>
<td>(0.242)</td>
<td>(0.685)</td>
<td>(2.141)</td>
<td>(2.430)</td>
<td>(2.665)</td>
<td>(2.836)</td>
<td>(3.290)</td>
<td>(3.845)</td>
<td>(4.391)</td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td>-0.447</td>
<td>0.323</td>
<td>2.760</td>
<td>4.185</td>
<td>5.208</td>
<td>5.572</td>
<td>7.556</td>
<td>10.767</td>
<td>14.783</td>
</tr>
<tr>
<td></td>
<td>(-0.820)</td>
<td>(-0.788)</td>
<td>(-1.102)</td>
<td>(-1.320)</td>
<td>(-1.520)</td>
<td>(-1.903)</td>
<td>(-2.313)</td>
<td>(-2.767)</td>
<td>(-3.166)</td>
</tr>
<tr>
<td>$VRP_t$</td>
<td>0.038</td>
<td>0.206</td>
<td>0.329</td>
<td>0.309</td>
<td>0.284</td>
<td>0.226</td>
<td>0.232</td>
<td>0.261</td>
<td>0.299**</td>
</tr>
<tr>
<td></td>
<td>(0.067)</td>
<td>(0.471)</td>
<td>(1.226)</td>
<td>(1.264)</td>
<td>(1.243)</td>
<td>(1.088)</td>
<td>(1.300)</td>
<td>(1.639)</td>
<td>(1.982)</td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td>-0.567</td>
<td>0.786</td>
<td>5.265</td>
<td>9.242</td>
<td>12.722</td>
<td>16.799</td>
<td>22.164</td>
<td>28.342</td>
<td>34.477</td>
</tr>
</tbody>
</table>
Table 10: Stock Market Volatility around MNAs Bucketed into Variance Risk Premium Quintiles. Table takes the 10-minute return of the stock market in the ±5 minutes around a MNA and the daily return of the stock market for the day of the MNA and calculates standard deviations (bps) in the “10-Minute Std.” and “1-Day Std.” columns, respectively. Standard deviations are calculated for each $VRP_t$ quintile, with the 1st quintile corresponding to the smallest values and the 5th quintile corresponding to the largest values. The “Fraction of Std.” column divides the “10-Minute Std.” column by the “1-Day Std.” column. $VRP_t$ is the “Monthly Averages” variance risk premium series, which corresponds to the monthly time series in Panel B of Figure 4. The intraday and daily return data are the same as those plotted on the horizontal and vertical axes of Figure 2, respectively. Refer to the Figure 2 caption for details. Table below covers the whole period from November, 1997 to March, 2014.

<table>
<thead>
<tr>
<th>$VRP_t$ Quintile</th>
<th>10-Minute Std.</th>
<th>1-Day Std.</th>
<th>Fraction of Std.</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>14.791</td>
<td>64.703</td>
<td>0.229</td>
<td>632</td>
</tr>
<tr>
<td>2</td>
<td>20.407</td>
<td>89.368</td>
<td>0.228</td>
<td>636</td>
</tr>
<tr>
<td>3</td>
<td>21.994</td>
<td>108.013</td>
<td>0.204</td>
<td>636</td>
</tr>
<tr>
<td>4</td>
<td>26.375</td>
<td>137.742</td>
<td>0.191</td>
<td>643</td>
</tr>
<tr>
<td>5</td>
<td>36.587</td>
<td>205.910</td>
<td>0.178</td>
<td>642</td>
</tr>
</tbody>
</table>
Table 11: Replication of Results Using the Relative Price-to-Earnings Ratio to Bucket the Data. Panel A shows summary statistics for \( CAPE_t \) and \( DCAPE_t \), the two variables plotted in Panels A and B of Figure 9, respectively. Panel B replicates Panel B of Table 3 and provides summary statistics for the standardized news variable \( S_t \) bucketed according to \( DCAPE_t \) quintiles, with the 1st quintile corresponding to the smallest values and the 5th quintile corresponding to the largest values. Panel C replicates Table 8 and shows the stock market reaction to MNAs bucketed into \( DCAPE_t \) quintiles. Tables below cover the whole period from November, 1997 to March, 2014.

