2018

Two Essays on the Role of Uncertainty in Financial Markets

Raluca Stan

Follow this and additional works at: <https://researchrepository.wvu.edu/etd>

Recommended Citation

Stan, Raluca, "Two Essays on the Role of Uncertainty in Financial Markets" (2018). *Graduate Theses, Dissertations, and Problem Reports*. 7261.

<https://researchrepository.wvu.edu/etd/7261>

This Dissertation is protected by copyright and/or related rights. It has been brought to you by the The Research Repository @ WVU with permission from the rights-holder(s). You are free to use this Dissertation in any way that is permitted by the copyright and related rights legislation that applies to your use. For other uses you must obtain permission from the rights-holder(s) directly, unless additional rights are indicated by a Creative Commons license in the record and/ or on the work itself. This Dissertation has been accepted for inclusion in WVU Graduate Theses, Dissertations, and Problem Reports collection by an authorized administrator of The Research Repository @ WVU. For more information, please contact researchrepository@mail.wvu.edu.

Two Essays on the Role of Uncertainty in Financial Markets

Raluca Stan

Dissertation submitted to the
College of Business and Economics
at West Virginia University

in partial fulfillment of the requirements for the degree of

Doctor of Philosophy in Business Administration
Concentration in Finance

Ann Marie Hibbert, Ph. D., Co-Chair
Alex Kurov, Ph. D., Co-Chair
Costanza Meneghetti, Ph. D.
Bingxin Li, Ph. D.
Feng Yao, Ph. D.

Department of Finance

Morgantown, West Virginia
2018

Keywords: Monetary Policy; Macroeconomic Announcements; Financial Markets; Intraday Data; Ambiguity; Knightian Uncertainty; Earnings Announcements; Stock Returns; Market Efficiency; Systematic Risk.

Copyright 2018 Raluca Stan

ABSTRACT

Two Essays on the Role of Uncertainty in Financial Markets

Raluca Stan

This dissertation includes two essays investigating the role of uncertainty in financial markets. The first essay examines whether monetary policy uncertainty influences the reaction of the equity, Treasury security, foreign exchange and crude oil markets, as well as medium-term interest rates, to U.S macroeconomic announcements. The empirical results show that in the presence of higher policy uncertainty the response to macroeconomic news weakens in the stock and crude oil markets and strengthens in the Treasury, interest rate and foreign exchange markets. In times of elevated monetary policy uncertainty, macroeconomic announcements impact the financial and crude oil markets to a large extent through expectations of future monetary policy.

The second essay investigates whether ambiguity is priced in the cross-section of stock returns. The results show that investors require a premium for being exposed to high levels of ambiguity, in addition to the premium they require for bearing risk. As ambiguity increases, small firms, firms that are unprofitable, non-dividend payers, firms that are riskier, and those with higher levels of earnings management, underperform relative to their counterparts. This essay also provides new evidence on how ambiguity affects the price discovery process in the stock market. In particular, during times of elevated ambiguity, firms with greater information asymmetry benefit from a weaker stock market reaction to bad earnings news.

TABLE OF CONTENTS

LIST OF TABLES.....	V
LIST OF FIGURES.....	VIII
INTRODUCTION.....	IX
ESSAY 1: MONETARY POLICY UNCERTAINTY AND THE MARKET REACTION TO MACROECONOMICS ANNOUNCEMENTS.....	1
1.1. INTRODUCTION.....	1
1.2. HYPOTHESIS	5
1.3. DATA.....	9
1.3.1. Macroeconomic Announcements	9
1.3.2. Futures Returns.....	10
1.3.3. Sample Selection and Monetary Policy Uncertainty.....	11
1.4. EMPIRICAL RESULTS	14
1.4.1. Baseline Results.....	14
1.4.2. Effect of Policy Uncertainty on the Market Response to Macroeconomic Announcements	17
1.4.3. Time-Varying Response to Macroeconomic News.....	19
1.4.4. Robustness Checks	25
1.5. CONCLUSION	27
1.6. APPENDIX A- ESSAY 1	40
ESSAY 2: AMBIGUITY AND THE CROSS-SECTION OF STOCK RETURNS	57
2.1. INTRODUCTION.....	57
2.2. RELATED LITERATURE AND HYPOTHESES	60
2.2.1. Measuring Ambiguity.....	60
2.2.2. Ambiguity in Asset Pricing	64
2.2.3. Ambiguity and Market Efficiency.....	68
2.3. THE AMBIGUITY MEASURE	69
2.3.1. The Ambiguity Measure.....	69
2.3.2. Estimating Expected Ambiguity.....	72
2.4. DATA.....	73
2.4.1. Firm-Specific Characteristics	73
2.4.2. Control Variables.....	75
2.5.1. Long-Short Portfolios by Firm Characteristics	76
2.5.2. Two-way sorts of Stock Returns by Firm Characteristics and Expected Ambiguity.....	76
2.5.3. Univariate Evidence	78
2.5.4. Multivariate Analysis	79
2.6. AMBIGUITY AND MARKET EFFICIENCY	81
2.6.1. The Stock Market's Marginal Response to Earnings News.....	82
2.6.2. Baseline Regression.....	83
2.6.3. Asymmetric Reaction to Good vs. Bad Earnings News.....	84

2.6.4. The Marginal Response to Earnings News- By Firm Characteristics	85
2.6.5. The Magnitude of the Earnings Surprise and the Marginal Response to Earnings News	86
2.7. ROBUSTNESS ANALYSIS.....	88
2.8. CONCLUSION	90
LIST OF REFERENCES.....	123

LIST OF TABLES

Table 1-1: Direct and Indirect Effects of Macroeconomic News on the Stock, Bond, Foreign Exchange, and Crude Oil Markets.....	29
Table 1-2: U.S. Macroeconomic Announcements	30
Table 1-3: Time Variation in Monetary Policy Uncertainty	31
Table 1-4: Response of Stock, Bond, Foreign Exchange and Crude Oil Futures to Macroeconomic News in a Period of Low Monetary Policy Uncertainty	32
Table 1-5: Effect of Monetary Policy Uncertainty on the Market Response to Macroeconomic News	33
Table 1-6: Effect of Monetary Policy Uncertainty on the Response of Medium-term Interest Rates to Macroeconomic News	34
Table 1-7: Average Effect of Monetary Policy Uncertainty on the Market Response to Macroeconomic News	35
Table 1-8: Average Effect of Monetary Policy Uncertainty on the Market Response to Macroeconomic News (with controls)	36
Table A-1: Average Effect of Monetary Policy Uncertainty on the Market Response to Macroeconomic News (Controlling for the VIX and other variables).....	46
Table A-2: Average Effect of Monetary Policy Uncertainty on the Market Response to Macroeconomic News (Controlling for the VIX components and other variables)	47
Table A-3: Test for Asymmetry in the Response of Markets to Macroeconomic Announcements	48
Table A-4: Test for Asymmetry in the Response of Medium-term Interest Rates to Macroeconomic Announcements	49
Table A-5: Test of Autocorrelation in Macroeconomic Surprises	50
Table A-6: Accounting for Nonlinearity in the Market Response to Macroeconomic Announcements	51
Table A-7: Absolute Value of Surprises and MPU	52
Table A-8: Investor Disagreement and MPU	53
Table A-9: Average Effect of MPU on the Market Response to Macroeconomic News (with moving average of realized volatility as proxy for MPU).....	54

Table A-10: Effect of MPU on the Market Response to Macroeconomic News (OLS and Weighted Least Squares estimates)	55
Table 2-1: Descriptive Statistics of Ambiguity and other Measures of Risk/Uncertainty	92
Table 2-2: The Correlation between Ambiguity, other measures of Market Uncertainty, and Systematic Risk Factors	93
Table 2-3: Correlogram of $\ln(\bar{U})$	94
Table 2-4: Summary Statistics of Firm-Specific Characteristics	95
Table 2-5: Summary Statistics of Control Variables.....	96
Table 2-6: Time Series Regressions of Portfolio Returns	97
Table 2-7: Statistics of Earnings Surprises and Cumulative Abnormal Returns.....	99
Table 2-8: The Stock Market Reaction to Earnings News – Baseline Regression	100
Table 2-9: The Stock Market Reaction to Earnings News in times of High Ambiguity.....	101
Table 2-10: The Stock Market Reaction to Good vs. Bad Earnings News- Baseline Regression	102
Table 2-11: The Stock Market Reaction to Good vs. Bad Earnings News in times of High Ambiguity.....	103
Table 2-12: The Stock Market Reaction to Earnings News in times of High Ambiguity- Firm Specific Characteristics	104
Table 2-13: Frequency of Good and Bad Earnings News in times of High vs. Low Expected Ambiguity.....	109
Table 2-14: The Magnitude of Earnings Surprises in times of High Expected Ambiguity	110
Table 2-15: The Stock Market Reaction to Earnings News (Controlling for the Magnitude of the Earnings Surprise)	111
Table 2-16: The Stock Market Reaction to Earnings News in times of High Ambiguity (Controlling for the Magnitude of the Earnings Surprise)	112
Table 2-17: Ambiguity Effect on the Stock Market Reaction to Earnings News (Controlling for the Business Cycle).....	113
Table 2-18: Ambiguity Effect on the Stock Market Reaction to Earnings News (Controlling for Sentiment).....	114
Table 2-19: Ambiguity Effect on the Stock Market Reaction to Earnings News (Controlling for Investor Attention).....	115

Table 2-20: Ambiguity Effect on the Stock Market Reaction to Earnings News (Controlling
for VIX and VIX Components)..... 116

LIST OF FIGURES

Figure 1-2. Response of Stock, Bond, Foreign Exchange and Crude Oil Markets to Macroeconomic News	38
Figure 1-3. Response of Medium-term Interest Rates to Macroeconomic News	39
Figure 2-1. Ambiguity and other Measures of Risk/Uncertainty	117
Figure 2-2. Expected Ambiguity	118
Figure 2-3. Two-Way Sorted Average Stock Returns.....	119
Figure 2-4. Average Abnormal Returns during Periods of Low vs. High Expected Ambiguity	121
Figure 2-5. PEAD during Periods of Low vs. High Expected Ambiguity	122

INTRODUCTION

This dissertation consists of two essays having as central theme the role of uncertainty in financial markets. The first essay entitled ‘*Monetary Policy Uncertainty and the Market Reaction to Macroeconomic News*’ examines the impact of monetary policy uncertainty on the reaction of the equity, Treasury security, foreign exchange and crude oil markets, as well as medium-term interest rates, to U.S macroeconomic announcements. Economic news can impact the financial and commodity markets directly, through information about future economic conditions, and/or indirectly, through the expected reaction of monetary policy. This indirect effect is known in the literature as the ‘policy anticipation hypothesis’ (Cook and Korn, 1991). I posit that in times of high monetary policy uncertainty, macroeconomic indicators have a greater role in shaping investors’ expectations about future policy. This should have an impact on the markets’ response to macroeconomic announcements. By using intra-day futures data around the release time of macroeconomic indicators, the first essay provides evidence that higher monetary policy uncertainty weakens the reaction of the stock and crude oil markets to macroeconomic news, and strengthens the reaction of the bond and foreign exchange markets to such news. The findings indicate that during periods of elevated uncertainty about monetary policy, macroeconomic announcements impact the financial and crude oil markets to a large extent through expectations of future monetary policy.

The second essay entitled ‘*Ambiguity and the Cross-section of Stock Returns*’ investigates whether ambiguity is priced in the cross-section of stock returns. Ambiguity is the other dimension of uncertainty, in addition to risk (Knight, 1921). While risk refers to uncertainty regarding future potential outcomes, ambiguity refers to uncertainty about the *probabilities* of future potential outcomes. There is a substantial amount of work on how systematic risk affects the cross-section

of stock returns, but in contrast, less is known about the effect of ambiguity. This essay attempts to fill this gap.

I construct a measure of systematic ambiguity based on the theoretical framework of expected utility with uncertain probabilities proposed by Izhakian (2017). The ambiguity measure is independent of attitudes towards ambiguity, risk, and attitudes towards risk. The results of the second essay indicate that investors require a premium for bearing ambiguity, in addition to the premium they require for bearing risk. I provide evidence that when ambiguity is expected to increase, stocks of firms with high information asymmetry and firms which are difficult to value and/or arbitrage, such as firms that are smaller, riskier, and less profitable, non-dividend payers, and firms with higher levels of earnings management, underperform relative to their counterparts.

The second essay also examines the role of ambiguity in the relation between asset prices and firm-specific fundamentals. In particular, I examine how ambiguity affects the stock market reaction to earnings news. The results show that during ambiguous times, analysts tend to make less accurate forecasts, and so earnings surprises are larger in magnitude. This weakens the stock market marginal response to earnings news. In addition, I also provide evidence that ambiguity affects the stock market reaction to earnings news, beyond its impact on the magnitude of the earnings surprise. I attribute this finding to the impact of ambiguity on stock returns directly, via the rate used to discount future cash flows. This is motivated by the rational expectations equilibrium model of Veronesi (1999), according to which the discount rate can change with the level of uncertainty.

Essay 1: Monetary Policy Uncertainty and the Market Reaction to Macroeconomic Announcements¹

‘Like tipsy drinkers, financial markets are seeing the world upside down. Bad economic news is good news if it means more central bank action to support growth. Good news that means central banks may withdraw the punchbowl is bad news.’

The Financial Times, July 12, 2013

1.1. Introduction

Is monetary policy uncertainty important? According to the former Fed Chairman Alan Greenspan (2003), ‘uncertainty is not just an important feature of the monetary policy landscape; it is the defining characteristic of that landscape.’ Although Greenspan was referring to the uncertainty that policymakers face when they make decisions about monetary policy, the implementation of the policy itself can also generate uncertainty. In this context, clear communication of the central bank’s decisions and future intentions is important, particularly when the short-term interest rates are close to zero and conventional policy tools become ineffective.

Irrespective of how clear and efficient the communication of the central bank is, there is always some uncertainty surrounding the future path of monetary policy. That is, it can be difficult for a central bank to commit to its plans because unexpected macroeconomic developments may call for a different policy stance. In this respect, forward guidance must be understood to be conditional on incoming economic data (Siklos, 2017). In the United States, the Federal Reserve links monetary policy to economic conditions, which brings substantial uncertainty to the markets (e.g., Wu, 2014).

The aim of this paper is to investigate whether monetary policy uncertainty affects the reaction of the stock, bond, foreign exchange and crude oil markets to macroeconomic news.

¹ This essay is based on a paper coauthored with Alexander Kurov.

Economic news can impact the financial and commodity markets directly, through information about future economic conditions, and/or indirectly, through the expected reaction of monetary policy. This indirect effect is known in the literature as the ‘policy anticipation hypothesis’ (Cook and Korn, 1991). We posit that in times of high monetary policy uncertainty macroeconomic indicators have a greater role in shaping investors’ expectations about future policy. This should influence the response of the stock, bond, foreign exchange, and crude oil markets to macroeconomic news.

Our sample covers the period from January 26, 2012 to December 15, 2015 and captures significant variation in the degree of uncertainty about future monetary policy. Our sample period begins immediately after January 25, 2012, the date when the Federal Open Market Committee (FOMC) started providing its members’ assessments of the appropriate level of the federal funds target rate in the next few years and in the longer term.² The FOMC statement of September 13, 2012 mentioned plans to keep the federal funds rate near zero ‘at least through mid-2015.’ These communications reduced monetary policy uncertainty in the first part of our sample. The second part of our sample is characterized by considerable uncertainty about the rate of reduction in the amount of monetary stimulus. Speaking before Congress on May 22, 2013, Fed Chairman Ben Bernanke stated that the Fed would start reducing asset purchases under the quantitative easing (QE) program if warranted by economic data. On June 19, 2013, Bernanke suggested that, if the economy continued to improve, the bond-buying program could end in 2014. In what later became known as the ‘taper tantrum,’ stock and bond prices fell on the news. Although the actual reductions in asset purchases did not start until December 2013, after May 2013 monetary policy uncertainty increased dramatically, since market participants interpreted incoming economic data

² See for example Figure 2 in <http://www.federalreserve.gov/monetarypolicy/files/fomcprojtabl20120125.pdf>

in the light of their possible effect on the QE program and on the timing of the eventual increases of short-term interest rates.

We consider 33 U.S. macroeconomic announcements and find that monetary policy uncertainty can significantly affect the response of different asset classes to macroeconomic news. In the presence of higher monetary policy uncertainty, the reactions of the equity and crude oil futures markets to macroeconomic news weaken substantially, and the reactions of the Treasury and foreign exchange futures markets become much stronger. We also examine the effect of macroeconomic news on medium-term interest rates. The results are generally consistent with the results for Treasury securities, with monetary policy uncertainty having the biggest effect on the response to news of one- and two-year-ahead Eurodollar rates. Our results remain robust when controlling for other factors that could lead to time-varying response of these markets to news: changes in the macroeconomic conditions, changes in investor risk aversion, expected time until liftoff from the zero lower bound.

This paper makes several contributions to the literature. First, we contribute to research on the relation between asset prices and macroeconomic fundamentals by showing that monetary policy uncertainty is an important determinant of the response of different asset classes to macroeconomic news. Previous papers have argued that the response of financial markets to macroeconomic news depends on the state of the economy. For example, Blanchard (1981) and Orphanides (1992) argue that the same news can sometimes be good news and sometimes bad news for financial assets, depending on the state of the economy. Boyd, Hu and Jagannathan (2005) show that an announcement of rising unemployment is generally good news for stocks during economic expansions and bad news during economic contractions. An announcement of rising unemployment conveys information about lower interest rates (good news for stocks), and

declining future corporate earnings (bad news for stocks). Boyd, Hu and Jagannathan (2005) show that information about interest rates prevails during economic expansions and information about future corporate cash flows dominates during recessions. Similarly, Andersen, Bollerslev, Diebold and Vega (2007) find that good economic news is bad (good) for stocks during economic expansions (recessions).

We contribute to this literature by showing that the impact of economic news on a variety of markets can be affected by uncertainty about monetary policy. When monetary policy uncertainty is high, policy expectations become more sensitive to economic news, which affects the response of a variety of markets to such fundamental news. To our knowledge, we are the first to investigate whether monetary policy uncertainty affects the reaction of a variety of asset classes to macroeconomic announcements. Since our entire sample period is expansionary, our findings raise the possibility that the state dependence in the stock market response to economic news shown in prior studies has more to do with concerns about future monetary policy than with the stage of the business cycle.

Our second contribution is to show that the zero lower bound can become less binding on medium-term interest rates well before the actual rate liftoff from the zero bound. This complements the results of Swanson and Williams (2014) who show that the zero lower bound reached in December 2008 became a binding constraint on medium-term interest rates (one- and two-year Treasury yields) only in late 2011. Such findings are useful because they show that if the zero lower bound is not simultaneously a binding constraint on intermediate-term yields, the Fed can still stimulate the economy by influencing expectations of future short-term interest rates through guidance about future policy.

Finally, we show that uncertainty in central bank communication has important side effects. Absent clear statements from the Fed, market participants update their expectations of monetary policy based on incoming macroeconomic data. For instance, good news about the economy – such as stronger than expected GDP growth – increases the likelihood that the Fed will tighten monetary policy sooner rather than later. In times of high monetary policy uncertainty, macroeconomic announcements impact the financial and crude oil markets to a large extent through the expected reaction of monetary policy. This strengthens the reaction of the bond market and the U.S. dollar exchange rate to macroeconomic news and weakens the reaction of the stock and crude oil markets to such news. Therefore, our findings contribute to the literature on central bank communication with the financial markets.³

1.2. Hypothesis

Many theoretical models describe how information is impounded into asset prices in different economic environments. The intertemporal rational expectations equilibrium model of Veronesi (1999) shows that uncertainty about the state of the economy causes stock market investors to overreact to bad news in good economic times and underreact to good news in bad economic times. For example, when investors believe that the economy is in the good state and bad news arrives, investors become more uncertain about the state of the economy. The negative impact of the news on prices is strengthened by a rising discount rate generated by the increased investor uncertainty. The general equilibrium model of David and Veronesi (2013) predicts that implications of inflation news for future economic growth depend on the investors' beliefs about the current inflation regime. This model explains the time-varying comovement of stocks and Treasury bonds.

³ For a survey of the literature on central bank communication, see Blinder, Ehrmann, Fratzscher, De Haan and Jansen (2008).

Our paper investigates empirically how uncertainty about future monetary policy affects the reaction of the stock, bond, foreign exchange, and crude oil markets to macroeconomic news. Economic news can have direct and/or indirect effects on financial and commodity markets. The direct effect is driven by information about future economic conditions contained in a given announcement. The indirect effect of macroeconomic news on asset prices occurs through expectations about future monetary policy. For example, Cook and Korn (1991) explain that the interest rate reaction to employment news is affected by the impact of the news on the market expectations of future monetary policy actions. Economic news affects expectations of future monetary policy (Lapp and Pierce, 2012). These expectations can have a significant effect on asset prices (Faust, Rogers, Wang, and Wright, 2007). Table 1-1 summarizes the expected signs of direct and indirect effects of good and bad economic news for the four asset markets we examine.

The Fed conditions monetary policy on incoming economic data. Good economic news increases the likelihood of QE tapering and accelerates the pace of policy firming, whereas bad news signals that the policy is likely to remain more accommodative. A reduction in Fed's bond purchases increases long-term interest rates. It also advances the expected date of policy rate increases (e.g., Blinder, 2014; Wu, 2014), leading to an immediate increase in interest rates, particularly for intermediate maturities, and to a decrease in bond prices. Therefore, good (bad) economic news will have a negative (positive) indirect effect on returns of Treasury securities. The bond market should have a stronger reaction to macroeconomic news in the presence of high uncertainty about monetary policy because the news has a larger effect on market participants' expectations regarding the future monetary policy, including the expected amounts of bond purchases and the timing of the possible changes in the target rate.

Macroeconomic announcements reveal three types of information relevant for valuing stocks: information about future interest rates, the equity risk premium, and future corporate earnings and dividends (Boyd, Hu and Jagannathan, 2005). Good news signals a healthy economy and has a direct positive effect on the stock market through the change in expectations of corporate earnings. It also has an indirect effect through the increase in interest rates and the equity premium due to the expected tightening reaction of monetary policy (Bernanke and Kuttner, 2005).⁴ In times of high policy uncertainty, economic news has a greater effect on expectations of future monetary policy. Thus, we expect a stronger sensitivity of interest rates and the risk premium to such news in the presence of high monetary policy uncertainty. Overall, due to the indirect effect, the response of stocks to economic news should weaken in times of high monetary policy uncertainty.

Macroeconomic announcements can affect the value of the U.S. dollar as well. Good economic news increases the likelihood of tighter monetary policy, which could signal a possible decrease in the money supply and higher expected interest rates in the future, both having a positive (indirect) effect on the U.S. dollar. In this regard, Almeida, Goodhart, and Payne (1998) find evidence of such an indirect effect, showing that the response of the DEM/USD exchange rate to macroeconomic announcements appears to be driven by the likely reaction of the monetary authorities.⁵ Neely (2015) shows that unconventional monetary policy has a substantial effect on the value of the U.S. dollar at the zero lower bound. In times of high monetary policy uncertainty, macroeconomic announcements have a greater role in shaping expectations about the future path

⁴ Bernanke and Kuttner (2005) find that the impact of monetary policy on equity prices is driven primarily by its effect on the risk premium.

⁵ Economic news may also affect the exchange rates without mediation of monetary policy. However, as Almeida, Goodhart and Payne (1998) note, the direction of this effect is uncertain because it depends on the particular theoretical model used.

of monetary policy. Thus, we would expect a stronger reaction of the U.S. dollar exchange rate to macroeconomic news in the presence of high monetary policy uncertainty.

We also investigate whether the sensitivity of crude oil futures prices to macroeconomic news changes in the presence of high monetary policy uncertainty. Energy prices are driven by supply and demand, and supply and demand shocks for energy are often induced by changes in macroeconomic activity (Kilian, 2009). If energy futures prices respond to changes in expectations of economic activity, these prices should react positively to good economic news (direct effect). Good economic news also increases the likelihood of the Fed tightening its policy sooner rather than later. In this respect, Basistha and Kurov (2015) and Rosa (2014) show that oil prices decline in response to unexpected tightening of monetary policy.⁶ When future monetary policy is conditioned on incoming economic data and policy uncertainty is high, economic news exerts a larger influence on expectations of future policy. This is likely to produce an indirect effect on energy futures prices that counteracts the effect of information about demand for energy contained in macroeconomic news. Therefore, we expect a weaker reaction of the crude oil market to macro news in times of high monetary policy uncertainty. We test the following hypothesis:

Hypothesis: In the presence of higher monetary policy uncertainty, the reactions of stocks and crude oil to macroeconomic news become weaker and the reactions of Treasury securities and the dollar exchange rate become stronger.

⁶ Barsky and Killian (2002, 2004) argue that monetary policy affects commodity prices through inflation expectations and economic growth. Frankel (2007) summarizes three channels through which monetary policy can affect commodity prices: (i) the inventory channel – low interest rates can increase the demand for commodities and reduce the opportunity cost of carrying inventories; (ii) the supply channel – low interest rates can decrease the supply for commodities and provide incentives not to extract the commodity today; and (iii) the financial channel – lower interest rates reduce the carrying cost of speculative positions, potentially leading to higher commodity prices.

1.3. Data

1.3.1. Macroeconomic Announcements

We examine the market reaction to 33 scheduled U.S. macroeconomic announcements. In addition to 23 macroeconomic announcements examined in Andersen, Bollerslev, Diebold and Vega (2003), we include ten other announcements that are frequently covered in the financial media: Automatic Data Processing (ADP) Employment, Building Permits, Existing Home Sales, the Institute for Supply Management (ISM) Non-Manufacturing Index, Pending Home Sales, Preliminary and Final University of Michigan (UM) Consumer Sentiment Index, Empire State Manufacturing Survey, Philadelphia Fed Business Outlook and Chicago Purchasing Manager Index. A brief description of the macroeconomic announcements considered in our study is presented in Table 1-2. Similarly to Andersen, Bollerslev, Diebold and Vega (2003), we group the indicators into seven categories: real activity, consumption, investment, government purchases, net exports, prices, and forward looking.

In line with the theory of market efficiency, the market should only react to the unanticipated component of the macroeconomic news releases. Therefore, we focus on the announcement surprise, computed as the difference between the actual and the expected value of the economic statistic. Because different economic variables are measured in different units, we follow Balduzzi, Elton, and Green (2001) and standardize the announcement surprises as follows:

$$S_{mt} = \frac{A_{mt} - E_{t-\tau}(A_{mt})}{\hat{\sigma}_m}, \quad (1)$$

where A_{mt} is the announced value of indicator m , $E_{t-\tau}(A_{mt})$ is the expected value of indicator m based on the Bloomberg median forecast, and $\hat{\sigma}_m$ is the sample standard deviation of $A_{mt} - E_{t-\tau}(A_{mt})$. Standardizing the surprises allows comparing the market response to different announcements.

1.3.2. Futures Returns

We use five-minute futures data for the E-mini S&P 500, 10-year Treasury, the U.S. Dollar Index and WTI crude oil. We also use similar data for 5-year Treasury futures and for Eurodollar futures with 4-5, 8-9 and 12-13 quarters to expiration. The futures data are obtained from Genesis Financial Technologies. We use the nearby futures contracts for the S&P 500, Treasury, U.S. Dollar Index and crude oil. The nearby contract becomes relatively illiquid in its last few days of trading. Therefore, in the last three days of trading of the nearby contract we substitute prices of the next closest contract. Most of the U.S. macroeconomic announcements are made at 8:30 a.m. ET, when the stock market is closed but futures markets are open. Therefore, using futures market data allows examining the stock market reaction to macroeconomic news. For studying the impact of macroeconomic announcements on the foreign exchange market, we use the U.S. Dollar Index futures. This index is the world's most widely recognized currency index, computed as a geometric average of six exchange rates (the Euro, the Japanese Yen, the British Pound, the Canadian Dollar, the Swedish Krona and the Swiss Franc) against the U.S. dollar.

We use continuously compounded (i.e., log) returns from five minutes before to five minutes after a macroeconomic news release.^{7,8} Using a narrow intraday window around the announcement allows estimating market sensitivity to macroeconomic news more precisely than, for example, using daily data.

⁷ Existing studies (e.g., Ederington and Lee, 1995; Balduzzi, Elton and Green, 2001) show that the price adjustment to scheduled macroeconomic news is very rapid.

⁸ As discussed in the Robustness Checks section, the results with wider event windows are very similar.

1.3.3. Sample Selection and Monetary Policy Uncertainty

Our sample period starts on January 26, 2012, the day after the FOMC started providing its members' assessments of the appropriate level of the fed funds target rate for several years ahead and in the long run. This reduced monetary policy uncertainty, increased transparency, and improved the central bank communication with the financial markets. Our sample period ends on December 15, 2015, the day before the FOMC initiated liftoff from the zero lower bound.

To examine how monetary policy uncertainty affects the market reaction to economic news, we need a proxy for monetary policy uncertainty. Realized volatility of interest rate futures has been used in the literature as a measure of monetary policy uncertainty (Chang and Feunou, 2014). Gürkaynak, Sack and Swanson (2007) provide evidence that Eurodollar futures contracts reflect market expectations about future monetary policy. Kurov and Gu (2016) use the rates of Eurodollar futures with 8-9 quarters to expiration to measure changes in expectations of monetary policy at the zero lower bound. Therefore, we use realized volatility of Eurodollar futures rates with 8-9 quarters to expiration to construct a measure of monetary policy uncertainty.

Panel A of Figure 1-1 shows the daily realized volatility of the changes in the Eurodollar futures rate with 8-9 quarters to expiration, computed from five-minute futures prices. The realized volatility varies considerably across our sample period. A dramatic increase in volatility occurred on May 22, 2013, the day when the Fed Chairman Ben Bernanke testified in front of the Joint Economic Committee of Congress that the Fed could begin reducing its bond purchases if economic data supported it. This increased the concerns about future monetary policy. The Bai-Perron (2003) multiple breakpoint test identifies the presence of a structural break in realized volatility on May 28, 2013, a few days after Bernanke's testimony.⁹

⁹ The Quandt-Andrews breakpoint test for one or more unknown structural breakpoints identifies a shift in the mean of the realized volatility on May 22, 2013, which coincides with the day of Bernanke's testimony.

Consistent with Wang and Yang (2009), we find that realized volatility is a long memory process, as indicated by its extremely slowly decaying autocorrelations. To account for this characteristic when constructing the monetary policy uncertainty proxy, we use the realized volatility model proposed by Corsi (2009). Specifically, we measure monetary policy uncertainty as the fitted values from the heterogeneous autoregressive realized volatility (HAR-RV) model shown in equation (2) below. This model includes past volatilities aggregated over different time horizons as explanatory variables. We denote rv_t^D as the realized volatility on day t . The average realized volatility in the past h days (including day t) is $rv_t^h = \frac{1}{h} \sum_{s=t-h+1}^t rv_s^D$. The average weekly ($h = 5$), monthly ($h = 22$), and quarterly ($h = 66$) volatilities are denoted as rv_t^W, rv_t^M, rv_t^Q , respectively.

$$rv_t^D = \omega + \sum_{k=D}^Q \beta^k rv_{t-k}^k + \xi_t, \quad (2)$$

where ξ_t is an error term; ω and β^k are parameters; and $k = D$ (day), W (week), M (month), and Q (quarter).

This model is motivated by the heterogeneity of market participants, which induces the dependence of current daily volatility on previous daily, weekly, monthly, and quarterly volatilities. The combination of a small number of realized volatilities with different aggregation frequencies has been shown to provide a good approximation to long-memory dependencies found in the data (Corsi, 2009; Andersen, Bollerslev and Diebold, 2007; Wang and Yang, 2009). Using a volatility forecasting model to measure uncertainty is conceptually similar to the approach of Bekaert, Hoerova, and Lo Duca (2013), who use a forecast of realized variance to measure stock market uncertainty.

Panel B of Figure 1-1 plots the monetary policy uncertainty variable. The uncertainty variable captures important events and policy changes in the US monetary policy. Ben Bernanke's

testimony of May 22, 2013 regarding the possibility of tapering the QE program brought significant uncertainty related to the start of the tapering process and to the timing of an eventual liftoff from the zero lower bound. Bernanke's discussion on June 19, 2013 of the roadmap for the tapering process increased the uncertainty on that day. The FOMC statement of September 18, 2013 about delaying the QE taper also increased uncertainty about the future policy. A higher than average level of uncertainty is also observed on December 18, 2013, the day when the tapering of the QE program started. Furthermore, statements of James Bullard, President of the Federal Reserve Bank of St. Louis, made on October 16, 2014 regarding the possibility of extending the bond buying program increased monetary policy uncertainty. The FOMC decision on October 29, 2014 to end the QE program temporarily decreased monetary policy uncertainty. However, the uncertainty increased later on, likely reflecting concerns about the timing of the liftoff from the zero lower bound.

The two main factors influencing monetary policy uncertainty in our sample period are the timing of the beginning of the QE tapering and the timing of the first increase in the fed funds target rate. To test whether our proxy for monetary policy uncertainty captures uncertainty about these policy changes, we estimate the following regression:

$$MPU_t = \omega + \gamma_1 D_{Taper,t} + \gamma_2 TimeToLiftoff_t + \xi_t, \quad (3)$$

where D_{Taper} is a dummy variable with values of 1 from May 22, 2013 (Bernanke's speech) until the actual start of the tapering process, and 0 otherwise. The variable $TimeToLiftoff_t$ captures the median anticipated number of quarters until the liftoff from the zero lower bound, according to the primary dealer surveys conducted by the Federal Reserve Bank of New York.¹⁰ The results reported in Table 1-3 show that Bernanke's tapering testimony increased monetary policy

¹⁰ The survey results are available at https://www.newyorkfed.org/markets/primarydealer_survey_questions.html.

uncertainty. The negative coefficient estimate of the liftoff variable indicates that monetary policy uncertainty increased as the expected rate liftoff drew closer.

1.4. Empirical Results

1.4.1. Baseline Results

We begin by looking at the average effect of macroeconomic announcements on the returns in stock index, Treasury security, foreign exchange and crude oil markets. To isolate the impact of the macroeconomic news on the markets, our analysis centers on a tight intraday window surrounding the macroeconomic releases. We estimate the following regression:

$$R_t = \alpha + \sum_{m=1}^M \beta_m S_{mt} + \varepsilon_t, \quad (4)$$

where R_t is the continuously compounded futures return from five minutes before to five minutes after a macroeconomic news release and S_{mt} is the standardized surprise corresponding to announcement m . Only intervals containing at least one of the considered announcements are included in estimation. In intervals for which there is no surprise for a given announcement, we set the corresponding surprise to zero. Several announcements are often released at the same time. This model specification accounts for such simultaneous releases. We estimate the regression in (4) for all 33 announcements considered in our analysis, using the part of our sample period before May 22, 2013. This corresponds to a period of relatively low monetary policy uncertainty, as indicated by the Bai-Perron (2003) breakpoint test.

The results are presented in Table 1-4. As expected, the estimated response coefficients for the stock and bond markets generally have opposite signs. For example, the estimated response coefficient for GDP news is positive for stocks and negative for bonds. Higher than expected GDP growth signals higher corporate earnings, which is good news for stocks. On the other hand, if the

GDP growth exceeds expectations, the Fed is more likely to tighten monetary policy. As a consequence, yields increase and bond prices drop. The coefficient estimate for the GDP news is positive for crude oil and the U.S. Dollar Index futures. Better than expected output of the U.S. economy increases demand for energy, leading to higher oil prices. Since, as discussed above, good news about U.S. GDP leads to higher interest rates, the U.S. dollar appreciates in response.

Similarly to GDP news, almost all announcements in the ‘real activity’ category aside from the unemployment rate and initial unemployment claims have a positive impact on the stock market, crude oil market and the dollar exchange rate and a negative impact on the bond market. Judging by the number of significant response estimates, the effect seems to be the strongest in the bond market, followed by the stock market and then by the crude oil and the foreign exchange markets. Only nonfarm employment, ADP employment and GDP releases have a statistically significant effect on all four markets.

Next, most of the announcements categorized under the GDP components (consumption, investment, government purchases, and net exports) have positive effects on the stock and crude oil markets, and negative effects on the bond market. The most significant impacts of these releases are on the stock and crude oil markets. For example, news about durable goods orders has a positive and significant effect on the stock market, since the increase in durable goods purchases likely signals higher corporate profits. The impact of a jump in orders is also positive and significant for the crude oil market, but is negative for the bond market. Unsurprisingly, unexpected increases in the consumer price index have a significant negative effect on the returns of the Treasury note futures.

Finally, most of the forward-looking macroeconomic indicators have a positive and significant effect on the equity market and a negative and significant effect on the bond market.

For example, the Institute for Supply Management (ISM) Manufacturing Survey is the first piece of news about the U.S. economy released every month. According to Baumohl (2013), ISM's Purchasing Managers Index (PMI) is the most influential statistic released by the private sector. If the economy is in an expansionary phase (and our sample period is expansionary), an increase in the PMI can signal rising inflationary pressures, leading to higher interest rates and hence negative bond returns. An increase in the PMI would also lead to a positive reaction from the equity and crude oil markets and to an appreciation of the U.S. dollar.

Our significant results for the crude oil market are in contrast to the findings of Kilian and Vega (2011), who show that macroeconomic announcements have no significant effect on crude oil prices. For example, we find that Initial Unemployment Claims, Nonfarm Employment, Unemployment Rate, Personal Income, Consumer Credit, Durable Goods Orders, PPI, ISM's Manufacturing PMI, and University of Michigan Confidence have a significant impact on crude oil futures price, whereas in the Kilian and Vega (2011) analysis these announcements do not move crude oil prices. This difference in results may be explained by our use of intraday data and by a more recent sample period used in our analysis.¹¹

Overall, out of the 33 announcements that we analyze, 20 have a statistically significant effect on the stock market and 22 significantly affect the Treasury security market. 15 of these announcements significantly influence the crude oil market, and only 10 significantly impact the U.S. dollar exchange rate. We estimate the regression in equation (4) simultaneously for all markets and perform a joint test for significance of the response coefficients for a given announcement. The p -values of this test are shown in the last column of Table 1-4. In the analysis

¹¹ Chatrath, Miao, and Ramchander (2012) find a significant response of crude oil prices to several macroeconomic announcements during the financial crisis of 2007-2009. Our results show that this responsiveness is not limited to the crisis period.

that follows, we consider only the 22 macroeconomic announcements that have a significant effect on the markets (at the 10 percent significance level) based on the joint test.

1.4.2. Effect of Policy Uncertainty on the Market Response to Macroeconomic Announcements

Next, we investigate whether monetary policy uncertainty affects the market reaction to macroeconomic news. In this part of the analysis, we focus on the 22 macroeconomic announcements for which the joint test mentioned above is significant at least at the 10 percent level. For each of these announcements, we estimate the following regression simultaneously for the E-mini S&P 500, 10-year Treasury note, the U.S. Dollar Index and the crude oil futures over the period from January 26, 2012 to December 15, 2015:

$$R_t = \alpha + b MPU_t + \sum_{m=1}^{22} \beta_m S_{mt} + \sum_{m=1}^{22} \gamma_m S_{mt} MPU_t + \varepsilon_t, \quad (5)$$

where R_t and S_{mt} are defined above and MPU_t is the monetary policy uncertainty variable constructed as described in section 1.3.3. The γ_m coefficient captures the change in the market response to announcement m in the presence of higher monetary policy uncertainty.

The estimation results are reported in Table 1-5. For the stock and the crude oil markets, almost all significant estimates of γ_m (except those for Empire Manufacturing for the stock market and Philadelphia Fed Business Outlook for the crude oil market) have an opposite sign compared to the estimated β_m reported in Table 1-4. This indicates that the effect of macroeconomic news on stocks and the crude oil prices becomes weaker in times of higher monetary policy uncertainty. The change in the stock market response is statistically significant for nine announcements, and the change in the crude oil market response is significant for eight announcements. The results are generally consistent with our hypothesis that higher monetary policy uncertainty reduces the impact of macroeconomic announcements on equity and crude oil futures returns.

The reaction of the Treasury security market to macroeconomic news grows stronger in the presence of higher monetary policy uncertainty. For the bond market, almost all of the significant estimates of γ_m (except that for the Unemployment rate) have the same sign as the corresponding estimates of β_m reported in Table 1-4. It is noteworthy that the response of the Treasury market to both nonfarm employment and ADP employment announcements becomes significantly stronger in the presence of high monetary policy uncertainty. The Fed made the withdrawal of monetary stimulus conditional on continuing improvement in the labor market. Because news about the labor market affects the likelihood of QE tapering and the expected timing of rate increases, it has a stronger effect on the interest rates when the policy uncertainty is higher. Overall, the sensitivity of bond prices to eight out of 22 macroeconomic announcements used in the estimation significantly increases in the presence of higher policy uncertainty. The foreign exchange market behaves similarly to the bond market in terms of the change in its response to macroeconomic news in the presence of higher monetary policy uncertainty. 10 of the 22 macroeconomic releases included in this analysis have a stronger impact on the foreign exchange market in the presence of higher monetary policy uncertainty.