Panel A: Summary Statistics of \( CAPE_t \) and \( DCAPE_t \)

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
<th>Max.</th>
<th>Min.</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>AC(1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( CAPE_t )</td>
<td>27.016</td>
<td>25.650</td>
<td>7.300</td>
<td>44.190</td>
<td>13.320</td>
<td>0.871</td>
<td>0.009</td>
<td>0.990</td>
</tr>
<tr>
<td>( DCAPE_t )</td>
<td>-0.225</td>
<td>0.241</td>
<td>2.808</td>
<td>5.158</td>
<td>-8.282</td>
<td>-0.671</td>
<td>0.136</td>
<td>0.927</td>
</tr>
</tbody>
</table>

Panel B: Summary Statistics of MNA Surprises, with Sample Bucketed into \( DCAPE_t \) Quintiles

<table>
<thead>
<tr>
<th>( DCAPE_t ) Quintile</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
<th>Max.</th>
<th>Min.</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>( \hat{\beta}^+ ) (bps)</th>
<th>( \hat{\beta}^- ) (bps)</th>
<th>( \hat{\beta}^+ - \hat{\beta}^- ) (bps)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.019</td>
<td>0.000</td>
<td>1.227</td>
<td>8.018</td>
<td>-5.514</td>
<td>0.391</td>
<td>3.495</td>
<td>779</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0.009</td>
<td>0.000</td>
<td>1.016</td>
<td>4.866</td>
<td>-4.315</td>
<td>0.311</td>
<td>2.537</td>
<td>802</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>0.044</td>
<td>0.000</td>
<td>0.970</td>
<td>6.257</td>
<td>-3.527</td>
<td>0.533</td>
<td>3.198</td>
<td>805</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>0.014</td>
<td>0.052</td>
<td>0.912</td>
<td>3.303</td>
<td>-4.171</td>
<td>-0.495</td>
<td>1.437</td>
<td>788</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>0.100</td>
<td>0.017</td>
<td>0.895</td>
<td>3.332</td>
<td>-3.452</td>
<td>-0.141</td>
<td>0.749</td>
<td>811</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel C: Stock Market Reaction to MNAs Bucketed into \( DCAPE_t \) Quintiles