Table 1-5 also shows the p -values of the Wald test for the joint significance of the γ coefficients for a given market (with the null hypothesis of no significant $\gamma_m, m = \overline{1, 22}$). The p -values are extremely low, indicating that sensitivity of all four markets to macroeconomic news is significantly affected by increased policy uncertainty. Overall, the results are supportive of our hypothesis regarding change in the market reaction to macroeconomic news in the presence of higher monetary policy uncertainty.

Uncertainty about monetary policy can be expected to influence the response of interest rates to macroeconomic news. We have seen that higher policy uncertainty is associated with a

stronger reaction of long-term interest rates. Do medium-term interest rates react in a similar way? We use Eurodollar futures with 4-5, 8-9, and 12-13 quarters to expiration and the 5-year Treasury note futures and estimate the regression in equation (5). The only difference here is that the dependent variable is the change in Eurodollar futures rates (expressed in basis points) or the change in the yield of 5-year Treasuries.¹²

The regression results reported in Table 1-6 provide evidence of a stronger reaction of the medium-term yields to macroeconomic news in times of higher monetary policy uncertainty. Almost all of the γ_m estimates for the Eurodollar futures rates with 12 quarters to maturity are significant for the same announcements that have a significant effect on the 10-year Treasury futures market, although the coefficient signs are opposite because here we use rate changes rather than returns. Overall, these results are consistent with our results for the Treasury futures market shown in Table 1-5. The low p -values of the joint test of γ_m estimates show that the sensitivity of all four rate maturities to macroeconomic news is significantly affected by monetary policy uncertainty.

1.4.3. Time-Varying Response to Macroeconomic News

Next, we examine the time-varying sensitivity of the stock, bond, foreign exchange and crude oil markets to macroeconomic news. One way of doing this would be to run the regression in equation (4) over rolling windows. However, this approach suffers from small-sample problems because most of the macroeconomic announcements that we consider are released monthly and even a one-year rolling window would include only 12 releases of a given type. To overcome this problem, we follow the procedure proposed by Swanson and Williams (2014). The procedure assumes that

¹² The 5-year Treasury yield changes are computed by dividing the intraday return on the 5-year Treasury futures by the duration of the underlying bond.

the relative magnitudes of the response coefficients in equation (4) are constant over time, and only the overall magnitude of these coefficients varies. This assumption allows us to ‘pool’ the surprises for all announcements in a single estimation.

We begin by running the regression in equation (4) simultaneously for all markets for the period before May 22, 2013 and saving the estimated coefficients $\hat{\beta}_m$.¹³ We then use these estimates to compute normalized announcement surprises as $\hat{S}_{mt} = \hat{\beta}_m S_{mt}$ for the 22 significant macroeconomic announcements. Sometimes several of these announcements occur at the same time. Since we want to collapse all announcement surprises into a single variable, we sum up the normalized surprises for announcements that occurred at the same time. We then generalize the regression in (4) to the following specification:

$$R_t = a + b\widehat{SS}_t + u_t, \quad (6)$$

where R_t is the continuously compounded futures return from five minutes before to five minutes after a macroeconomic news release and $\widehat{SS}_t = \sum_{m=1}^{22} \hat{\beta}_m S_{mt}$ is the sum of the normalized surprises for announcements that occurred in that interval. This specification reduces the small-sample problem in the rolling regression because we no longer need to estimate a separate response coefficient for each announcement type. Due to the transformation of announcement surprises discussed above, the b coefficient in equation (6) has an average value of unity from the beginning of the sample period to May 22, 2013. Changes in the b estimate after May 22, 2013 show whether the market reaction to news changed in a period of increased monetary policy uncertainty.

We estimate the regression in (6) using a rolling window that includes 128 observations, roughly corresponding to a six-month period. We then plot the estimated coefficients b for the

¹³ The period preceding Bernanke’s tapering testimony is characterized by relatively low monetary policy uncertainty, as indicated by the Bai-Perron (2003) multiple breakpoint test.

stock, bond, foreign exchange, and crude oil markets in Figure 1-2. The time-varying responses of the stock and crude oil markets to macroeconomic news seem to be similar. In particular, the estimated b coefficients for both the stock and crude oil market show a marked decline after May 22, 2013. The weaker response of the stock and crude oil markets to macroeconomic news following May 2013 supports our hypothesis and is consistent with our previous findings. The responses of the bond and foreign exchange markets also follow a similar pattern across time. For these two markets, the estimated coefficient b increases during the period characterized by greater monetary policy uncertainty that begins after May 22, 2013. Hence, consistent with the regression results in Table 1-5, the bond and the foreign exchange markets generally react stronger to macroeconomic news in the presence of higher policy uncertainty.

It is noteworthy that the strongest reaction of the bond and foreign exchange markets to macroeconomic news occurred between September and December 2013, and between October and November 2015. During these periods, the reaction of the stock and crude oil markets to macroeconomic news was the weakest. Monetary policy uncertainty was elevated during these periods. Uncertainty increased in September 2013, when the Fed surprised the markets by delaying the beginning of QE tapering until December 2013. Similarly, monetary policy uncertainty increased in October 2015 after the Fed surprised the markets by leaving the interest rates unchanged until December of the same year.

Figure 1-3 plots the estimated b coefficients for the Eurodollar futures rates and the 5-year Treasury yield. All four panels illustrate a similar pattern to the one found in Figure 1-2 for the bond market. That is, the estimated coefficient b increases relative to the period of low monetary policy uncertainty (i.e., before May 22, 2013). This suggests a stronger reaction of the medium-term interest rates to macroeconomic news in the presence of higher monetary policy uncertainty.

To conduct a statistical test of the influence of monetary policy uncertainty on the market response to news, we estimate the following regression:

$$R_t = a + b_{MPU}MPU_t + b_S\widehat{SS}_t + c_{MPU}\widehat{SS}_tMPU_t + u_t. \quad (7)$$

The coefficient c_{MPU} captures the impact of greater monetary policy uncertainty on the market response to the normalized surprises.

Panel A of Table 1-7 shows that the average responses of the stock and crude oil markets to macroeconomic news decrease significantly in the presence of higher monetary policy uncertainty. The responses of the bond and the foreign exchange markets to macroeconomic news strengthen in times of higher monetary policy uncertainty. Similarly, the responses of the one-, two-, and three-year-ahead Eurodollar rates, and the five-year Treasury yield to macroeconomic news also strengthen significantly in the presence of higher monetary policy uncertainty. The responses of the one- and two-year-ahead Eurodollar rates strengthen the most. This finding is consistent with the changes in the two-year rate being a good indicator of changes in expectations of future monetary policy (e.g., Hanson and Stein, 2015). Our results indicate that in times of higher monetary policy uncertainty expectations of future policy become more sensitive to macroeconomic news. Overall, the estimates in Table 1-7 confirm that the effect of monetary policy uncertainty on the market reaction to macroeconomic news is economically important for a variety of asset classes.

Previous literature shows that other factors could lead to time-varying response of markets to macroeconomic news. One of these factors may be investors' degree of risk aversion.¹⁴ Risk aversion seems to be closely related to monetary policy: lax monetary policy decreases risk aversion (Bekaert, Hoerova, and Lo Duca, 2013; Drechsler, Savov, and Schnabl, 2018), while tight

¹⁴ For example, the model of Veronesi (1999) decomposes the stock price sensitivity to news into an uncertainty component and a risk-aversion component stemming from the investors' degree of risk aversion.

policy increases risk aversion (Inekwe, 2016).¹⁵ Furthermore, Husted, Rogers, and Sun (2016) argue that time-varying risk aversion could potentially contaminate measures of monetary policy uncertainty. Therefore, we need to control for changes in investor risk aversion. We follow Bekaert, Hoerova, and Lo Duca (2013) and construct a proxy for risk aversion by decomposing the VIX into a risk aversion component and expected stock market volatility.¹⁶ Our monetary policy uncertainty measure is positively and significantly correlated with the VIX (with correlation coefficient of 0.08) and with the risk aversion component (with correlation coefficient of 0.09). We re-run the regression in equation (7) while controlling for the VIX and the VIX components, and report our results in Panels B and C of Table 1-7. Our results remain robust when controlling for the VIX or for the VIX components. Monetary policy uncertainty weakens the reaction of the stock and crude oil markets to macroeconomic news, and strengthens the reaction of the bond and the foreign exchange markets to such fundamental news. In addition, risk aversion seems to strengthen the response of the stock and the crude oil markets to macroeconomic announcements.

Another potential concern about our results is that our regression models do not account for business cycle variation. Although our entire sample period is expansionary, the real business conditions change over time. To control for changing real business conditions, we use the daily Aruoba-Diebold-Scotti (ADS) business conditions index, introduced by Aruoba, Diebold and Scotti (2009). This index is based on in real-time values of several economic indicators, including initial jobless claims, monthly payroll employment, industrial production, personal income less transfer payments, manufacturing and trade sales, and quarterly real GDP. Positive values of the index indicate better-than-average economic conditions, and negative values indicate worse-than-

¹⁵ In contrast, Nave and Ruiz (2015) find that a lax monetary policy increases the short-run risk aversion if one accounts for the simultaneity between domestic monetary policy and the stock market behavior.

¹⁶ For details of this decomposition of the VIX, see Bekaert, Hoerova, and Lo Duca (2013).

average conditions. We run the regression in (7) with an additional interaction term between $\widehat{SS}_t$ and the (lagged) ADS index, and report the results in Panel A of Table 1-8. The effect of monetary policy uncertainty on the response of stock, bond, foreign exchange and crude oil markets to macroeconomic news remains significant after controlling for changes in the real business conditions. The estimated coefficient of the additional interaction term is significant for the bond and the foreign exchange markets only.

An additional potential concern is that our results may be influenced by the market expectations regarding the timing of the liftoff from the zero lower bound. We estimate the regression in equation (7) with an additional interaction term between $\widehat{SS}_t$ and the median expected number of quarters until the first target rate increase, based on the primary dealer surveys. The results in Panel B of Table 1-8 are consistent with our previous findings. Monetary policy uncertainty weakens the reaction of the stock and the crude oil markets to macroeconomic news, and strengthens the reaction of the bond market to such news. These results may be affected by multicollinearity, since the expected time until liftoff is strongly correlated with monetary policy uncertainty (as seen in Table 1-3). However, the estimated coefficients of the policy uncertainty interaction term are significant at the 1% significance level for three of the four markets. For the foreign exchange market, the shorter the expected time until liftoff (and therefore the greater the corresponding policy uncertainty), the stronger the market reaction to macroeconomic news.

On December 12, 2012, the FOMC statements omitted the ‘mid-2015’ forward guidance and started including specific targets for the unemployment rate that would have to be met for the Fed to consider raising the target rate. One can argue that the reaction of markets to macroeconomic announcements can potentially be affected by this ‘data driven’ monetary policy. To account for the effect of the data driven policy, we run the regression in (7) with an additional

interaction term between $\widehat{SS}_t$ and a data driven policy dummy, taking values of 1 after December 12, 2012, for the periods when unemployment rate is above the 6.5% threshold mentioned in the FOMC statements, and 0 otherwise. The results, reported in Panel C of Table 1-8, are generally consistent with our previous findings. In addition, the data driven monetary policy seems to strengthen the reaction of the bond and foreign exchange markets to macroeconomic news.

In order to test that our results are not driven by the economic uncertainty in general, but rather by the uncertainty about monetary policy, we estimate the regression in equation (7) with an additional interaction term between $\widehat{SS}_t$ and the economic policy uncertainty index constructed by Baker, Bloom, and Davis (2016). The estimates reported in Panel D of Table 1-8 suggest that our main results remain robust after controlling for the economic policy uncertainty.

We also investigate whether our main results still hold when controlling for the VIX or for the VIX components, in addition to the other controls used in Table 1-8 regressions. The results are reported in Tables A-1 and A-2 in the Appendix. The coefficient estimates of the MPU interaction term are similar to those in Table 1-8.

1.4.4. Robustness Checks

It is possible that other economic news may affect the results of the event study regressions. Using a narrow intraday window around the announcement helps to exclude most such events. As a robustness check, we re-estimate our regressions using wider event windows, (-10 minutes, +10 minutes) and (-15 minutes, 15 minutes) around each macroeconomic release.¹⁷ The results are very similar to those reported in Tables 1-4, 1-5 and 1-6. The results are also similar when the

¹⁷ We include a longer pre-announcement interval in the event window to capture the pre-announcement price drift found by Kurov, Sancetta, Strasser and Wolfe (2016) for several U.S. macroeconomic announcements.

regressions are estimated for different event windows starting five minutes before the announcement.

We investigate whether our main results remain robust when using an alternative proxy for monetary policy uncertainty. For this purpose, we measure uncertainty as a moving average of the daily realized volatility of Eurodollar futures with 8-9 quarters to expiration. We compute the moving average of the realized volatility over the last 21 trading days, excluding the current day. Using the moving average of realized volatility as a proxy for uncertainty reduces the noise in the realized volatility. We re-estimate the regression in equation (7) using this proxy for uncertainty, while also controlling for VIX or VIX components. The results summarized in Table A-9 in the Appendix indicate that our findings remain qualitatively similar.

A possible concern with this proxy for monetary policy uncertainty is that the length of the window used for the moving average is selected arbitrarily. To address this issue, we considered reasonable variation in the length of the window used for computing the moving average of realized volatility. Untabulated results indicate that our findings remain robust when monetary policy uncertainty is measured as the moving average of the daily realized volatility over the last 42, 10 and five trading days.

Additional robustness checks, including a test for asymmetry in the market reaction to good and bad macroeconomic news, a test of autocorrelation in the announcement surprises, and a test of nonlinearity in the market response to news, can be found in the Appendix.¹⁸ Overall, the robustness checks support the conclusion that the responses of the bond and foreign exchange markets to macroeconomic news strengthen in the presence of high monetary policy uncertainty, and the responses of stock and crude oil markets become weaker.

¹⁸ Other robustness checks are also discussed in the Appendix.

1.5. Conclusion

This study investigates whether monetary policy uncertainty affects the reaction of the stock, bond, foreign exchange and crude oil markets to macroeconomic announcements. We find that uncertainty about future monetary policy weakens the reaction of the equity and crude oil markets to macroeconomic news and strengthens the reactions of the medium- and long-term interest rates and of the U.S. dollar exchange rate to such fundamental news.

Understanding the role of monetary policy uncertainty in the relation between asset prices and macroeconomic surprises is important for traders. It helps them anticipate the market reaction to the news if they attempt to forecast the announcement surprises (Kurov, Sancetta, Strasser and Wolfe, 2016) or execute high-frequency trading strategies after the announcement (Scholtus, van Dijk, and Frijns, 2014). Our results suggest that the responses of stock and bond prices to economic developments in period of stable policy expectations may be quite different from those in times of high monetary policy uncertainty. This finding may be useful to investors using tactical asset allocation techniques.

Beechey and Wright (2009) show that news about real activity affects the term structure of interest rates primarily by moving expectations of future real short-term rates. Our results suggest that expectations of future rates become particularly sensitive to economic news and therefore less stable in periods of high monetary policy uncertainty. This instability of rate expectations should have an effect on consumption and investment decisions and therefore on the overall economic activity. This is important for central banks because it highlights the key role of clear communications for implementing effective monetary policy. Understanding how monetary policy uncertainty affects market reaction to macroeconomic news should also be useful to central banks planning exit from unconventional monetary policy programs.

We also contribute to the literature on how markets process information. Many studies show that it is difficult to explain price variation with fundamental news.¹⁹ Based on the existing literature, only the state of the economy should matter for the market response to macroeconomic news. In contrast, we show that uncertainty about monetary policy also influences the effect of economic news on asset prices. Our findings also raise the possibility that the business cycle variation in the stock market reaction to economic news documented in prior studies has more to do with monetary policy expectations than with the state of the economy. We leave examination of this issue to future research.

¹⁹ See, for example, Roll (1988), Cutler, Poterba, and Summers (1989), Mitchell and Mulherin (1994), and Boudoukh, Richardson, Shen, and Whitelaw (2007).

Table 1-1: Direct and Indirect Effects of Macroeconomic News on the Stock, Bond, Foreign Exchange, and Crude Oil Markets

This table shows the expected signs of the effects of good and bad macroeconomic news on asset returns.

		U.S. Stocks	Crude Oil	U.S. Treasury Security	U.S. Dollar
Good News	Direct Effect (News about Economy)	+	+	n/a	n/a
	Indirect Effect (Due to reaction of monetary policy)	—	—	—	+
Bad News	Direct Effect (News about Economy)	—	—	n/a	n/a
	Indirect Effect (Due to reaction of monetary policy)	+	+	+	—

Table 1-2: U.S. Macroeconomic Announcements

¹ Bureau of Economic Analysis (BEA), Employment and Training Administration (ETA), Automatic Data Processing, Inc. (ADP) and Macroeconomic Advisers, LLC (MALLC), Bureau of the Census (BC), Federal Reserve Board (FRB), National Association of Realtors (NAR), Bureau of Labor Statistics (BLS), U.S. Department of Treasury (USDT), Federal Reserve Bank of New York (FRBNY), Conference Board (CB), Institute for Supply Management (ISM), Federal Reserve Bank of Philadelphia (FRBP), Thomson Reuters and University of Michigan (TRUM), National Association of Purchasing Management (NAPM).

² The total number of observations in the sample

³ U.S. Eastern Time

The sample period is from 01/26/2012 to 12/15/2015.

Announcement	Source ¹	Obs. ²	Frequency	Announcement Time ³
Real Activity				
GDP advance final preliminary	BEA	47	Monthly	8:30 AM
Initial unemployment claims	ETA	203	weekly	8:30 AM
Nonfarm employment	BLS	47	monthly	8:30 AM
Unemployment Rate	BLS	47	monthly	8:30 AM
ADP employment	ADP/MALLC	47	monthly	8:15 AM
Advance retail sales	BC	47	monthly	8:30 AM
Existing home sales	NAR	46	monthly	10:00 AM
Industrial production	FRB	46	monthly	9:15 AM
Capacity utilization	FRB	46	monthly	9:15 AM
Personal income	BEA	47	monthly	8:30 AM
Consumer Credit	FRB	47	monthly	3:00 PM
Consumption				
New home sales	BC	46	monthly	10:00 AM
Personal Spending	BEA	47	monthly	8:30 AM
Investment				
Durable goods orders	BC	48	monthly	8:30 AM
Construction spending	BC	46	monthly	10:00 AM
Factory orders	BC	46	monthly	10:00 AM
Wholesale inventories	BC	47	monthly	10:00 AM
Government Purchases				
Government budget	USDT	47	monthly	2:00 PM
Net Exports				
Trade balance	BEA	47	monthly	8:30 AM
Prices				
Consumer price index	BLS	47	monthly	8:30 AM
Producer price index	BLS	47	monthly	8:30 AM
Forward Looking				
ISM Manufacturing	ISM	47	monthly	10:00 AM
ISM Non-manufacturing	ISM	47	monthly	10:00 AM
Consumer confidence	CB	47	monthly	10:00 AM
U. of Michigan Conf-Prelim	TRUM	47	monthly	9:55 AM
U. of Michigan Conf-Final	TRUM	47	monthly	9:55 AM
Housing starts	BC	44	monthly	8:30 AM
Pending home sales	NAR	46	Monthly	10:00 AM
Building permits	BC	45	Monthly	8:30 AM
Empire Manufacturing	FRBNY	47	Monthly	8:30 AM
Philadelphia Fed Business Outlook	FRBP	46	Monthly	10:00 AM
Chicago Purchasing Manager Index	NAPM	47	Monthly	9:45 AM
Index of leading indicators	CB	47	Monthly	10:00 AM

Table 1-3: Time Variation in Monetary Policy Uncertainty

This table reports the estimated coefficients for the following model: $MPU_t = \omega + \gamma_1 D_{Taper,t} + \gamma_2 TimeToLiftoff_t + \xi_t$, where MPU_t is the monetary policy uncertainty variable computed as described in section 1.3.3, $D_{Taper,t}$ is the tapering dummy variable with values of 1 from May 22, 2013 until December 17, 2013, the day before the QE taper started, and $TimeToLiftoff_t$ is the median expected number of quarters until the liftoff from the zero lower bound based on the primary dealer surveys conducted by the Federal Reserve Bank of New York. The sample period is from 01/26/2012 to 12/15/2015.

	Coefficient	<i>p</i> -value
$D_{Taper,t}$	0.172***	<.0001
$TimeToLiftoff_t$	-0.034***	<.0001
R ²	52.47%	

Table 1-4: Response of Stock, Bond, Foreign Exchange and Crude Oil Futures to Macroeconomic News in a Period of Low Monetary Policy Uncertainty

The table reports estimates for the following model: $R_t = \alpha + \sum_{m=1}^{33} \beta_m S_{mt} + \varepsilon_t$, where R_t is the continuously compounded return of the S&P 500 futures, 10-year Treasury note futures, the U.S. Dollar Index futures or WTI crude oil futures. R_t is from five minutes before to five minutes after a macroeconomic announcement. S_{mt} is the standardized surprise for the announcement of type m . The last column of the table shows the p -values corresponding to the Wald joint test of significance with the null hypothesis that the given announcement has no significant effect on any of the four markets. The sample period is from 01/26/2012 to 05/22/2013. The regressions are estimated using OLS with White (1980) heteroskedasticity consistent covariance matrix. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively

Announcement	S&P 500	10-Year T-note	US Dollar Index	Crude Oil	Prob. Wald Test
Real Activity					
GDP (advance, preliminary, final)	0.052*	-0.036***	0.029*	0.059*	0.001
Initial Unemployment Claims	-0.072***	0.043***	-0.009	-0.097***	<0.0001
Nonfarm Employment	0.360***	-0.216***	0.129***	0.382***	<0.0001
Unemployment rate	-0.104***	0.070*	-0.019	-0.150***	0.001
ADP Employment	0.080***	-0.051***	0.041***	0.031*	<0.0001
Advance Retail Sales	0.092***	-0.068***	0.050***	0.046	<0.0001
Existing Home Sales	0.115***	-0.027***	-0.039**	0.045	<0.0001
Industrial Production	-0.013	-0.006	-0.007	0.076	0.535
Capacity Utilization	0.017	-0.012	0.026*	-0.059	0.305
Personal Income	0.032***	-0.013***	0.005	0.036***	<0.0001
Consumer Credit	0.016*	-0.002	-0.007	0.037**	0.109
Consumption					
New Home Sales	0.175***	-0.028***	0.036	0.185***	<0.0001
Personal Spending	0.007	0.003	-0.003	0.013	0.923
Investment					
Durable Goods Orders	0.068***	-0.028*	-0.013	0.114***	<0.0001
Construction Spending	-0.005	-0.005	0.005	-0.028	0.853
Factory Orders	0.033	-0.011	-0.002	0.072	0.351
Wholesale Inventories	0.003	0.003	-0.017	0.051	0.318
Government Purchases					
Government Budget	-0.020*	-0.007	0.014***	0.000	0.027
Net Exports					
Trade Balance	-0.004	0.005	0.018	0.005	0.838
Prices					
Consumer Price Index	0.005	-0.019**	-0.012	0.032	0.144
Producer Price Index	0.035***	-0.008	0.009	0.073**	0.002
Forward Looking					
ISM Manufacturing	0.291***	-0.098***	0.020	0.182***	<0.0001
ISM Non-manufacturing	0.081**	-0.029***	0.041***	0.034	<0.0001
Consumer Confidence	0.040	-0.022***	0.001	0.044	0.012
U. of Michigan Conf-Prelim	0.092***	-0.041***	-0.002	0.113***	<0.0001
U. of Michigan Conf-Final	0.030	-0.019**	0.011	0.065	0.047
Housing Starts	0.052***	-0.042***	0.040***	0.014	<0.0001
Pending Home Sales	0.097***	-0.029***	-0.003	0.093***	<0.0001
Building Permits	0.014	-0.002	-0.007	-0.013	0.599
Empire Manufacturing	0.014	-0.023**	0.044***	-0.014	0.001
Philadelphia Fed business Outlook	0.100***	-0.022*	0.036	0.156*	0.003
Chicago Purchasing Manager	0.198***	-0.043***	-0.008	0.233***	<0.0001
Index of Leading Indicators	0.023	-0.016*	0.009	-0.013	0.343
Nr. Obs.	408	408	408	408	
R ²	53.55%	60.67%	23.22%	32.20%	

Table 1-5: Effect of Monetary Policy Uncertainty on the Market Response to Macroeconomic News

The table reports estimates for the following model: $R_t = \alpha + b MPU_t + \sum_{m=1}^{22} \beta_m S_{mt} + \sum_{m=1}^{22} \gamma_m S_{mt} MPU_t + \varepsilon_t$, where R_t is the continuously compounded return of the S&P 500 futures, the 10-year Treasury note futures, the U.S. Dollar Index futures, or the WTI crude oil futures. R_t is from five minutes before to five minutes after a macroeconomic announcement. S_{mt} is the standardized surprise for announcement m , while MPU_t is the monetary policy uncertainty variable, computed as described in section 1.3.3. The table also shows the p-values of the Wald joint significance test with the null hypothesis of no significant γ_m ($m=1,22$) for each given market. The sample period is from 01/26/2012 to 12/15/2015. The regressions are estimated using OLS with White (1980) heteroskedasticity consistent covariance matrix. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively.

Announcement	S&P 500		10-Year T-note		US Dollar Index		Crude Oil	
	β	γ	β	γ	β	γ	β	γ
Real Activity								
GDP (advance, preliminary, final)	0.049	0.023	0.027	-0.129*	-0.024	0.144**	-0.044	0.091
Initial Unemployment Claims	-0.100***	0.089***	0.066***	-0.040	0.001	-0.030	-0.167***	0.177***
Nonfarm Employment	0.823***	-0.830**	0.315**	-0.814***	-0.501**	0.978***	1.344***	-1.582***
Unemployment rate	-0.340**	0.427**	0.457***	-0.591***	-0.286**	0.388**	-0.424**	0.492*
ADP Employment	0.169***	-0.172***	0.081*	-0.224***	-0.147***	0.304***	0.402**	-0.599**
Advance Retail Sales	0.063	0.039	0.034	-0.174***	-0.090*	0.227***	-0.019	0.098
Existing Home Sales	0.177*	-0.160	-0.050**	0.030	-0.107**	0.141***	0.409***	-0.533***
Personal Income	0.013	0.001	-0.089	0.126	0.097*	-0.147*	-0.054	0.126
Consumption								
New Home Sales	0.051	-0.014	0.008	-0.050	-0.005	0.045	0.119	-0.124
Investment								
Durable Goods Orders	-0.023	0.072	0.193***	-0.291***	-0.288***	0.384***	0.606**	-0.758*
Government Purchases								
Government Budget	-0.127***	0.162***	0.016	-0.029	0.037	-0.041	-0.007	0.021
Prices								
Producer Price Index	0.107***	-0.111***	0.007	-0.042	-0.025	0.066*	0.039	-0.012
Forward Looking								
ISM Manufacturing	0.361**	-0.280	-0.109**	0.022	-0.054	0.144*	0.312**	-0.254
ISM Non-manufacturing	0.083	-0.050	0.015	-0.079***	-0.001	0.089	0.160	-0.206
Consumer Confidence	0.098	-0.033	0.000	-0.036	-0.019	0.061	0.157	-0.162
U. of Michigan Conf-Prelim	0.149**	-0.113	-0.048**	0.025	-0.026	0.040	0.137	-0.110
U. of Michigan Conf-Final	0.171	-0.223	0.031	-0.066	-0.009	0.025	0.457*	-0.590*
Housing Starts	0.194***	-0.214***	0.018	-0.080	0.030	0.022	0.053	-0.072
Pending Home Sales	0.237***	-0.262***	-0.016	-0.002	-0.047*	0.071**	0.142	-0.176
Empire Manufacturing	-0.133	0.217*	0.036	-0.095	0.001	0.053	-0.188	0.280
Philadelphia Fed Business Outlook	0.112	-0.086	0.035	-0.085***	0.070	-0.042	-0.185	0.391*
Chicago Purchasing Manager	0.194	-0.161	-0.052	0.008	-0.007	0.053	0.297	-0.328
p-value of Wald Test	<.0001		<.0001		<.0001		✕	<.0001
Nr. Obs.	985		985		985		985	
R ²	26.55%		59.88%		42.37%		12.40%	

Table 1-6: Effect of Monetary Policy Uncertainty on the Response of Medium-term Interest Rates to Macroeconomic News

The table reports estimates for the following model: $\Delta Rate_t = \alpha + b MPU_t + \sum_{m=1}^{22} \beta_m S_{mt} + \sum_{m=1}^{22} \gamma_m S_{mt} MPU_t + \varepsilon_t$, where $\Delta Rate_t$ represents the change in the interest rate (Eurodollar rate or Treasury yield) from five minutes before to five minutes after a macroeconomic announcement. The rate and yield changes are in basis points. S_{mt} is the standardized surprise for announcement m , while MPU_t is the monetary policy uncertainty variable, computed as described in section 1.3.3. The table also shows the p -values of the Wald joint significance test with the null hypothesis of no significant γ_m ($m=1,22$) for the given market. The sample period is from 01/26/2012 to 12/15/2015. The regressions are estimated using OLS with White (1980) heteroskedasticity consistent covariance matrix. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively

Announcement	Eurodollar 4-5 Quarters to Expiration		Eurodollar 8-9 Quarters to Expiration		Eurodollar 12-13 Quarters to Expiration		5-year Treasury Note	
	β	γ	β	γ	β	γ	β	γ
Real Activity								
GDP (advance, preliminary, final)	-0.374	1.388*	0.267	1.562	0.111	2.131	-0.291	1.841*
Initial Unemployment Claims	-0.221	0.018	-0.328	-0.204	-0.884*	0.255	-0.714**	0.313
Nonfarm Employment	-9.869***	16.284***	-12.279***	22.686***	-9.644***	20.964***	-9.001***	17.533***
Unemployment rate	-2.271	2.607	-4.797**	6.029*	-7.139**	9.005**	-5.505***	7.065***
ADP Employment	-1.559***	2.971***	-2.752***	5.583***	-2.342**	5.561***	-1.964***	4.204***
Advance Retail Sales	-2.521***	4.250***	-2.787***	5.456***	-1.652**	4.563***	-1.445***	3.713***
Existing Home Sales	0.132	-0.043	0.641	-0.422	1.051*	-0.727	0.528**	-0.302
Personal Income	1.396**	-1.995**	2.045***	-3.016**	2.216*	-3.262*	1.766**	-2.585**
Consumption								
New Home Sales	-0.856	1.326*	0.343	0.330	0.161	0.596	-0.350	1.048
Investment								
Durable Goods Orders	-1.876***	2.799***	-3.974***	5.753***	-4.476***	6.684***	-3.177***	4.700***
Government Purchases								
Government Budget	-0.316	0.449	-0.620	0.899	-0.478	0.739	-0.110	0.304
Prices								
Producer Price Index	0.276	0.059	0.133	0.466	0.376	0.338	-0.127	0.741
Forward Looking								
ISM Manufacturing	-0.227	0.862	0.311	1.050	1.327	0.505	0.876	0.378
ISM Non-manufacturing	-0.256	0.867*	-0.697	1.800***	-0.674	1.990***	-0.355	1.355***
Consumer Confidence	0.122	0.171	-0.298	0.998	-0.204	1.109	-0.228	0.748
U. of Michigan Conf-Prelim	0.153	0.078	0.151	0.342	0.550*	-0.180	0.455*	-0.155
U. of Michigan Conf-Final	-0.589	0.866	-0.736	1.362*	-0.806	1.616**	-0.450	0.982*
Housing Starts	-0.540	1.057	-0.943	2.160	-0.783	2.170	-0.523	1.430
Pending Home Sales	-0.051	0.219	0.217	0.115	0.553**	-0.121	-0.023	0.273
Empire Manufacturing	-1.346*	2.180**	-1.797	3.109*	-1.571	2.898	-1.028	2.042*
Philadelphia Fed Business Outlook	-0.217	0.609*	-0.805**	1.637***	-1.011*	2.082***	-0.750**	1.497***
Chicago Purchasing Manager	-0.249	0.726**	-0.130	0.984**	1.603**	-0.773	0.104	0.629
p-value of Wald Test		<.0001		<.0001		<.0001		<.0001
Nr. Obs.		986		986		986		986
R ²		47.96%		59.46%		60.77%		60.37%

Table 1-7: Average Effect of Monetary Policy Uncertainty on the Market Response to Macroeconomic News

Panel A reports the estimates for the following model: $R_t = \alpha + b_{MPU} MPU_t + b_S \sum_{m=1}^{22} \hat{\beta}_m S_{mt} + c_{MPU} \sum_{m=1}^{22} \hat{\beta}_m S_{mt} MPU_t + u_t$, where R_t is the continuously compounded return of the S&P 500 futures, the 10-year Treasury note futures, the U.S. Dollar Index futures, the WTI crude oil futures, or the change in the Eurodollar rate of the stated contract maturity or the change in the 5-year Treasury yield. The returns and rate changes are computed from five minutes before to five minutes after a macroeconomic news release. S_{mt} is the standardized surprise for announcement m . MPU_t is the monetary policy uncertainty variable, computed as explained in section 3.3. $\hat{\beta}_m$ estimates are obtained from running the regression in equation (4) using the part of the sample before May 22, 2013. Panel B reports the estimates of the following model: $R_t = \alpha + b_{MPU} MPU_t + b_{VIX} VIX_t + b_S \sum_{m=1}^{22} \hat{\beta}_m S_{mt} + c_{MPU} \sum_{m=1}^{22} \hat{\beta}_m S_{mt} MPU_t + c_{VIX} \sum_{m=1}^{22} \hat{\beta}_m S_{mt} VIX_t + u_t$, where VIX_t is the CBOE's Volatility Index measuring the market expectations of near-term volatility conveyed by S&P 500 stock index option prices. Panel C reports the estimates of the model: $R_t = \alpha + b_{MPU} MPU_t + b_{RA} RA_t + b_{UC} UC_t + b_S \sum_{m=1}^{22} \hat{\beta}_m S_{mt} + c_{MPU} \sum_{m=1}^{22} \hat{\beta}_m S_{mt} MPU_t + c_{RA} \sum_{m=1}^{22} \hat{\beta}_m S_{mt} RA_t + c_{UC} \sum_{m=1}^{22} \hat{\beta}_m S_{mt} UC_t + u_t$, where RA_t and UC_t are the risk aversion and the uncertainty components of the VIX index and are constructed as described in section 2.1. in Bekaert, Hoerova, and Lo Duca (2013). For all panels, only the announcements that are significant according to the joint Wald test listed in Table 1-4 are included. The sample period is from 01/26/2012 to 12/15/2015. The regressions are estimated using OLS with White (1980) heteroskedasticity consistent covariance matrix. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively.

Panel A: Basic Regression	b_S	c_{MPU}	c_{VIX}	c_{RA}	c_{UC}	R^2
<i>Stock, bond, foreign exchange and crude oil (N=985)</i>						
S&P 500	1.561***	-1.375***	-	-	-	20.97%
10-year Treasury note	0.297	1.242***	-	-	-	47.89%
U.S. Dollar Index	-0.514	2.680***	-	-	-	27.73%
WTI Crude Oil	1.895***	-1.975***	-	-	-	6.39%
<i>Medium-term interest rates (N=986)</i>						
Eurodollar 4-5 quarters to expiration	-2.086*	5.974***	-	-	-	22.34%
Eurodollar 8-9 quarters to expiration	-1.509***	4.440***	-	-	-	45.82%
Eurodollar 12-13 quarters to expiration	-0.474	2.528***	-	-	-	52.27%
5-year Treasury note	-0.762*	3.097***	-	-	-	48.82%
Panel B: Controlling for the VIX						
<i>Stock, bond, foreign exchange and crude oil (N=984)</i>						
S&P 500	0.261	-1.402***	0.300***	-	-	27.89%
10-year Treasury note	0.484	1.242***	-0.042	-	-	48.00%
U.S. Dollar Index	0.321	2.702***	-0.194	-	-	28.15%
WTI Crude Oil	0.825*	-1.934***	0.236***	-	-	8.26%
<i>Medium-term interest rates (N=984)</i>						
Eurodollar 4-5 quarters to expiration	-0.846	6.057***	-0.304	-	-	22.46%
Eurodollar 8-9 quarters to expiration	-0.579	4.457***	-0.215	-	-	45.85%
Eurodollar 12-13 quarters to expiration	0.182	2.494***	-0.146*	-	-	51.76%
5-year Treasury note	-0.018	3.113***	-0.173*	-	-	48.56%
Panel C: Controlling for the VIX components						
<i>Stock, bond, foreign exchange and crude oil (N=960)</i>						
S&P 500	0.809*	-1.370***	-	0.026***	0.051	25.51%
10-year Treasury note	2.116***	1.292***	-	0.006	-0.227***	48.17%
U.S. Dollar Index	1.486	2.511***	-	-0.006	-0.203*	29.51%
WTI Crude Oil	1.687**	-1.905***	-	0.025***	-0.017	7.82%
<i>Medium-term interest rates (N=960)</i>						
Eurodollar 4-5 quarters to expiration	3.083	6.338***	-	0.008	-0.655**	23.17%
Eurodollar 8-9 quarters to expiration	1.952*	4.655***	-	0.003	-0.431***	46.92%
Eurodollar 12-13 quarters to expiration	1.662**	2.599***	-	-0.001	-0.258***	52.03%
5-year Treasury note	1.993**	3.157***	-	0.001	-0.330***	49.66%

Table 1-8: Average Effect of Monetary Policy Uncertainty on the Market Response to Macroeconomic News (with controls)

The table reports the estimates for the following model: $R_t = \alpha + b_{MPU} MPU_t + b_X X_t + b_S \sum_{m=1}^{22} \hat{\beta}_m S_{mt} + c_{MPU} \sum_{m=1}^{22} \hat{\beta}_m S_{mt} MPU_t + c_X \sum_{m=1}^{22} \hat{\beta}_m S_{mt} X_t + u_t$. R_t , S_{mt} , and $\hat{\beta}_m$ are defined in the paper. MPU_t is the monetary policy uncertainty variable computed as explained in section 3.3. X_t is a control variable, that accounts for the (lagged) Aruoba-Diebold-Scotti business conditions index in Panel A, the median anticipated number of quarters until the liftoff from the ZLB (based on primary dealer survey by the FRBNY) in Panel B, the data driven monetary policy dummy (with values of 1 when unemployment rate was above 60.5% after 12/12/2012, and 0 otherwise) in Panel C, and the Baker-Bloom-Davis economic policy uncertainty index (divided by 100) in Panel D. The sample period is from 01/26/2012 to 12/15/2015. The regressions are estimated using OLS with White (1980) heteroskedasticity consistent covariance matrix. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively.

Panel A: Controlling for the State of the Economy				
	b_S	c_{MPU}	c_X	R^2
<i>Stock, bond, foreign exchange and crude oil (N=983)</i>				
S&P 500	1.595***	-1.448***	-0.251	21.44%
10-year Treasury note	0.369	1.113***	-0.404***	48.44%
U.S. Dollar Index	-0.349	2.275***	-1.360***	29.43%
WTI Crude Oil	1.936***	-2.045***	-0.168	6.48%
<i>Medium-term interest rates (N=984)</i>				
Eurodollar 4-5 quarters to expiration	-1.972	5.706***	-0.927	22.56%
Eurodollar 8-9 quarters to expiration	-1.454***	4.330***	-0.370	46.02%
Eurodollar 12-13 quarters to expiration	-0.457	2.495***	-0.121	52.36%
5-year Treasury note	-0.703	2.976***	-0.414	49.16%
Panel B: Controlling for Market Expectations of the Liftoff from the Zero Lower Bound				
<i>Stock, bond, foreign exchange and crude oil (N=983)</i>				
S&P 500	0.897**	-0.867**	0.042*	22.46%
10-year Treasury note	0.121	1.404**	0.009	48.16%
U.S. Dollar Index	1.761	0.658	-0.116*	28.60%
WTI Crude Oil	0.589	-0.935**	0.079***	8.10%
<i>Medium-term interest rates (N=984)</i>				
Eurodollar 4-5 quarters to expiration	7.208**	-1.719	-0.523***	27.48%
Eurodollar 8-9 quarters to expiration	0.499	2.785***	-0.114**	46.60%
Eurodollar 12-13 quarters to expiration	-0.657	2.688***	0.009	51.66%
5-year Treasury note	0.469	2.069**	-0.069	48.93%
Panel C: Controlling for Data Driven Monetary Policy				
<i>Stock, bond, foreign exchange and crude oil (N=985)</i>				
S&P 500	1.633***	-1.399***	-0.137	21.43%
10-year Treasury note	0.092	1.355***	0.341***	48.64%
U.S. Dollar Index	-0.951	3.005***	0.545**	28.36%
WTI Crude Oil	1.929***	-1.992***	-0.057	6.46%
<i>Medium-term interest rates (N=986)</i>				
Eurodollar 4-5 quarters to expiration	-1.135	5.420***	-1.371**	23.53%
Eurodollar 8-9 quarters to expiration	-1.550**	4.463***	0.061	45.84%
Eurodollar 12-13 quarters to expiration	-0.725**	2.676***	0.383***	52.98%
5-year Treasury note	-0.873*	3.161***	0.172	48.93%
Panel D: Controlling for Economic Policy Uncertainty				
<i>Stock, bond, foreign exchange and crude oil (N=985)</i>				
S&P 500	0.989***	-0.982***	0.003***	22.65%
10-year Treasury note	0.839**	0.834*	-0.002**	48.25%
U.S. Dollar Index	0.575	1.824*	-0.004*	28.18%
WTI Crude Oil	1.209***	-1.505***	0.003***	7.47%
<i>Medium-term interest rates (N=986)</i>				
Eurodollar 4-5 quarters to expiration	0.511	4.256**	-0.013***	23.60%
Eurodollar 8-9 quarters to expiration	-0.243	3.487***	-0.006***	46.53%
Eurodollar 12-13 quarters to expiration	0.225	1.998***	-0.003**	52.71%
5-year Treasury note	0.363	2.264***	-0.005***	49.69%

Figure 1-1. Volatility of Eurodollar Futures with 8-9 Quarters to Expiration and Monetary Policy Uncertainty

Panel A shows the daily realized volatility of Eurodollar futures with 8-9 quarters to expiration. The annualized realized volatility is computed using five-minute price changes. Panel B shows the monetary policy uncertainty variable computed as explained in section 3.3.