<table>
<thead>
<tr>
<th>( DCAPE_t ) Quintile</th>
<th>( \hat{\alpha} ) (bps)</th>
<th>( \hat{\beta}^+ ) (bps)</th>
<th>( \hat{\beta}^- ) (bps)</th>
<th>Adj. ( R^2 )</th>
<th>( \hat{\beta}^+ - \hat{\beta}^- ) (bps)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4.443**</td>
<td>3.763*</td>
<td>14.080***</td>
<td>9.958</td>
<td>779</td>
</tr>
<tr>
<td></td>
<td>(2.533)</td>
<td>(1.941)</td>
<td>(7.293)</td>
<td></td>
<td>(-10.317*** (12.473)</td>
</tr>
<tr>
<td>2</td>
<td>2.346*</td>
<td>4.217**</td>
<td>7.445***</td>
<td>4.272</td>
<td>802</td>
</tr>
<tr>
<td></td>
<td>(1.848)</td>
<td>(2.473)</td>
<td>(4.079)</td>
<td></td>
<td>(-3.228 (1.387)</td>
</tr>
<tr>
<td>3</td>
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<td>1.356</td>
<td>5.318**</td>
<td>1.765</td>
<td>805</td>
</tr>
<tr>
<td></td>
<td>(3.875)</td>
<td>(1.120)</td>
<td>(2.136)</td>
<td></td>
<td>(-3.962 (2.570)</td>
</tr>
<tr>
<td>4</td>
<td>1.651</td>
<td>3.876**</td>
<td>5.079***</td>
<td>3.270</td>
<td>788</td>
</tr>
<tr>
<td></td>
<td>(1.572)</td>
<td>(2.024)</td>
<td>(3.268)</td>
<td></td>
<td>(-1.203 (0.212)</td>
</tr>
<tr>
<td>5</td>
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<td>-1.836</td>
<td>7.032***</td>
<td>2.108</td>
<td>811</td>
</tr>
<tr>
<td></td>
<td>(3.200)</td>
<td>(-1.141)</td>
<td>(3.883)</td>
<td></td>
<td>(-8.869*** (11.759)</td>
</tr>
</tbody>
</table>
Figure 1: Graphical Representation of Model Predictions. Each panel plots in the solid blue line $p_1(n) - p_0$, the change in price of the risky asset after the arrival of a piece of news $n$ at $t = 1$ versus the prevailing price at $t = 0$, against the value of the news $n$. Panel A corresponds to the benchmark in which there is no news ambiguity. The solid blue line has slope $\overline{\phi} = \phi$ to the left and right of the y-axis and intersects the origin. The asymmetry effect, no news is good news effect, and ambiguity premium are all equal to zero. Panel B corresponds to the case in which the news is ambiguous. The solid blue line has a steeper slope $\overline{\phi} > \phi$ to the left of the y-axis and a gentler slope $\phi < \overline{\phi}$ to the right of the y-axis. This line intersects the y-axis at $p_1(0) - p_0 > 0$, which measures the size of the no news is good news effect. A dashed blue line connects the solid blue line at symmetric points around the y-axis and intersects the y-axis at $\overline{p}_1 - p_0 > 0$, which measures the size of the ambiguity premium. The distance between the intersections of the solid and dashed blue lines, $\overline{p}_1 - p_1(0) < 0$, measures the asymmetry effect.
Figure 2: Comparison of Intraday versus Daily Stock Market Data. The scatterplot compares the 10-minute return of the stock market in the ±5 minutes around a MNA (horizontal axis) and the daily return of the stock market for the day of the MNA (vertical axis). Intraday returns are calculated as the % change in the price level associated with the front ES futures contract, and daily returns are calculated as the % change in the S&P 500 index. The sample plotted includes all MNAs from Table 1 excluding those that occur on days in which the S&P 500 was closed. I do not double count MNAs that occur at exactly the same time (e.g., 8:30 AM ET on the same day), but I treat MNAs that occur at different times on the same day as separate data points (associated with the same daily stock market return). The annotated arrow points to the 10/16/2008 9:15 AM ET release of industrial production data associated with a −1.024% 10-minute ES return and a 4.251% daily S&P 500 return. Figure below covers the whole period from November, 1997 to March, 2014. Lighter colors indicate earlier dates.
Figure 3: Time Series of Standardized News for the Whole Sample of MNAs. Figure plots standardized news $S_t$ for all the MNAs, as defined in Table 2. Figure below covers the whole period from November, 1997 to March, 2014.
Figure 4: Time Series of Variance Risk Premium and Components. Panel A plots a daily time series of the variance risk premium, “VRP,” or $VRP_{t,t+22}$; the squared VIX, “sq. VIX,” or $VIX^2_t/12$; and the physical expectation of realized variance, “cond. var.,” or $\mathbb{E}_t^P[RV_{t+1,t+22}]$. $VIX^2_t/12$ is the square of the day-end CBOE VIX index divided by 12. $\mathbb{E}_t^P[RV_{t+1,t+22}]$ is the one-step-ahead forecasts from regressing realized variance $RV_{t+1,t+22}$ on lagged realized variance and lagged squared VIX in Eq. (24): $RV_{t+1,t+22} = 2.130 + 0.310 \times R_{t-21,t} + 0.464 \times VIX^2_{t-22}/12 + e_t$. I construct $RV_{t+1,t+22}$ as the sum of 22 daily realized variances between $t+1$ and $t+22$ (inclusive), with daily realized variance calculated as the sum of squared five-minute log returns on ES futures from 9:30 AM ET to 4:00 PM ET and the squared close-to-open log return. The variance risk premium is the difference between “sq. VIX” and “cond. var.”: $VRP_{t,t+22} = VIX^2_t/12 - \mathbb{E}_t^P[RV_{t+1,t+22}]$.