Panel A: Daily Realized Volatility (%)

Panel B: Monetary Policy Uncertainty (%)

Figure 1-2. Response of Stock, Bond, Foreign Exchange and Crude Oil Markets to Macroeconomic News

The time-varying response coefficient is estimated using a rolling OLS regression with a window of 128 observations (approximately 6 months). Grey lines are one-standard-error bands.

Figure 1-3. Response of Medium-term Interest Rates to Macroeconomic News

The time-varying response coefficient is estimated using a rolling OLS regression with a window of 128 observations (approximately 6 months). Grey lines are one-standard-error bands.

APPENDIX A

Appendix A: Essay 1 - Additional Robustness Checks

I. Asymmetry in the Response of Markets to Macroeconomic Announcements

Previous literature has shown that asset prices tend to respond asymmetrically to good and bad economic news (e.g., Andersen, Bollerslev, Diebold, and Vega, 2003; Hautsch and Hess, 2001; Beber and Brandt, 2010), and more strongly to larger news (Andersen, Bollerslev, Diebold and Vega, 2003; Ehrmann and Fratzscher, 2005). If such asymmetry is present in our sample, one could argue that the results might not be driven by the high monetary policy uncertainty itself, but rather by a string of negative surprises in a period of high uncertainty, or by a string of larger surprises. To address this concern, we first examine whether the markets respond asymmetrically to positive and negative macroeconomic news, by estimating the following regression:

$$R_t = a_0 + \sum_{m=1}^{22} a_m^+ S_{mt}^+ + \sum_{m=1}^{22} a_m^- S_{mt}^- + \varepsilon_t, \quad (\text{A1})$$

where $S_{mt}^+ = \max(S_{mt}, 0)$, $S_{mt}^- = \min(S_{mt}, 0)$, and S_{mt} is the standardized surprise for the announcement type m . R_t is the continuously compounded futures return from five minutes before to five minutes after a macroeconomic news release. We test the null hypothesis $a_m^+ = a_m^-$ for each individual macroeconomic announcement. The results reported in Tables A-3 and A-4 indicate that, in general, the markets do not respond asymmetrically to positive and negative news. As an additional robustness check, we re-run the model in equation (A1) for periods of low and high monetary policy uncertainty, namely for periods when uncertainty is in the first and the last quintile over our sample period. Untabulated results indicate that in general the markets do not respond asymmetrically to positive and negative news when monetary policy uncertainty is low or high.

To investigate whether our results are driven by a string of negative surprises in the presence of high monetary policy uncertainty, we look at the autocorrelation in each of the

macroeconomic surprises by estimating the following two regressions for each announcement type:

$$S_{mt} = a_0 + a_1 S_{mt-1} + \varepsilon_t, \quad (\text{A2})$$

$$S_{mt} = b_0 + b_1 S_{mt-1} + b_2 MPU_t + b_3 S_{mt-1} MPU_t + \varepsilon_t. \quad (\text{A3})$$

The periods t and $t - 1$ represent the announcement dates, while MPU denotes the monetary policy uncertainty variable computed as explained in section 3.3. The results reported in Table A-5 show that, in general, there is no significant autocorrelation in these macroeconomic surprises. Therefore, it is not very likely that our results are driven by a string of negative surprises during times of monetary policy uncertainty.

If our results were driven by a string of larger macroeconomic surprises, we would expect to see a nonlinear relationship between the returns and the macroeconomic surprises. A possible way of testing for such nonlinearity is by running the following regression:

$$R_t = a_0 + \sum_{m=1}^{22} a_{1m} S_{mt} + \sum_{m=1}^{22} a_{2m} S_{mt}^2 \text{sign}(S_{mt}) + \varepsilon_t. \quad (\text{A4})$$

The results reported in Table A-6 show that the estimates of a_{2m} are usually insignificant at the 10% significance level. Therefore, it is unlikely that our results are driven by a string of large surprises during periods of high monetary policy uncertainty. As an additional robustness check, we find that, in general, the absolute values of the macroeconomic surprises are not larger in the presence of high monetary policy uncertainty. This additional result is reported in Table A-7.

One could also argue that our results may reflect changes in investors' disagreement, as mentioned by Pericoli and Veronese (2015). To address this concern, we proxy investor disagreement by the standard deviation of analyst forecasts for each macroeconomic statistic and run a simple OLS regression of the standard deviation of analyst forecasts on the monetary policy uncertainty variable. The results reported in Table A-8 show that, in general, the standard deviation

of analyst forecasts is not significantly higher in the presence of higher monetary policy uncertainty. This indicates that our results probably do not reflect changes in investor disagreement.

II. Alternative Proxy for Monetary Policy Uncertainty

As a robustness check, we re-estimate the results from Table 1-7 with an alternative proxy of monetary policy uncertainty. For this purpose, we measure uncertainty as a moving average of the daily realized volatility of Eurodollar futures with 8-9 quarters to expiration. We compute the moving average of the realized volatility over the last 21 trading days, excluding the current day. Using the moving average of realized volatility as a proxy for uncertainty reduces the noise in the realized volatility. Figure A-1 plots the pattern followed over time by this alternative proxy of uncertainty.

The results reported in Table A-9 are qualitatively similar to our previous findings. That is, the reactions of the stock and crude oil markets to macroeconomic announcements weaken, while the reactions of the bond and the foreign exchange markets to such announcements strengthen in times of high monetary policy uncertainty. The results are also robust when controlling for the VIX or the VIX components.

A possible concern with this proxy for monetary policy uncertainty is that the length of the window used for the moving average is selected arbitrarily. To address this issue, we considered reasonable variation in the length of the window used for computing the moving average of realized volatility. We compute the moving average of the daily realized volatility over the last 42, 10 and five trading days. Untabulated results indicate that our findings remain robust.

III. *Weighted Least Squares*

Intraday asset returns that we use in our regressions are heteroskedastic due to volatility clustering, intraday periodicity of volatility, and possibly different effect of different announcement types on volatility. We use event study regressions with heteroskedasticity-consistent standard errors. This increases the coefficient standard errors relative to a model that captures heteroskedasticity of returns. It should, therefore, make it more difficult for us to find significant results. However, our regression results are strongly statistically significant, suggesting that our results are quite strong. To improve estimation efficiency, we perform a robustness check that uses a weighted least squares (WLS) estimation procedure similar to the one used by Andersen, Bollerslev, Diebold and Vega (2007). We first estimate the following equation (equation (7) in the paper), with OLS:

$$R_t = a + b_{MPU}MPU_t + b_S\widehat{SS}_t + c_{MPU}\widehat{SS}_tMPU_t + u_t, \quad (A5)$$

where R_t is the return or rate change computed from five minutes before to five minutes after a macroeconomic news release and the other variables are defined in the paper. We then use the residuals of this equation to estimate the following volatility model:

$$\ln(\hat{u}_t^2) = \beta \ln(\hat{u}_{t-1}^2) + \sum_{d=1}^N \gamma_d D_d + \delta_1 |\widehat{SS}_t| + \delta_2 MPU_t + \delta_3 |\widehat{SS}_t| MPU_t + \varepsilon_t. \quad (A6)$$

The dummy variables D_d capture systematic differences in volatility across different times of the day. $N = 6$, based on the number of different times of the day (8:15 a.m., 8:30 a.m., 9:45 a.m., 9:55 a.m., 10:00 a.m., and 2:00 p.m.) when market-moving macro announcements are released. The first lag of volatility is included in the model to capture the possible volatility clustering. After estimating equation (A6), we use the estimated volatility $\exp(\ln(\hat{u}_t^2) - \hat{\varepsilon}_t)$ in the WLS estimation of equation (A5). The results are provided in Table A-10. As expected, the coefficient standard errors are smaller than the White (1980) standard errors. The conclusions, however, remain unchanged: in the presence of high monetary policy uncertainty the response to macroeconomic

news weakens in the stock and crude oil markets and becomes stronger in the Treasury, interest rate and foreign exchange markets.

Table A-1: Average Effect of Monetary Policy Uncertainty on the Market Response to Macroeconomic News (Controlling for the VIX and other variables)

The table reports the estimates for the following model: $R_t = \alpha + b_{MPU} MPU_t + b_{VIX} * VIX_t + b_X X_t + b_S \sum_{m=1}^{22} \hat{\beta}_m S_{mt} + c_{MPU} \sum_{m=1}^{22} \hat{\beta}_m S_{mt} MPU_t + c_{VIX} \sum_{m=1}^{22} \hat{\beta}_m S_{mt} VIX_t + c_X \sum_{m=1}^{22} \hat{\beta}_m S_{mt} X_t + u_t$. R_t , S_{mt} , and $\hat{\beta}_m$ are defined in the paper. MPU_t is the monetary policy uncertainty variable computed as explained in section 3.3. VIX_t is the CBOE's Volatility Index measuring the market expectations of near-term volatility conveyed by S&P 500 stock index option prices. X_t is a control variable, that accounts for the (lagged) Aruoba-Diebold-Scotti business conditions index in Panel A, the median anticipated number of quarters until the liftoff from the ZLB (based on primary dealer survey by the FRBNY) in Panel B, the data driven monetary policy dummy (with values of 1 when unemployment rate was above 6.5% after 12/12/2012, and 0 otherwise) in Panel C, and the Baker-Bloom-Davis economic policy uncertainty index (divided by 100) in Panel D. The sample period is from 01/26/2012 to 12/15/2015. The regressions are estimated using OLS with White (1980) heteroskedasticity consistent covariance matrix. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively.

Panel A: Controlling for the State of the Economy	b_S	c_{MPU}	c_{VIX}	c_X	R^2
<i>Stock, bond, foreign exchange and crude oil (N=982)</i>					
S&P 500	0.301	-1.446***	0.296***	-0.146	28.06%
10-year Treasury note	0.612	1.105***	-0.054	-0.424***	48.58%
U.S. Dollar Index	0.639	2.284***	-0.228*	-1.431***	30.04%
WTI Crude Oil	0.853**	-1.964***	0.233***	-0.069	8.28%
<i>Medium-term interest rates (N=982)</i>					
Eurodollar 4-5 quarters to expiration	-0.642	5.787***	-0.326	-0.983	22.71%
Eurodollar 8-9 quarters to expiration	-0.458	4.324***	-0.228	-0.446	46.10%
Eurodollar 12-13 quarters to expiration	0.225	2.447***	-0.150*	-0.162	51.87%
5-year Treasury note	0.092	2.980***	-0.184*	-0.461**	48.95%
Panel B: Controlling for Market Expectations of the Liftoff from the Zero Lower Bound					
<i>Stock, bond, foreign exchange and crude oil (N=984)</i>					
S&P 500	-0.100	-1.072***	0.284***	0.028	28.53%
10-year Treasury note	0.268	1.432**	-0.040	0.010	48.27%
U.S. Dollar Index	2.411*	0.757	-0.172	-0.111	28.95%
WTI Crude Oil	-0.118	-1.045**	0.196***	0.068***	9.48%
<i>Medium-term interest rates (N=984)</i>					
Eurodollar 4-5 quarters to expiration	7.260***	-1.628	-0.037	-0.518***	27.52%
Eurodollar 8-9 quarters to expiration	1.070	2.908***	-0.167	-0.105*	46.87%
Eurodollar 12-13 quarters to expiration	-0.166	2.801***	-0.145*	0.017	52.13%
5-year Treasury note	0.945	2.201**	-0.143	-0.061	49.27%
Panel C: Controlling for Data Driven Monetary Policy					
<i>Stock, bond, foreign exchange and crude oil (N=984)</i>					
S&P 500	0.318	-1.415***	0.296***	-0.069	28.02%
10-year Treasury note	0.142	1.352***	-0.009	0.333***	48.69%
U.S. Dollar Index	-0.292	2.970***	-0.137	0.457*	28.57%
WTI Crude Oil	0.804*	-1.929***	0.238***	0.026	8.26%
<i>Medium-term interest rates (N=984)</i>					
Eurodollar 4-5 quarters to expiration	0.803	5.476***	-0.446	-1.514***	23.87%
Eurodollar 8-9 quarters to expiration	-0.524	4.439***	-0.221	-0.052	45.86%
Eurodollar 12-13 quarters to expiration	-0.206	2.619***	-0.107	0.338**	52.28%
5-year Treasury note	-0.123	3.144***	-0.163	0.093	48.59%
Panel D: Controlling for Economic Policy Uncertainty					
<i>Stock, bond, foreign exchange and crude oil (N=984)</i>					
S&P 500	0.150	-1.272***	0.283***	0.001	28.19%
10-year Treasury note	0.830*	0.824*	0.006	-0.002*	48.31%
U.S. Dollar Index	0.867	2.084**	-0.140	-0.003	28.38%
WTI Crude Oil	0.618	-1.663***	0.193**	0.002*	8.76%
<i>Medium-term interest rates (N=984)</i>					
Eurodollar 4-5 quarters to expiration	0.700	4.373***	-0.079	-0.012**	23.51%
Eurodollar 8-9 quarters to expiration	0.034	3.695***	-0.122	-0.004*	46.23%
Eurodollar 12-13 quarters to expiration	0.449	2.162***	-0.106	-0.002	51.92%
5-year Treasury note	0.558	2.415***	-0.090	-0.004**	49.05%

Table A-2: Average Effect of Monetary Policy Uncertainty on the Market Response to Macroeconomic News (Controlling for the VIX components and other variables)

The table reports the estimates for the following model: $R_t = \alpha + b_{MPU} MPU_t + b_{RA} * RA_t + b_{UC} * UC_t + b_X X_t + b_S \sum_{m=1}^{22} \beta_m S_{mt} + c_{MPU} \sum_{m=1}^{22} \beta_m S_{mt} MPU_t + c_{RA} \sum_{m=1}^{22} \beta_m S_{mt} RA_t + c_{UC} \sum_{m=1}^{22} \beta_m S_{mt} UC_t + c_X \sum_{m=1}^{22} \beta_m S_{mt} X_t + u_t$. R_t , S_{mt} , and β_m are defined in the paper. MPU_t is the monetary policy uncertainty variable computed as explained in section 3.3. RA_t and UC_t are the risk aversion and the uncertainty components of the VIX index and are constructed as described in section 2.1. in Bekaert, Hoerova, and Lo Duca (2013). X_t is a control variable, that accounts for the (lagged) Aruoba-Diebold-Scotti business conditions index in Panel A, the median anticipated number of quarters until the liftoff from the ZLB (based on primary dealer survey by the FRBNY) in Panel B, the data driven monetary policy dummy (with values of 1 when unemployment rate was above 6.5% after 12/12/2012, and 0 otherwise) in Panel C, and the Baker-Bloom-Davis economic policy uncertainty index (divided by 100) in Panel D. The sample period is from 01/26/2012 to 12/15/2015. The regressions are estimated using OLS with White (1980) heteroskedasticity consistent covariance matrix. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively.

Panel A: Controlling for the State of the Economy	b_S	c_{MPU}	c_{RA}	c_{UC}	c_X	R^2
<i>Stock, bond, foreign exchange and crude oil (N=960)</i>						
S&P 500	0.789*	-1.430***	0.024***	0.057	-0.276*	26.02%
10-year Treasury note	2.049***	1.214***	0.004	-0.214***	-0.382**	48.51%
U.S. Dollar Index	1.579*	2.312***	-0.011	-0.212**	-1.311***	30.84%
WTI Crude Oil	1.696**	-1.937***	0.024***	-0.015	-0.080	7.85%
<i>Medium-term interest rates (N=960)</i>						
Eurodollar 4-5 quarters to expiration	2.968	6.211***	0.004	-0.634*	-0.635	23.27%
Eurodollar 8-9 quarters to expiration	1.927*	4.613***	0.002	-0.426***	-0.240	46.98%
Eurodollar 12-13 quarters to expiration	1.647**	2.599***	-0.001	-0.256***	-0.049	52.05%
5-year Treasury note	1.953**	3.119***	-0.001	-0.323***	-0.267	49.78%
Panel B: Controlling for Market Expectations of the Liftoff from the Zero Lower Bound						
<i>Stock, bond, foreign exchange and crude oil (N=960)</i>						
S&P 500	0.216	-1.035**	0.023***	0.071	0.030	26.35%
10-year Treasury note	1.947*	1.420**	0.006	-0.224***	0.007	48.39%
U.S. Dollar Index	4.078**	0.510	-0.003	-0.248**	-0.118*	30.36%
WTI Crude Oil	0.310	-1.037**	0.020***	0.022	0.070***	9.11%
<i>Medium-term interest rates (N=960)</i>						
Eurodollar 4-5 quarters to expiration	14.544***	-1.563	0.041	-0.917***	-0.555***	28.82%
Eurodollar 8-9 quarters to expiration	4.238**	3.011***	0.009	-0.474***	-0.116**	48.10%
Eurodollar 12-13 quarters to expiration	1.340	2.850***	-0.001	-0.253***	0.014	52.38%
5-year Treasury note	3.307**	2.185***	0.004	-0.351***	-0.067	50.42%
Panel C: Controlling for Data Driven Monetary Policy						
<i>Stock, bond, foreign exchange and crude oil (N=960)</i>						
S&P 500	0.863*	-1.378***	0.026***	0.047	-0.040	25.59%
10-year Treasury note	1.786**	1.414***	0.008	-0.215***	0.300**	48.71%
U.S. Dollar Index	1.110	2.754***	-0.002	-0.202*	0.357	29.76%
WTI Crude Oil	1.651*	-1.897***	0.025***	-0.015	0.031	7.83%
<i>Medium-term interest rates (N=960)</i>						
Eurodollar 4-5 quarters to expiration	5.109*	5.628***	-0.003	-0.734**	-1.705***	24.91%
Eurodollar 8-9 quarters to expiration	2.108*	4.594***	0.002	-0.436***	-0.143	46.97%
Eurodollar 12-13 quarters to expiration	1.348	2.747***	0.002	-0.253**	0.318**	52.47%
5-year Treasury note	1.980**	3.164***	0.001	-0.330***	0.015	49.67%
Panel D: Controlling for Economic Policy Uncertainty						
<i>Stock, bond, foreign exchange and crude oil (N=960)</i>						
S&P 500	0.614	-1.221***	0.024***	0.051	0.001	25.91%
10-year Treasury note	2.475***	0.955**	0.009	-0.221***	-0.002	48.40%
U.S. Dollar Index	1.968	2.070**	-0.003	-0.198*	-0.002	29.64%
WTI Crude Oil	1.307	-1.631***	0.020***	-0.014	0.002**	8.34%
<i>Medium-term interest rates (N=960)</i>						
Eurodollar 4-5 quarters to expiration	5.105*	4.727***	0.026	-0.630**	-0.012**	24.19%
Eurodollar 8-9 quarters to expiration	2.661**	3.999***	0.010	-0.420***	-0.004*	47.22%
Eurodollar 12-13 quarters to expiration	1.914**	2.348***	0.001	-0.252***	-0.001	52.14%
5-year Treasury note	2.608**	2.583***	0.006	-0.318***	-0.003*	50.03%

Table A-3: Test for Asymmetry in the Response of Markets to Macroeconomic Announcements

The table reports the estimates of the following model: $R_t = a_0 + \sum_{m=1}^{22} a_m^+ S_{mt}^+ + \sum_{m=1}^{22} a_m^- S_{mt}^- + \varepsilon_t$, where R_t is the continuously compounded return for the S&P 500 futures, the WTI crude oil futures, the 10-year Treasury note futures, and the U.S. Dollar Index futures. The returns are computed from five minutes before to five minutes after a macroeconomic news release. S_{mt} is the standardized surprise for the announcement of type m , and $S_{mt}^+ = \max(S_{mt}, 0)$ and $S_{mt}^- = \min(S_{mt}, 0)$. The table also reports the difference in the markets' responses to positive vs. negative news of each macroeconomic announcement. The sample period is from 01/26/2012 to 12/15/2015. The regressions are estimated using OLS with White (1980) heteroskedasticity consistent covariance matrix. Only the announcements that are significant according to the joint Wald test listed in Table 1-4 are included. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent respectively.