Panel B plots monthly time series of the same three variables as in Panel A taking a simple average of daily data within each month. Panel C plots monthly time series of the same three variables as in Panels A and B constructed in the following manner. “sq. VIX” is the end-of-month squared VIX $VIX^2_t/12$, with $t$ the last trading day of a given month. $\mathbb{E}_t^P[RV_{t+1,t+22}]$ is the one-step-ahead forecasts from the monthly regression of realized variance on one-month lagged realized variance and one-month lagged squared VIX in Eq. (25): $RV_{t+1,t+22} = 0.195 + 0.282 \times R_{t-21,t} + 0.511 \times VIX^2_{t-22}/12 + e_t$. Monthly realized variance $RV_{t+1,t+22}$ is the sum of daily realized variances for the month that includes days $t+1$ to $t+22$. The variance risk premium for the month with $t$ as its last trading day is the difference between “sq. VIX” and “cond. var.”: $VRP_{t,t+22} = VIX^2_t/12 - \mathbb{E}_t^P[RV_{t+1,t+22}]$. Note that I keep all notation the same as before, but obviously some months have more trading days than other months. All three panels below cover the whole period from November, 1997 to March, 2014.

Panel A: Daily
Panel B: Monthly Averages

Panel C: Monthly End-of-Month
Figure 5: Monthly Variance Risk Premium with Annotations. The figure graphs the variance risk premium from Panel B of Figure 4 and annotates major peaks and troughs. Figure below covers the whole period from November, 1997 to March, 2014.
Figure 6: Time Series of Macroeconomic Forecast Dispersions. Panel A plots two forecast dispersion series at a short forecast horizon. I obtain dispersion data from Bloomberg on the standard deviation and the range (maximum minus minimum) of forecasts for all MNAs in the sample (see Table 1). To allow for comparison across events with different units, I separately standardize the two types of dispersion data for each event to have standard deviations equal to one over the entire sample. For each day $t$ in the plotted series, I average the dispersion data for all MNAs contained in the 1-year window centered at $t$ to produce dispersion series based on the standard deviation of forecasts (“stdev”) and the range of forecasts “range.” The centered window ranges from 3/12/1998 to 12/19/2013. Panel B plots forecast dispersion series at long forecast horizons ranging from 1 quarter (“1q”) to 4 quarters (“4q”). Data are quarterly from 1997Q1 to 2014Q3 for q/q real GDP growth and come from the Philadelphia Fed’s SPF. Dispersion is measured as the 75th percentile minus the 25th percentile.

Panel A: Short-Horizon Forecast Dispersion Time Series
Panel B: Long-Horizon Forecast Dispersion Time Series
Figure 7: Stock Market Reaction to MNAs Bucketed into Variance Risk Premium Quintiles. All panels plot data from Table 8 with the y-axis denominated in bps and the x-axis representing variance risk premium $V R P_t$ quintiles, with the 1st quintile corresponding to the smallest values and the 5th quintile corresponding to the largest values. Panel A plots $\hat{\beta}^+ (“p\_beta”)$ and $\hat{\beta}^- (“n\_beta”)$. Panel B plots $\hat{\beta}^+ - \hat{\beta}^-$. Panel C plots $\hat{\alpha}$.

Panel A: $\hat{\beta}^+$ and $\hat{\beta}^-$ versus $V R P_t$

Panel B: $\hat{\beta}^+ - \hat{\beta}^-$ versus $V R P_t$
Panel C: $\hat{\alpha}$ versus $VRP_t$
Figure 8: Time Series of Intraday and Daily Returns around MNAs. Panel A plots the 10-minute return of the stock market in the ±5 minutes around a MNA. Panel B plots the daily return of the stock market for the day of the MNA. The data in Panels A and B are the same as those plotted on the horizontal and vertical axes of Figure 2, respectively. Refer to the Figure 2 caption for details. Figures below cover the whole period from November, 1997 to March, 2014.

Panel A: Intraday Returns around MNAs

Panel B: Daily Returns around MNAs
Figure 9: Time Series of Absolute and Relative Price-to-Earnings Ratios. Panel A plots the time series of the cyclically adjusted price-to-earnings ratio $CAPE_t$ from Robert Shiller’s website. Panel B plots the time series of the relative cyclically adjusted price-to-earnings ratio $DCAPE_t$ calculated as $CAPE_t$ less its own trailing 12-month average. Figures below cover the whole period from November, 1997 to March, 2014.

Panel A: Cyclically-Adjusted Price-to-Earnings Ratio

Panel B: Relative Cyclically-Adjusted Price-to-Earnings Ratio
Appendix A: Math Formulas

A.1 Conditional Distribution

Let

\[ X = \begin{pmatrix} X_1 \\ X_2 \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}, \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix}\right). \]

Then the conditional distribution of \( X_2 \) given \( X_1 \) is

\[ \mathcal{N}\left(\mu_2 + \Sigma_{21} \Sigma_{11}^{-1} (X_1 - \mu_1), \Sigma_{22} - \Sigma_{21} \Sigma_{11}^{-1} \Sigma_{12}\right). \]

A.2 Conditional Means of Normal and Squared Normal Random Variables

For \( z \sim \mathcal{N}(0, \sigma_z^2) \), the conditional mean of the normal random variable is

\[
\mathbb{E}[z|z > 0] = \frac{1}{\mathbb{P}[z > 0]} \frac{1}{\sigma_z \sqrt{2\pi}} \int_0^\infty z \times \exp\left(-\frac{z^2}{2\sigma_z^2}\right) dz
\]

\[
= \frac{\sqrt{2}}{\sigma_z \sqrt{\pi}} \int_0^\infty \sigma_z^2 \times \exp(-y) dy
\]

\[
= - \frac{\sigma_z \sqrt{2}}{\sqrt{\pi}} \times \exp(-y)|_0^\infty
\]

\[
= \frac{\sigma_z \sqrt{2}}{\sqrt{\pi}}.
\]

The second step uses the change of variables, with \( y = z^2/2\sigma_z^2 \).

The conditional mean of the squared normal random variable is

\[
\mathbb{E}[z^2|z > 0] = \frac{1}{\mathbb{P}[z > 0]} \frac{1}{\sigma_z \sqrt{2\pi}} \int_0^\infty z^2 \times \exp\left(-\frac{z^2}{2\sigma_z^2}\right) dz
\]

\[
= \frac{\sqrt{2}}{\sigma_z \sqrt{\pi}} \int_0^\infty z^2 \times \exp(-az^2) dz, a = \frac{1}{2\sigma_z^2}
\]

\[
= \frac{\sqrt{2}}{\sigma_z \sqrt{\pi}} \left(\frac{1}{4} \sqrt{\frac{\pi}{a^3}} \times \text{erf}(\sqrt{a}z) - \frac{z}{2a} \times \exp(-az^2)\right)|_0^\infty
\]

\[
= \frac{\sqrt{2}}{\sigma_z \sqrt{\pi}} \frac{1}{4} \sqrt{\frac{\pi}{a^3}}
\]

\[
= \sigma_z^2.
\]

The third step uses \( \text{erf}(\cdot) \) to denote the error function.