Announcement	S&P 500			Crude Oil			10-Year T-note			US Dollar Index		
	a_m^+	a_m^-	$a_m^+ - a_m^-$	a_m^+	a_m^-	$a_m^+ - a_m^-$	a_m^+	a_m^-	$a_m^+ - a_m^-$	a_m^+	a_m^-	$a_m^+ - a_m^-$
Real Activity												
GDP (advance, preliminary, final)	0.083**	0.054***	0.029	0.053	0.038	0.015	-0.086***	-0.064***	-0.022	0.122***	0.065***	0.057**
Initial Unemployment Claims	-0.034***	-0.023*	-0.011	-0.032*	-0.008	-0.024	0.024***	0.046***	-0.022*	-0.014**	-0.038***	0.024*
Nonfarm Employment	0.007	0.389***	-0.382**	-0.046	0.337***	-0.384**	-0.350***	-0.295***	-0.055	0.315***	0.192***	0.124
Unemployment rate	0.195**	-0.151***	0.346***	0.087	-0.194***	0.280*	-0.027	-0.006	-0.022	0.087	0.039	0.048
ADP Employment	0.037**	0.067***	-0.031	0.006	-0.097	0.103	-0.071***	-0.093***	0.023	0.050***	0.108***	-0.058*
Advance Retail Sales	0.155***	0.077**	0.078**	0.112***	0.047	0.065	-0.095***	-0.126***	0.031	0.067***	0.117***	-0.049*
Existing Home Sales	0.023	0.048*	-0.025	-0.025	-0.068	0.043	-0.025**	-0.021***	-0.004	0.008	0.023	-0.016
Personal Income	0.010	0.036	-0.026	0.015	0.072	-0.057	-0.004	-0.001	-0.003	0.001	-0.011	0.012
Consumption												
New Home Sales	0.057***	0.025	0.032	0.097	-0.046	0.143**	-0.030***	-0.036***	0.006	0.020	0.040***	-0.020
Investment												
Durable Goods Orders	0.001	0.084***	-0.083**	0.016	-0.006	0.022	-0.008	-0.075**	0.067*	-0.014	0.058*	-0.072**
Government Purchases												
Government Budget	0.004	-0.013	0.017	0.008	0.013	-0.005	-0.006	-0.013	0.007	0.003	0.011	-0.008
Prices												
Producer Price Index	0.000	0.016	-0.016	-0.016	0.052**	-0.067	-0.041***	-0.021**	-0.020	0.029*	0.030***	-0.002
Forward Looking												
ISM Manufacturing	0.098**	0.169***	-0.071	0.095**	0.120***	-0.025	-0.085***	-0.097***	0.012	0.056***	0.065***	-0.009
ISM Non-manufacturing	0.000	0.139***	-0.139***	-0.027	0.030	-0.057	-0.049***	-0.058***	0.008	0.063***	0.099***	-0.037*
Consumer Confidence	0.052***	0.090***	-0.038	0.015	0.026	-0.011	-0.039***	-0.021***	-0.017	0.036***	0.031*	0.004
U. of Michigan Conf-Prelim	0.071**	0.050***	0.021	0.011	0.066	-0.054	-0.042***	-0.018***	-0.024	0.007	0.007	0.000
U. of Michigan Conf-Final	0.025	-0.053	0.078**	0.053	-0.084	0.137	-0.036***	0.008	-0.044***	0.009	0.014	-0.005
Housing Starts	0.044**	0.000	0.044	-0.025	0.013	-0.038	-0.070***	-0.036	-0.033	0.071***	0.031*	0.040
Pending Home Sales	0.033	-0.001	0.034	-0.041	0.010	-0.051	-0.027**	-0.010*	-0.017	0.007	0.018***	-0.011
Empire Manufacturing	0.048**	0.051**	-0.003	0.086***	0.030	0.056	-0.069***	-0.030**	-0.039	0.035*	0.048***	-0.013
Philadelphia Fed Business Outlook	0.007	0.063*	-0.056	0.107**	0.148**	-0.041	-0.055***	-0.023**	-0.032**	0.051***	0.033*	0.018
Chicago Purchasing Manager	0.019	0.090**	-0.070	-0.004	0.032	-0.036	-0.045***	-0.046***	0.001	0.035***	0.039***	-0.004
Nr. Obs.	985			985			985			985		
R ²	27.04%			8.16%			53.42%			36.78%		

Table A-4: Test for Asymmetry in the Response of Medium-term Interest Rates to Macroeconomic Announcements

The table reports the estimates of the following model: $\Delta Rate_t = a_0 + \sum_{m=1}^{22} a_m^+ S_{mt}^+ + \sum_{m=1}^{22} a_m^- S_{mt}^- + \varepsilon_t$, where $\Delta Rate_t$ measures the change in the interest rate (Eurodollar rate or Treasury yield) from five minutes before to five minutes after a macroeconomic announcement. The rate and yield changes are in basis points. S_{mt} is the standardized surprise for the announcement m , and $S_{mt}^+ = \max(S_{mt}, 0)$ and $S_{mt}^- = \min(S_{mt}, 0)$. The table also reports the difference in the markets' responses to positive vs. negative news of each macroeconomic announcement. The sample period is from 01/26/2012 to 12/15/2015. The regressions are estimated using OLS with White (1980) heteroskedasticity consistent covariance matrix. Only the announcements that are significant according to the joint Wald test listed in Table 1-4 are included. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent respectively.

Announcement	Eurodollar 4-5 Quarters to Expiration			Eurodollar 8-9 Quarters to Expiration			Eurodollar 12-13 Quarters to Expiration			5-Year Treasury Note		
	a_m^+	a_m^-	$a_m^+ - a_m^-$	a_m^+	a_m^-	$a_m^+ - a_m^-$	a_m^+	a_m^-	$a_m^+ - a_m^-$	a_m^+	a_m^-	$a_m^+ - a_m^-$
Real Activity												
GDP (advance, preliminary, final)	0.831**	0.639***	0.192	1.646***	1.296***	0.349	1.972***	1.573***	0.399	1.281***	1.036***	0.245
Initial Unemployment Claims	-0.131**	-0.305***	0.175	-0.359***	-0.691***	0.332*	-0.492***	-0.936***	0.444*	-0.312***	-0.665***	0.353**
Nonfarm Employment	3.506***	2.072*	1.434	6.320***	4.511***	1.809	7.273***	6.335***	0.938	5.232***	4.229***	1.003
Unemployment rate	-0.257	0.361	-0.618	-0.021	0.588	-0.609	0.003	0.203	-0.199	0.357	0.306	0.051
ADP Employment	0.445***	0.769***	-0.324	1.050***	1.563***	-0.513	1.503***	1.822***	-0.319	0.879***	1.338***	-0.459
Advance Retail Sales	0.311*	1.492***	-1.181***	1.048***	2.312***	-1.264***	1.642***	2.588***	-0.946**	1.113***	2.034***	-0.921***
Existing Home Sales	0.084	0.089	-0.005	0.271	0.262**	0.009	0.436*	0.352***	0.085	0.312**	0.206**	0.106
Personal Income	-0.067	0.135	-0.203	-0.034	-0.046	0.012	0.031	-0.129	0.160	-0.010	-0.024	0.015
Consumption												
New Home Sales	0.214	0.312***	-0.097	0.555***	0.629***	-0.074	0.617***	0.652***	-0.036	0.510***	0.526***	-0.015
Investment												
Durable Goods Orders	0.081	0.668**	-0.588*	0.020	1.368**	-1.348*	0.239	1.587**	-1.348*	0.131	1.076**	-0.945
Government Purchases												
Government Budget	0.038	0.049	-0.011	0.121	0.031	0.090	0.159	0.023	0.136	0.116	0.200	-0.085
Prices												
Producer Price Index	0.432**	0.149	0.283	0.749***	0.293	0.456	0.955***	0.410**	0.545*	0.689***	0.343**	0.346
Forward Looking												
ISM Manufacturing	0.425***	0.497***	-0.072	1.092***	1.205***	-0.113	1.758***	1.708***	0.050	1.079***	1.264***	-0.185
ISM Non-manufacturing	0.512***	0.353*	0.159	0.783***	0.905***	-0.121	0.984***	1.065***	-0.081	0.777***	0.813***	-0.036
Consumer Confidence	0.256**	0.289**	-0.033	0.706***	0.341***	0.364	0.923***	0.492***	0.431	0.541***	0.234**	0.307
U. of Michigan Conf-Prelim	0.274*	0.180**	0.095	0.576***	0.340***	0.236	0.503**	0.318**	0.185	0.521***	0.203**	0.319
U. of Michigan Conf-Final	0.262***	-0.284***	0.546***	0.556***	-0.153	0.710***	0.695***	-0.028	0.723***	0.491***	-0.027	0.518***
Housing Starts	0.678***	0.099	0.579**	1.176***	0.618*	0.558	1.429***	0.757	0.671	0.977***	0.475	0.502
Pending Home Sales	0.182*	0.104	0.078	0.410**	0.243***	0.167	0.511***	0.385***	0.126	0.326*	0.124*	0.202
Empire Manufacturing	0.657**	0.387*	0.271	1.311***	0.567	0.744	1.387***	0.583	0.804	1.129***	0.456*	0.673
Philadelphia Fed Business Outlook	0.499***	0.162	0.338**	0.957***	0.288**	0.669***	1.278***	0.322*	0.957***	0.872***	0.234	0.639***
Chicago Purchasing Manager	0.211***	0.524***	-0.313***	0.487***	0.927***	-0.440**	1.033***	0.839***	0.194	0.580***	0.695***	-0.115
Nr. Obs.	986			986			986			986		
R ²	35.42%			53.35%			51.06%			49.14%		

Table A-5: Test of Autocorrelation in Macroeconomic Surprises

The second column of this table reports estimation results for the following regression: $S_{mt} = a_0 + a_1 S_{mt-1} + \varepsilon_t$, where S_{mt} is the standardized surprise for the announcement m . The periods t and $t - 1$ refer to the announcement dates. The third and fourth columns report the estimation results for the following regression: $S_{mt} = b_0 + b_1 S_{mt-1} + b_2 MPU_t + b_3 S_{mt-1} MPU_t + \varepsilon_t$. MPU denotes the monetary policy uncertainty variable computed as explained in section 3.3. The sample period is from 01/26/2012 to 12/15/2015. The regressions are estimated using OLS with White (1980) heteroskedasticity consistent covariance matrix. Only the announcements that are significant according to the joint Wald test listed in Table 1-4 are included. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent respectively.

Announcement	Without Accounting for MPU	Accounting for MPU	
	a_1	b_1	b_3
Real Activity			
GDP (advance, preliminary, final)	0.113	-0.368	0.579
Initial Unemployment Claims	0.075	-0.361	0.519*
Nonfarm Employment	-0.058	-0.178	0.149
Unemployment rate	0.005	-0.144	0.153
ADP Employment	0.167	0.973	-1.237
Advance Retail Sales	-0.009	-1.023**	1.154*
Existing Home Sales	-0.192	-0.665	0.523
Personal Income	-0.388*	-2.155***	2.626**
Consumption			
New Home Sales	-0.281**	-1.324**	1.142**
Investment			
Durable Goods Orders	-0.135*	-0.623	0.625
Government Purchases			
Government Budget	-0.183	-0.683	0.652
Prices			
Producer Price Index	0.029	-0.206	0.284
Forward Looking			
ISM Manufacturing	0.038	0.328	-0.378
ISM Non-manufacturing	-0.122	1.160	-1.527
Consumer Confidence	-0.372**	-0.666	0.340
U. of Michigan Conf-Prelim	-0.037	-0.020	-0.031
U. of Michigan Conf-Final	0.278**	0.938*	-0.982
Housing Starts	-0.274	-0.118	-0.234
Pending Home Sales	-0.169	-1.024	1.133
Empire Manufacturing	-0.138	-0.135	-0.004
Philadelphia Fed Business Outlook	0.054	0.177	-0.168
Chicago Purchasing Manager	-0.153	0.063	-0.252

Table A-6: Accounting for Nonlinearity in the Market Response to Macroeconomic Announcements

This table reports estimation results for the following regression: $R_t = a_0 + \sum_{m=1}^{22} a_{1m} S_{mt} + \sum_{m=1}^{22} a_{2m} S_{mt}^2 \text{sign}(S_{mt}) + \varepsilon_t$, where R_t is the continuously compounded return for the E-mini S&P 500 futures, the WTI crude oil futures, the 10-year Treasury note futures, or the U.S. Dollar Index futures. R_t is from five minutes before to five minutes after a macroeconomic announcement. S_{mt} is the standardized surprise for the announcement m . The sample period is from 01/26/2012 to 12/15/2015. The regressions are estimated using OLS with White (1980) heteroskedasticity consistent covariance matrix. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent respectively.

Announcement	S&P 500		Crude Oil		10-Year T-note		US Dollar Index	
	a_{1m}	a_{2m}	a_{1m}	a_{2m}	a_{1m}	a_{2m}	a_{1m}	a_{2m}
Real Activity								
GDP (advance, preliminary, final)	0.072***	0.005	0.050	0.004	-0.077***	-0.003	0.100***	0.008**
Initial Unemployment Claims	-0.028***	0.000	-0.018	-0.001	0.040***	-0.002***	-0.030***	0.001**
Nonfarm Employment	0.188***	-0.036	0.131**	-0.042	-0.328***	-0.013	0.264***	0.015
Unemployment rate	-0.039	0.008	-0.085	0.010	-0.069	-0.015**	0.060	0.006
ADP Employment	0.045***	0.000	-0.072	0.019*	-0.091***	0.006**	0.091***	-0.009**
Advance Retail Sales	0.119***	0.009	0.060**	-0.003	-0.109***	0.003	0.087***	-0.007**
Existing Home Sales	0.036	0.002	-0.046	0.011	-0.025***	-0.002*	0.015	-0.004
Personal Income	0.011	0.000	0.039	-0.001	0.001	0.000	-0.007	0.000
Consumption								
New Home Sales	0.041**	0.003	0.023	0.010*	-0.031***	0.004*	0.029***	-0.004**
Investment								
Durable Goods Orders	0.062***	-0.003***	0.011	0.000	-0.057**	0.003**	0.027	-0.002
Government Purchases								
Government Budget	-0.005	0.002	0.002	0.003	-0.012***	0.002***	0.008	-0.001
Prices								
Producer Price Index	0.017	0.008***	0.017	-0.007	-0.031***	-0.001	0.030***	-0.001
Forward Looking								
ISM Manufacturing	0.130***	-0.005	0.109***	0.001	-0.089***	0.002	0.062***	0.000
ISM Non-manufacturing	0.084***	-0.020***	0.023	-0.016***	-0.055***	0.002	0.082***	-0.005
Consumer Confidence	0.071***	-0.003	0.026	0.004	-0.031***	-0.003	0.033***	-0.001
U. of Michigan Conf-Prelim	0.058***	0.002	0.040	-0.007	-0.029***	-0.002	0.005	-0.002
U. of Michigan Conf-Final	-0.014	0.021**	-0.012	0.028	-0.016**	-0.006	0.011	-0.001
Housing Starts	0.025	0.009	-0.004	-0.004	-0.051***	-0.002	0.052***	0.009
Pending Home Sales	0.021	0.005	-0.010	0.000	-0.022***	-0.003**	0.015	0.001
Empire Manufacturing	0.046***	-0.001	0.052*	0.005	-0.046***	-0.002	0.042***	-0.002
Philadelphia Fed Business Outlook	0.036	-0.009	0.131***	-0.006	-0.037***	-0.003	0.041***	0.003
Chicago Purchasing Manager	0.054***	-0.001	0.014	0.000	-0.046***	-0.001	0.037***	0.000
Nr. Obs.	985		985		985		985	
R ²	23.94%		7.10%		54.64%		36.04%	

Table A-7: Absolute Value of Surprises and MPU

This table reports estimation results for the following regression: $|S_{mt}| = a_0 + a_1 MPU_t + \varepsilon_t$, where S_{mt} is the standardized surprise for the announcement of type m , and MPU denotes the monetary policy uncertainty variable, computed as explained in section 3.3. The sample period is from 01/26/2012 to 12/15/2015. The regressions are estimated using OLS with White (1980) heteroskedasticity consistent covariance matrix. Only the announcements that are significant according to the joint Wald test listed in Table 1-4 are included. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent respectively.

	a_0	a_1
Real Activity		
GDP (advance, preliminary, final)	0.417	0.379
Initial Unemployment Claims	0.817***	-0.089
Nonfarm Employment	1.301***	-0.634
Unemployment rate	1.765***	-1.145*
ADP Employment	2.219***	-1.800***
Advance Retail Sales	0.401	0.474
Existing Home Sales	0.290	0.583
Personal Income	1.431*	-1.152
Consumption		
New Home Sales	0.538	0.223
Investment		
Durable Goods Orders	0.740*	-0.157
Government Purchases		
Government Budget	0.835	-0.237
Prices		
Producer Price Index	0.443	0.442
Forward Looking		
ISM Manufacturing	1.015**	-0.303
ISM Non-manufacturing	0.942***	-0.152
Consumer Confidence	0.747**	0.109
U. of Michigan Conf-Prelim	1.100***	-0.286
U. of Michigan Conf-Final	1.468***	-0.915**
Housing Starts	0.819**	-0.063
Pending Home Sales	0.422	0.422
Empire Manufacturing	0.916**	-0.090
Philadelphia Fed Business Outlook	1.075***	-0.337
Chicago Purchasing Manager	0.334	0.530

Table A-8: Investor Disagreement and MPU

This table reports estimation results for the following regression: $StdDev\ Forecasts_{m,t} = a_0 + a_1 MPU_t + \varepsilon_t$, where $StdDev\ Forecasts_m$ is the standard deviation of the analyst forecasts for announcement m , and MPU denotes the monetary policy uncertainty measured as explained in section 3.3. The sample period is from 01/26/2012 to 12/15/2015. The regressions are estimated using OLS with White (1980) heteroskedasticity consistent covariance matrix. Only the announcements that are significant according to the joint Wald test listed in Table 1-4 are included. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent respectively.

Announcement	a_0	a_1
Real Activity		
GDP (advance, preliminary, final)	0.214**	0.042
Initial Unemployment Claims	8.397***	-1.990
Nonfarm Employment	26.222***	-3.317
Unemployment rate	0.096***	-0.013
ADP Employment	27.417***	-9.760**
Advance Retail Sales	0.279***	-0.084*
Existing Home Sales	0.070***	-0.002
Personal Income	0.279**	-0.182
Consumption		
New Home Sales	6.416***	5.404**
Investment		
Durable Goods Orders	1.597***	-0.225
Government Purchases		
Government Budget	11.099	2.988
Prices		
Producer Price Index	0.369***	-0.238***
Forward Looking		
ISM Manufacturing	0.677***	0.018
ISM Non-manufacturing	0.676***	0.032
Consumer Confidence	2.300***	-0.783***
U. of Michigan Conf-Prelim	1.631***	-0.400*
U. of Michigan Conf-Final	1.049***	-0.269
Housing Starts	9.161**	17.292***
Pending Home Sales	1.708***	-0.497*
Empire Manufacturing	3.272***	-0.992**
Philadelphia Fed Business Outlook	2.674***	0.086
Chicago Purchasing Manager	0.923***	0.483*

**Table A-9: Average Effect of MPU on the Market Response to Macroeconomic News
(with moving average of realized volatility as proxy for MPU)**

Panel A reports the estimates for the following model: $R_t = \alpha + b_{MPU} MPU_t + b_S \sum_{m=1}^{22} \hat{\beta}_m S_{mt} + c_{MPU} \sum_{m=1}^{22} \hat{\beta}_m S_{mt} MPU_t + u_t$. R_t is the continuously compounded return of the S&P 500 futures, the 10-year Treasury note futures, the U.S. Dollar Index futures, the WTI crude oil futures, or the change in the Eurodollar rate of the stated contract maturity or the change in the 5-year Treasury yield. The returns and rate changes are computed from five minutes before to five minutes after a macroeconomic news release. S_{mt} is the standardized surprise for announcement m . MPU_t measures monetary policy uncertainty as the moving average of the past 21 trading days of the daily realized volatility of Eurodollar futures with 8-9 quarters to expiration. $\hat{\beta}_m$ estimates are obtained from running the regression in equation (4) using the part of the sample before May 22, 2013. Panel B reports the estimates of the following model: $R_t = \alpha + b_{MPU} MPU_t + b_{VIX} VIX_t + b_S \sum_{m=1}^{22} \hat{\beta}_m S_{mt} + c_{MPU} \sum_{m=1}^{22} \hat{\beta}_m S_{mt} MPU_t + c_{VIX} \sum_{m=1}^{22} \hat{\beta}_m S_{mt} VIX_t + u_t$, where VIX_t is the CBOE's Volatility Index measuring the market expectations of near-term volatility conveyed by S&P 500 stock index option prices. Panel C reports the estimates of the model: $R_t = \alpha + b_{MPU} MPU_t + b_{RA} RA_t + b_{UC} UC_t + b_S \sum_{m=1}^{22} \hat{\beta}_m S_{mt} + c_{MPU} \sum_{m=1}^{22} \hat{\beta}_m S_{mt} MPU_t + c_{RA} \sum_{m=1}^{22} \hat{\beta}_m S_{mt} RA_t + c_{UC} \sum_{m=1}^{22} \hat{\beta}_m S_{mt} UC_t + u_t$, where RA_t and UC_t are the risk aversion and the uncertainty components of the VIX index and are constructed as described in section 2.1. in Bekaert, Hoerova, and Lo Duca (2013). For all panels, only the announcements that are significant according to the joint Wald test listed in Table 1-4 are included. The sample period is from 01/26/2012 to 12/15/2015. The regressions are estimated using OLS with White (1980) heteroskedasticity consistent covariance matrix. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively.

Panel A: Basic Regression	b_S	c_{MPU}	c_{VIX}	c_{RA}	c_{UC}	R^2
<i>Stock, bond, foreign exchange and crude oil (N=985)</i>						
S&P 500	1.397***	-1.166***	-	-	-	20.65%
10-year Treasury note	0.416*	1.095***	-	-	-	48.03%
U.S. Dollar Index	-0.141	2.216***	-	-	-	27.78%
WTI Crude Oil	1.784***	-1.832***	-	-	-	6.73%
<i>Medium-term interest rates (N=986)</i>						
Eurodollar 4-5 quarters to expiration	-1.177	4.829***	-	-	-	22.21%
Eurodollar 8-9 quarters to expiration	-0.965*	3.759***	-	-	-	45.76%
Eurodollar 12-13 quarters to expiration	-0.259	2.261***	-	-	-	52.69%
5-year Treasury note	-0.428	2.681***	-	-	-	49.02%
Panel B: Controlling for the VIX						
<i>Stock, bond, foreign exchange and crude oil (N=984)</i>						
S&P 500	0.082	-1.094***	0.285***	-	-	26.91%
10-year Treasury note	0.561	1.086***	-0.031	-	-	48.12%
U.S. Dollar Index	0.644	2.182***	-0.173	-	-	28.13%
WTI Crude Oil	0.779*	-1.709***	0.206***	-	-	8.20%
<i>Medium-term interest rates (N=984)</i>						
Eurodollar 4-5 quarters to expiration	-0.245	4.777***	-0.208	-	-	22.18%
Eurodollar 8-9 quarters to expiration	-0.151	3.738***	-0.181	-	-	45.66%
Eurodollar 12-13 quarters to expiration	0.340	2.202***	-0.128	-	-	52.06%
5-year Treasury note	0.238	2.651***	-0.146	-	-	48.62%
Panel C: Controlling for the VIX components						
<i>Stock, bond, foreign exchange and crude oil (N=960)</i>						
S&P 500	0.394	-1.115***	-	0.022***	0.081	24.65%
10-year Treasury note	2.445***	1.251***	-	0.009	-0.266***	48.56%
U.S. Dollar Index	2.030**	2.252***	-	-0.001	-0.250**	29.75%
WTI Crude Oil	1.159	-1.713***	-	0.019***	0.036	7.72%
<i>Medium-term interest rates (N=960)</i>						
Eurodollar 4-5 quarters to expiration	5.051*	5.603***	-	0.029	-0.846**	23.35%
Eurodollar 8-9 quarters to expiration	3.116***	4.210***	-	0.014	-0.540***	47.35%
Eurodollar 12-13 quarters to expiration	2.285***	2.448***	-	0.005	-0.325***	52.75%
5-year Treasury note	2.803***	2.913***	-	0.008	-0.412***	50.30%

Table A-10: Effect of Monetary Policy Uncertainty on the Market Response to Macroeconomic News (OLS and Weighted Least Squares estimates)

The table reports estimates for the following model: $R_t = \alpha + b MPU_t + c \sum_{m=1}^{22} \hat{\beta}_m S_{mt} + c \sum_{m=1}^{22} \hat{\beta}_m S_{mt} MPU_t + u_t$. R_t is either the continuously compounded return of the S&P 500 futures, the 10-year Treasury note futures, the U.S. Dollar Index futures, the WTI crude oil futures, or the change in the Eurodollar rate of the stated contract maturity or the change in the 5-year Treasury yield. The returns and rate changes are computed from five minutes before to five minutes after a macroeconomic news release. S_{mt} is the standardized surprise for announcement m . MPU_t is the monetary policy uncertainty variable measured as explained in section 3.3. $\hat{\beta}_m$ estimates are obtained from running the regression in equation (4) using the part of the sample before May 22, 2013. Only the announcements that are significant according to the joint Wald test listed in Table 1-4 are included. The sample period is from 01/26/2012 to 12/15/2015. The results in Panel A are based on OLS with White (1980) heteroskedasticity consistent covariance matrix. The results in Panel B are obtained with weighted least squares (WLS). *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively

	<i>c</i>	<i>d</i>	R ²
<i>Panel A: OLS with White (1980) standard errors</i>			
S&P 500	1.560 (0.24)***	-1.374 (0.29)***	20.98%
10-year Treasury note	0.296 (0.28)	1.242 (0.38)***	47.89%
U.S. Dollar Index	-0.514 (0.66)	2.680 (0.86)***	27.73%
WTI Crude Oil	1.895 (0.31)***	-1.975 (0.38)***	6.39%
Eurodollar 4-5 quarters to expiration	-2.086 (1.22)*	5.974 (1.71)***	22.34%
Eurodollar 8-9 quarters to expiration	-1.509 (0.58)***	4.440 (0.79)***	45.82%
Eurodollar 12-13 quarters to expiration	-0.475 (0.36)	2.529 (0.48)***	52.28%
5-year Treasury note	-0.762 (0.45)*	3.098 (0.60)***	48.82%
<i>Panel B: Weighted Least Squares</i>			
S&P 500	1.546 (0.14)***	-1.312 (0.17)***	25.51%
10-year Treasury note	0.247 (0.21)	1.271 (0.26)***	50.98%
U.S. Dollar Index	-0.335 (0.34)	2.540 (0.43)***	37.93%
WTI Crude Oil	1.936 (0.23)***	-2.022 (0.28)***	9.30%
Eurodollar 4-5 quarters to expiration	-3.712 (1.14)***	9.175 (1.38)***	25.53%
Eurodollar 8-9 quarters to expiration	-2.349 (0.35)***	5.634 (0.44)***	57.37%
Eurodollar 12-13 quarters to expiration	-1.089 (0.17)***	3.363 (0.23)***	63.56%
5-year Treasury note	-1.679 (0.21)***	4.222 (0.28)***	57.25%

**Figure A-1. Moving Average of Realized Volatility of Eurodollar Futures
with 8-9 Quarters to Expiration (%)**

This figure shows an alternative proxy for monetary policy uncertainty computed as the moving average of the past 21 trading days of the daily realized volatility of Eurodollar futures with 8-9 quarters to expiration.

Essay 2: Ambiguity and the Cross-Section of Stock Returns¹

2.1. Introduction

The main goal of this essay is to investigate whether systematic ambiguity impacts the cross-section of stock returns. There has been a substantial amount of research on how investors make decisions when facing risk and on how systematic risk affects the cross-section of stock returns. In contrast, the effect of ambiguity, also known as Knightian uncertainty (Knight, 1921) is less known. Knight (1921) was the first to make the distinction between the two dimensions of uncertainty. While risk refers to uncertainty regarding future potential outcomes, ambiguity refers to uncertainty with respect to the *probabilities* of those potential outcomes.

Based on subjective expected utility theory (Savage, 1954), the variables influencing an uncertain choice are the potential outcomes and the probabilities associated with each potential outcome. In other words, the confidence of these probabilities does not play any (obvious) role. However, empirical research and various experiments have shown that the confidence of these probabilities matters, and that people are more willing to bet on risky outcomes than on ambiguous ones, holding the probability of outcomes constant. In reality, individual choices violate the postulates of subjective expected utility, as in for example, the well-known Ellsberg's paradox (Ellsberg, 1961).² In this paper, we distinguish between risk and ambiguity, and construct a measure of systematic ambiguity based on the theoretical framework of expected utility with uncertain probabilities (EUUP) proposed by Izhakian (2017).

¹ This essay is based on a paper coauthored with Ann Marie Hibbert.

²As an illustration, consider a choice between two decks of cards: (i) with 10 red and 10 blue cards (the risky deck), and (ii) with 20 red or blue cards, but the split between red and blue cards is completely unknown (the ambiguous deck). A bet on the color of a random card drawn for either deck pays a fixed sum if a card with the chosen color is drawn, and 0 otherwise. In lab experiments, subjects prefer the risky deck to the ambiguous one.

Most of the previous work on ambiguity is theoretical in nature and accounts for investors' attitudes towards ambiguity, rather than measuring the degree of ambiguity *per se*.³ These theoretical models do not generally simultaneously distinguish between risk, ambiguity, attitudes towards risk, and attitudes towards ambiguity.⁴ However, this separation is essential to quantify ambiguity appropriately. In our paper, we follow the procedure of Brenner and Izhakian (2017) and measure systematic ambiguity by the variance of probabilities of future potential outcomes. Relative to previous research, Brenner and Izhakian (2017) show that this measure is independent of risk, attitudes towards risk, and attitudes towards ambiguity. Furthermore, our measure is different from other empirical proxies of ambiguity used in the literature, such as the VIX index (Williams, 2015), or the variance risk premium (Drechsler, 2013; Zhou, 2015).

Our second goal is to examine whether ambiguity affects the price discovery process in the stock market. We focus our analysis on times when earnings news is released, and investigate how ambiguity affects the stock market reaction to such news. Veronesi (1999) shows that the time-varying discount rate can change with the level of uncertainty. We therefore anticipate that ambiguity can influence the stock market reaction to earnings news by affecting returns directly via the rate used to discount future cash flows. We also anticipate that during times of elevated ambiguity, analysts make less accurate forecasts, and so earnings surprises are larger in magnitude, relative to periods of low ambiguity. This can affect the stock market reaction to earnings news,

³ See for example Epstein and Schneider (2008), Cao, Wang, Zhang (2005), Chen and Epstein (2002). For a recent survey, please see Guidolin and Rinaldi (2013).

⁴ For example, under the max-min expected utility framework of Gilboa and Schmeidler (1989), the set of priors reflect both beliefs (i.e. information) and tastes (attitudes towards ambiguity), but these two concepts are not separable. Furthermore, the Choquet expected utility (CEU) theory (Schmeidler, 1989) deals with both ambiguity and aversion to ambiguity, but again the two concepts are not separable.

as earnings surprises of larger magnitude usually have a smaller stock market marginal response to earnings news (Freeman and Tse, 1992).

This paper makes several novel contributions to the literature. First, we contribute to research on the relation between systematic ambiguity and the cross-section of stock returns, by showing that during times of elevated ambiguity, investors require a premium for ambiguity, in addition to the premium they require for bearing risk. Our finding that systematic ambiguity is priced in the cross-section of stock returns complements the findings of Brenner and Izhakian (2017), who find that ambiguity has a significant impact on the excess return of the market portfolio. We also perform an in-depth analysis of the types of firms that are more impacted by this uncertainty factor by forming long-short portfolios based on various firm characteristics such as those that are measures of information asymmetry. Our results indicate that when ambiguity is expected to increase, stocks of firms with high information asymmetry; firms which are difficult to value and/or arbitrage, such as firms that are smaller, riskier, and less profitable; non-dividend payers, and firms with higher levels of earnings management, underperform their counterparts.

These findings suggest the need to extend modern portfolio theory, i.e. the mean-variance framework, to account for ambiguity as another dimension, in addition to the mean and standard deviation of returns (risk). We show that during normal times, i.e. when ambiguity is low, the standard risk-return relation holds. Specifically, riskier portfolios provide a higher return. On the other hand, during more uncertain times, characterized by high ambiguity, riskier portfolios provide lower returns, in violation of the standard positive risk-return relation.

Finally, we contribute to research on the relation between asset prices and firm-specific fundamentals by showing that ambiguity is an important determinant of the market response to news. Previous papers have argued that the stock market response to fundamental news depends

on the state of the economy (Boyd, Hu, and Jagannathan, 2005; Andersen, Bollerslev, Diebold, and Vega, 2007), limited investor attention (Hirshleifer, Lim, and Teoh, 2009; Dellavigna and Pollet, 2009), investor sentiment (Mian and Sankaraguruswamy, 2012), and market implied volatility (Williams, 2015). We contribute to this literature by showing that the stock market reaction to firm-specific news depends on the level of systematic ambiguity. Our results show that in times of elevated ambiguity, the stock market reacts less severely to bad earnings news. Furthermore, this weaker reaction is more significant for stocks of firms that have greater information asymmetry, are small, old, unprofitable, and riskier. Our results remain robust after controlling for other factors that could affect the stock market reaction to earnings news, such as the state of the economy, real business conditions, the VIX, the VIX components (risk aversion and stock market uncertainty as in Bekaert, Hoerova, and Lo Duca (2013)), sentiment, and investor attention. This finding suggests that ambiguity reduces stock market efficiency.

The rest of the paper is organized as follows: Section 2 discusses the related literature and introduces our hypotheses. Section 3 describes the construction of our ambiguity measure. Sections 4 and 5 present the empirical tests and the results of our hypotheses, while section 6 provides the results of robustness checks. We provide concluding remarks in Section 7.

2.2. Related Literature and Hypotheses

2.2.1. Measuring Ambiguity

A good measure of ambiguity needs to be independent of attitudes towards ambiguity (i.e. tastes for ambiguity), risk, and attitudes towards risk. To emphasize the importance of this separation, we comparatively refer to the risk literature, where the separation between risk and attitudes

towards risk was a crucial step towards empirically measuring risk independently of risk attitudes, and towards the investigation of risk attitudes independently of risk (Izhakian, 2017).

The models of decision making under ambiguity have been evolving towards the separation between ambiguity and risk, and between tastes (i.e. preferences/attitudes) and beliefs (i.e. information). For example, in the Choquet expected utility theory (CEU) of Schmeidler (1989) and the max-min expected utility theory (MEU) of Gilboa and Schmeidler (1989), ambiguity is distinguished from risk. Subsequently, the separation between tastes and beliefs regarding ambiguity is introduced by the $\alpha - MEU$ theory of Ghirardato, Klibanoff, and Marinacci (1998), and then improved by Klibanoff, Marinacci, and Mukerji (2005).

The theory of expected utility with uncertain probabilities (EUUP) of Izhakian (2017) introduces a theoretical framework to measure ambiguity independently of attitudes towards ambiguity, risk, and attitudes towards risk. Under this framework, the decision-making process consists of two stages. During the first stage, also known as the ‘probability formation phase’, the decision maker forms his perceived probabilities of all future potential outcomes that are important for his decision. In the second stage, also known as ‘the valuation phase’, the decision maker evaluates all future potential outcomes given his perceived probabilities, and acts consequently. Ambiguity is characteristic of the first stage, since ambiguity refers to uncertainty about probabilities, while risk is characteristic of the second stage, as it refers to uncertainty about consequences. Under the EUUP theory, ambiguity can be measured directly from data. For instance, if risk is generally proxied by the volatility of outcomes, the EUUP theory allows us to empirically measure ambiguity by the volatility of probabilities. In addition, if Rothschild and Stiglitz (1970) define risk aversion as aversion towards mean-preserving spreads in outcomes, the EUUP theory of Izhakian (2017) defines aversion towards ambiguity as aversion towards mean-

preserving spreads in probabilities. Attitudes towards ambiguity can then be attained directly from the ambiguity premium, as shown by Brenner and Izhakian (2017). In this essay, we focus on the degree of systematic ambiguity and not on attitudes towards ambiguity.

Empirical applications of ambiguity computed based on the EUUP theory have mainly been used in the corporate finance literature, as for example when investigating the effect of ambiguity on payout policy (Herron and Izhakian, 2018), the importance of ambiguity in capital structure decisions (Izhakian, Yermack, and Zender, 2017), and the importance of ambiguity in executives' stock option exercise decisions (Izhakian and Yermack, 2017). Our ambiguity measure is constructed based on the EUUP theory, but our application focuses on asset pricing and market efficiency. We investigate the impact of systematic ambiguity on the cross-section of stock returns, complementing the work of Brenner and Izhakian (2017), who investigate the role of systematic ambiguity on the excess return of the market portfolio.

Other empirical measures of ambiguity (obtained from market data, as opposed to controlled experiments) used in the literature are the entropy of information (Ulrich, 2013), the disagreement among analysts (Anderson, Ghysels and Juergens, 2009), the variance risk premium (Drechsler, 2013; Zhou, 2015), and the CBOE VIX index (Williams, 2015). Ulrich (2013) shows that ambiguity about trend inflation explains the time-varying term premium in the nominal U.S. Treasury bond yields. Ulrich assumes that the benchmark model for trend inflation comes from the median one-quarter ahead inflation forecast from the Survey of Professional Forecasters. However, the investor is exposed to ambiguity, because he is uncertain about the true model for trend inflation. Therefore, the investor compares all potential models that could have generated the exogenous process in the economy via a likelihood ratio test. Ambiguity, or the amount of relative entropy, is then measured by the likelihood ratio between the worst-case model and the benchmark

model. The investor requires an inflation ambiguity premium for unpredictable changes in trend inflation (relative entropy). In Ulrich's study, the investor has max-min preferences, meaning that he evaluates his expected lifetime utility under the worst-case scenario. This max-min expected utility framework captures both ambiguity and attitudes towards ambiguity, but does not distinguish between the two. In the current paper, we empirically measure the degree of systematic ambiguity, which is independent of attitudes towards ambiguity.

Another representative paper is the work of Drechsler (2013), who develops a model where a representative investor makes consumption and portfolio choice decisions, but faces ambiguity regarding the true model governing the economic fundamentals. Drechsler shows that the ambiguity about the true model is directly related to variance risk premium. The representative investor pays a large premium for equity index options because he hedges misspecification concerns about the model. Drechsler argues that a good measure for this premium is the difference between the option-implied expectations of return variance (such as the VIX) and the statistical (i.e. true) expectations of return variance. The option-implied expectation is equivalent to a variance swap that pays the buyer the realized variance over the lifetime of the contract. By buying the swap, the buyer receives protection against high realized variance. The difference between the swap price and the true expectation of variance is the (variance) premium investors pay for this hedge. Thus, the representative investor's desire to hedge his model uncertainty concerns leads to a price premium in index options, and the magnitude of this premium depends on the level of model uncertainty. The variance risk premium is also used to measure ambiguity by Zhou (2015), when studying the stock market reaction to macroeconomic announcements. However, the variance risk premium used as a measure of ambiguity does not allow the separation between attitudes towards risk and attitudes towards ambiguity. In fact, the variance risk premium has also

been used in the literature as a proxy of risk aversion (Bekaert, Hoerova, and Duca, 2013). In the current paper, we use a measure of the degree of systematic ambiguity that is different (by construction) from risk, attitudes towards risk, and attitudes towards ambiguity.

Ambiguity has also been empirically measured by the CBOE VIX Index in Williams's (2015) study of the stock market reaction to earnings news. Again, the VIX index does not allow the separation of attitudes towards risk and attitudes towards ambiguity. Our ambiguity measure, described in section 2.3, measures the degree of systematic ambiguity and not attitudes towards ambiguity, and is negatively correlated with the VIX index and the variance risk premium.

2.2.2. Ambiguity in Asset Pricing

We aim to shed light on the impact of systematic ambiguity on the cross-section of stock returns. There is ample evidence that the difference in the cross-section of stock returns is not only driven by compensation for systematic risk. In his survey paper on this topic, Subrahmanyam (2010) documents at least 50 variables used in the literature to predict stock returns in the cross-section, and summarizes them in four main categories: the 'informal Wall Street wisdom' including predictors that are not based on a theoretical reasoning, but are motivated by the wisdom of finance professionals, behavioral biases, frictions, and the theoretical motivation based on risk-return models. Considering ambiguity as a missing factor in asset pricing models has been mainly addressed from a theoretical perspective. For example, Izhakian and Benninga (2011) and Epstein and Schneider (2010) include ambiguity in their pricing model and argue that ambiguity can be one potential determinant of expected returns.

More closely related to our work is the recent paper by Brenner and Izhakian (2017), who empirically show that the market excess return is significantly affected by systematic ambiguity. Similarly, So, Driouchi, and Trigeorgis (2016) find that systematic ambiguity affects the market

excess return internationally, during the period of 1990 to 2012. In contrast to these two papers, we investigate whether systematic ambiguity affects the cross-section of stock returns directly and state our first hypothesis as:

Hypothesis 1: Ambiguity has a significant impact on the cross-section of stock returns.

According to the intertemporal capital asset pricing model of Merton (1973), investors have incentives to protect themselves against future stochastic shifts in investment and consumption opportunity sets. Since greater systematic ambiguity can reduce future consumption and investment opportunities, it can also have an impact on investors' intertemporal hedging demand for the future. This can ultimately affect asset prices and returns.

If ambiguity matters for the cross-section of stock returns, what types of stocks are more attractive to investors during periods of elevated ambiguity? Caballero and Krishnamurthy (2008) show that in times of high uncertainty, agents move towards holding un-contingent and safe assets. They develop a model of crises and central bank policy that incorporates ambiguity, and claim that severe flight to quality episodes do not only involve risk about asset payoffs, but also uncertainty about the environment. This suggests that although ambiguity-averse investors are reluctant to hold ambiguous assets in general (Bossaerts, Ghirardo, Guarnascheli, and Zame, 2010), such as assets with high information asymmetry, the 'flight to quality' phenomenon seems to be even more severe in times of elevated ambiguity, when investors are expected to move towards 'safe' assets. The idea is also supported by the former Fed Chairman Alan Greenspan.

‘When confronted with uncertainty, especially Knightian uncertainty, human beings invariably attempt to disengage from medium to long-term commitments in favor of safety and liquidity...’, Alan Greenspan (2004)⁵

Furthermore, research in the neuroscience literature shows that when investors make decisions in the presence of high ambiguity, the area in the brain responsible for fear and survival instincts (called the amygdala) is activated (Hsu, Bhatt, Adolphs, Tranel, and Camerer, 2005). Hsu, et. al (2005) also show that in the presence of uncertainty, ‘the brain is alerted... that information is missing..., and that cognitive and behavioral resources must be mobilized in order to seek out additional information from the environment’ (pp. 1683). Motivated by this finding, we conjecture that stocks that provide this *additional information* readily, would be more attractive during times of elevated systematic ambiguity. These stocks would most likely have low levels of information asymmetry (consistent with Bossaerts, Ghirardo, Guarnascheli, and Zame (2010)) and would be easy to value/arbitrage.

Stocks that are easy to value/arbitrage are more attractive than their counterparts during times of elevated ambiguity. Hard-to-arbitrage stocks are more frequently and more severely mispriced (Wurgler and Zhuravskaya, 2002), and the mispricing might last even longer during times of high ambiguity. In fact, when uncertainty is high, arbitrageurs may be reluctant to incur the potentially large costs of trying to exploit the arbitrage opportunity (Merton, 1987). Furthermore, the arbitrage activity can be deterred until arbitrageurs are able to determine the expected payoff with more accuracy. In addition, the expected payoff must be above the fixed costs to set up the arbitrage (Mitchell, Pulvino, and Stafford, 2002). We would therefore expect

⁵ <https://www.federalreserve.gov/BoardDocs/speeches/2004/20040103/default.htm>

that easy-to-value/arbitrage stocks would be more attractive than their counterparts during times of elevated systematic ambiguity. We state our second and third hypotheses as:

Hypothesis 2: During periods of high ambiguity, stocks with high information asymmetry underperform their counterparts.

Hypothesis 3: During periods of high ambiguity, stocks that are hard to value/arbitrage underperform their counterparts.

Our proxies for information asymmetry and difficulty to arbitrage are motivated by the prior literature. For example, Berger and Turtle (2012) show that firms with high information asymmetry (or opaque firms) tend to be volatile, small, young and intangible. In addition, Richardson (2000) and Schipper (1989) argue that for firms with high information asymmetry, the practice of earnings management is sustained by the fact that stakeholders do not have access to sufficient resources, incentives, or relevant information to monitor the manager's actions. Arbitrage tends to be costly and risky for young, small, unprofitable, and extreme growth stocks because of their high idiosyncratic risk (Wurgler and Zhuravskaya, 2002), their greater trading costs (Amihud and Mendelsohn, 1986), and their short selling difficulty (Duffie, Garleanu, and Pedersen, 2002). According to Baker and Wurgler (2006), hard-to-arbitrage stocks are highly volatile, young, small, unprofitable, non-dividend paying, and extreme growth stocks.

In our empirical tests we consider the following characteristics: idiosyncratic volatility, size, age, tangibility, profitability, book-to-market value, the level of earnings management, and whether the firm is a dividend-payer.

2.2.3. *Ambiguity and Market Efficiency*

We also investigate whether ambiguity affects the price discovery process in the stock market. We focus our analysis on times when earnings news is released, and empirically investigate whether ambiguity affects the stock market reaction to such news. Previous theoretical work describes how new information gets impounded into asset prices under different economic environments. For example, the theoretical rational expectations equilibrium model of Veronesi (1999) describes how uncertainty about the state of the economy can make investors in the stock market underreact to good economic news in bad times and overreact to bad economic news in good times. If bad news arrives and investors believe that the economy is in a good state, investors tend to become more uncertain about the state of the economy, causing the discount rate to increase. This strengthens the negative impact of news on prices. Similarly, if good economic news arrives when investors believe that the economy is in a bad state, investors again become more uncertain about the state of the economy, causing the discount rate to increase. This weakens the positive impact of news on prices.

We anticipate that ambiguity can affect the stock market reaction to earnings news through its impact on the time-varying discount rate, which can change with the level of uncertainty (Veronesi, 1999).⁶ At the same time, we expect that during periods of elevated ambiguity, analysts make less accurate forecasts and so earnings surprises can be greater in magnitude. Earnings surprises of greater magnitude have a smaller marginal response of the stock return to the news (Freeman and Tse, 1992). We state our fourth and fifth hypotheses as:

⁶ Previous research shows that the equity (risk) premium increases during times of greater uncertainty (Pastor and Veronesi, 2013; Andrei and Hasler, 2014; Brogaard and Detzel, 2012). However, these studies do not distinguish between risk and ambiguity. Brenner and Izhakian (2017) show that the equity premium consists of risk premium and ambiguity premium.

Hypothesis 4: Systematic ambiguity affects the stock market reaction to earnings news.

Hypothesis 5: Greater systematic ambiguity increases the magnitude of the earnings surprise.

A paper related to our analysis is the work of Williams (2015), who investigates how a shock in ambiguity affects the stock market reaction to earnings news. Williams measures ambiguity by the CBOE VIX index and finds that following an increase in the VIX, investors respond asymmetrically, weighting bad news more than good news. However, relative to Williams (2015), we consider different channels through which ambiguity can affect the stock market reaction to earnings news. Furthermore, our systematic ambiguity measure is independent (by construction) of risk, attitudes towards risk, and attitudes towards ambiguity, while the VIX measure does not separate between them. Our ambiguity measure is significantly negatively correlated with the VIX index and this is consistent with Brenner and Izhakian (2017), who provide evidence that the ambiguity measure based on the EUUP theory does not capture the same aspects of uncertainty as the VIX. However, to rule out the possibility that our results are driven by the VIX Index, we control for the VIX and the VIX components (risk aversion and stock market uncertainty computed as described in Bekaert, Hoerova, and Duca (2013)) in our analysis.

2.3. The Ambiguity Measure

2.3.1. The Ambiguity Measure

We measure systematic ambiguity by the variance of probabilities of future potential outcomes, following the procedure of Izhakian (2017), Brenner and Izhakian (2017), and Izhakian and Yermack (2017). We refer the interested reader to pages 15-17 in Brenner and Izhakian (2017).

By construction, this ambiguity measure is independent of risk, which is commonly proxied by the variance of future potential outcomes. The measure is also independent of attitudes towards risk and/or attitudes towards ambiguity⁷, which are defined as attitudes towards mean-preserving spreads in outcomes (Rothschild and Stiglitz, 1970), and attitudes towards mean-preserving spread in the probabilities of future potential outcomes, respectively (Izhakian, 2017).

However, in contrast to Brenner and Izhakian (2017), our ambiguity measure is obtained by using 5-minute intraday data for the E-mini S&P 500 futures contract, which is now the most popular equity index futures contract in the world. Also, our sample period is from September 9, 1997 until December 31, 2017. The starting date of our sample corresponds to the date when the Chicago Mercantile Exchange introduced the E-mini S&P 500 contract. Furthermore, we construct a measure of systematic ambiguity at the daily frequency, instead of monthly frequency. That is, the set of priors of the representative investor for any given day consists of 22 different probability distributions of the stock index: the probability distributions of the current day and of the previous 21 trading days.

We inspect the distribution of returns across the entire sample period, and eliminate observations below the first percentile and above the 99th percentile. For each day in our sample period, there are between 23 and 78 observations. To compute a daily measure of systematic ambiguity, we represent every daily return distribution by a histogram. We divide the range of returns in 20 different bins and for every day we calculate the probability of the future return being

⁷ Brenner and Izhakian (2017) show that the ambiguity measure obtained based on the EUUP theory is by construction independent of risk, attitudes towards risk, and attitudes towards ambiguity.

in each bin.⁸ We calculate the mean and the variance of probabilities for each of the 20 bins separately, and then estimate ambiguity as in relation (14) in Izhakian and Yermack (2017).

We plot our ambiguity variable in Panel A of Figure 2-1. The degree of ambiguity varies significantly over our sample period, experiencing relatively greater values towards the end of the sample. Although ambiguity is relatively lower in the first part of our sample, it does capture important events such as the beginning of the Russian financial crisis in August 1998, the beginning of the dot-com bubble burst in April 2000, the terrorist attacks in September 2001, the corporate accounting scandals in 2002 (particularly after the first quarter of 2002).⁹ Noticeably, our ambiguity measure experiences relatively higher levels from 2004 to 2007, period characterized by low levels of realized volatility, as shown in Panel B of Figure 2-1. During the recent financial crisis, our ambiguity measure experiences peak values from September 2008 until February 2009. More recently, periods with extreme ambiguity were encountered during December 2010, December 2013 - January 2014, June to September 2014, December 2014, and fall and winter of 2016. In addition, the end of 2017 was characterized by high ambiguity.

Over the last seven to eight quarters, the volatility of the stock market, or rather the lack of it (Panel B of Figure 2-1), has been a widely discussed topic in the financial media. The low levels of the CBOE Volatility fear gauge Index (the VIX - in Panel C of Figure 2-1) particularly during a time of uncertainty, related either to the unpredictability of the U.S. policy under president Donald Trump or to the geopolitical risk posed by North Korea, have raised concerns among investors. In an interview on March 15, 2017, professor Menachem Brenner from New York

⁸ First, we compute the probability of the return being lower than -0.16% (the first bin) and higher than 0.16% (the last bin). These values correspond approximately to the fifth and the 95th percentiles of futures returns over our sample period. Then we divide the range of returns, i.e. from -0.16% to 0.16% , into 18 equal intervals (bins).

⁹ <https://www.forbes.com/2002/07/25/accountingtracker.html#4f43447c57e8>

University, the pioneer of the VIX index, mentioned the need to quantitatively measure ambiguity for identifying the uncertainty that is not captured by the VIX.

‘Volatility alone doesn’t explain expected returns. Higher volatility is higher risk, but that is not enough and you also need ambiguity.’

Interview with Professor Menachem Brenner¹⁰

Table 2-1 reports the descriptive statistics of the ambiguity measure, the realized volatility, VIX index, and the VIX components: the variance risk premium (RA) and the stock market uncertainty (UC) computed as described in Bekaert, Hoerova, and Lo Duca (2013).¹¹ Our ambiguity measure varies from 0.005 to 0.335, having a mean of 0.037. To help us better understand how our ambiguity measure ($\bar{U}^2$) is related to risk, and to other measures of ambiguity used in the literature, Table 2-2 reports the Pearson correlation coefficients between $\bar{U}^2$, the realized volatility (ν) of the E-mini S&P 500 futures (as a proxy of risk), the VIX, RA, and UC. Ambiguity is significantly negatively correlated with the VIX index,¹² and with the variance risk premium (RA). Furthermore, Table 2-2 shows that ambiguity ($\bar{U}^2$) is negatively and weakly correlated with the daily realized volatility of E-mini S&P 500 futures, being consistent with the fact that ambiguity and risk are different concepts. Our $\bar{U}^2$ variable captures the degree of ambiguity and not attitudes towards ambiguity.

2.3.2. Estimating Expected Ambiguity

To obtain a forward-looking measure of ambiguity, we estimate the expected ambiguity for each day in our sample, by applying a similar procedure to Brenner and Izhakian (2017), but we adjust

¹⁰ <https://asia.nikkei.com/Markets/Equities/Volatility-index-creator-seeks-to-invent-new-tool-to-measure-ambiguity?page=1>

¹¹ We denote variance risk premium by RA because in Bekaert, Hoerova, and Lo Duca (2013), it is used to proxy for the level of risk aversion in the market.

¹² The results are consistent with the findings of Brenner and Izhakian (2017).

the procedure to daily frequency. We assume that when investors form expectations about future ambiguity, they also look at how ambiguity evolved over time. We find that the square root of ambiguity (i.e. $\bar{U}$) is positively skewed. So, in order to avoid negative values of conditional ambiguity and to adjust for skewness, we examine the natural logarithm of $\bar{U}$.

The correlogram of $\ln(\bar{U})$ from Table 2-3 indicates that an autoregressive moving average (ARMA) model would be appropriate for estimating expected ambiguity $\widehat{\ln(\bar{U})}$. We estimate the ARMA(p, q) model in (3) for each day, and select the optimal number of lags corresponding to the highest quality model, i.e. the model with the lowest Akaike (AIC) information criterion. Every day, we use data from the previous 30 months (i.e. the previous 660 trading days: from day $t-660$ to day $t-1$) to estimate the regression in (3) for each combination of p and q ($p=1, \dots, 10$ and $q=1, \dots, 10$). We have in total about $p*q=100$ combinations of (p, q) pairs for each day. After selecting the optimal number of lags, we estimate $\widehat{\ln \bar{U}_{t+1}}$ and then the expected ambiguity $(\bar{U}_{t+1}^2)^E$ similar to relation (16) in Yermack and Izhakian (2017). The plot of expected ambiguity in Figure 2-2 shows that the expected and the raw measures of ambiguity evolve similarly over time.

2.4. Data

2.4.1. Firm-Specific Characteristics

Our initial sample includes all U.S. companies with data in CRSP and Compustat. We limit our sample to only firms that: 1) are listed on NYSE, AMEX, or Nasdaq, 2) are not utilities or financial companies (SIC code between 4900-4999 and 6000-6999), and 3) have CRSP share code 10 or 11 (ordinary common share). The final sample consists of 8401 firms for which we collect daily returns from CRSP across our sample period from October 9, 1997 through December 31, 2017.

The start date of our sample is chosen based on the availability of the ambiguity measure described in section 2.3.1.

We collect the Fama and French (2016) five factors and the one-month Treasury bill rate from Kenneth French's website. We match the quarterly data from Compustat with the daily variables from CRSP and ensure that the accounting variables from Compustat are known before the returns they are used to explain. For example, we use a 6-month (minimum) gap between the fiscal year-end and the daily CRSP data (similarly to the procedure of Fama and French (1992)).

Table 2-4 reports the summary statistics of the firm-specific characteristics used in our analysis for the full sample (Panel A), and the difference in means for these characteristics between periods of high and low ambiguity (Panel B). The average firm in our analysis has a market cap (i.e. size, measured as price times shares outstanding) of 1.2 billions of dollars. The firm's *age* is calculated by the number of years since the firm appeared in CRSP for the first time, rounded to the nearest month. The average *age* of firms in our analysis is approximately 17 years. Since prior work mentions that stock volatility can be perceived as a good proxy for the difficulty of valuation and arbitrage (Baker and Wurgler, 2006), we also compute σ as the standard deviation of the daily returns over the previous 22 trading days. σ is on average smaller during periods of high ambiguity relative to periods of low ambiguity.

According to Baker and Wurgler (2006), asset tangibility can be a good proxy for the difficulty of valuation. As measures of asset tangibility, we include the research and development expense over assets, RD/A and the level of property, plant, and equipment over assets, PPE/A . We do not see a significant difference in RD/A (on average) between periods of high and low ambiguity. However, PPE/A is higher on average during times of elevated ambiguity. As a proxy of earnings management we use discretionary accruals (DCA), computed based on the modified

Jones (1991) model (Dechow, Sloan, and Sweeney, 1995).¹³ The absolute value of discretionary accruals seems to be larger on average during times of low ambiguity relative to periods of high ambiguity. In addition, for capturing growth opportunities, we include in our analysis the book-to-market equity, BE/ME .

As dividend characteristic, we consider the dividend on equity variable, $(Div * Shrout)/BE$, calculated as the number of shares outstanding from Compustat ($Shrout$) times the dividend per share at the ex-dividend date (Div), divided by the book value of equity (BE). BE is calculated as shareholders' equity together with balance sheet deferred taxes. We include in our analysis a dummy variable (D) which is one for firms with positive values of Div , by the ex-dividend date, and 0 otherwise. As profitability characteristic (used later in our analysis), we consider the return on equity, $ROE = Earnings/BE$, taking positive values for firms that are profitable and zero otherwise. If earnings are positive, the variable $Earnings$ refers to the income statement deferred taxes together with the income before extraordinary items and without preferred dividends. We include in our analysis a dummy variable (E) to help us distinguish between profitable and unprofitable firms. E is one for profitable firms and zero otherwise.

2.4.2. Control Variables

We report descriptive statistics of the main control variables employed in our analysis in Table 2-5. Panel A summarizes these statistics across our entire sample period, while Panels B and C summarize the statistics for periods of high and low ambiguity respectively. Panel D provides a test of the difference in the means of our control variables during times of high vs. low expected ambiguity. The low (high) ambiguity periods are those periods where the expected ambiguity is

¹³ More details about this computation can be found in Hutton, Marcus, and Tehranian (2009).

below (above) its sample median. The market excess return is not significantly different on average between periods of high and low ambiguity. However, the size (SMB), the value (HML), and the investment (CMA) factors of Fama and French (2016) experience lower levels on average during times of high ambiguity relative to periods of low ambiguity.

2.5. Ambiguity in Asset Pricing

2.5.1. Long-Short Portfolios by Firm Characteristics

For understanding whether ambiguity is priced, and whether it is priced differently across various categories of stocks, we form equally-weighted portfolios that are long on stocks with high values of a firm characteristic and short on stocks with low values of the same characteristic. These characteristics are: firm *size* and *age*, total risk (σ), dividends (D), profitability (E), property, plant, and equipment over assets (PPE/A), research and development expense over assets (RD/A), book-to-market ratio (BE/ME), and discretionary accruals ($DAccruals$). We rebalance our portfolios every quarter. We compute the 30th and 70th percentiles of each characteristic for the stocks listed on NYSE at the end of each quarter. We use these percentiles as benchmarks to determine whether stocks listed on NYSE, AMEX, or Nasdaq have high, medium, or low values of each characteristic. Firms in the top (bottom) three NYSE deciles are considered to have high (low) values of a certain firm-characteristic. The procedure is similar to Fama and French (2016) and Baker and Wurgler (2006).

2.5.2. Two-way sorts of Stock Returns by Firm Characteristics and Expected Ambiguity

As a first step in our analysis, we compute the average stock returns of these equally weighted portfolios for periods of low, medium, and high levels of expected ambiguity, and plot the results in Figure 2-3. The grey bars denote the average return during periods of low ambiguity, i.e. when

ambiguity is in the lowest three deciles across our sample period. Blue bars denote the average return during periods of high ambiguity, i.e. when ambiguity is in the highest three deciles across our sample period. Black bars denote the average return for when ambiguity is between the lowest three deciles and the highest three deciles across our sample period (moderate ambiguity).

When the expected ambiguity is low, on average, small firms earn higher returns than big firms, but this pattern seems to be reversed during times of high expected ambiguity. This result shows that the small firm effect is less likely to exist during periods of high ambiguity. Older firms seem to gain on average greater returns than young firms when expected ambiguity is low. Again, the pattern seems to be reversed during times of high expected ambiguity. Looking at the firm risk proxied by the standard deviation of daily returns from the previous 22 trading days, greater risk is associated with greater average return during times of low expected ambiguity. However, during times of high expected ambiguity, riskier firms earn a lower average return than safer or less risky firms. This pattern seems to confirm the different concepts captured by risk and ambiguity.

For PPE/A and RD/A, we notice that in times of elevated ambiguity, greater asset tangibility is associated with lower average returns. We also notice that growth stocks (low BE/ME) earn higher average returns than value stocks (high BE/ME) during periods of low expected ambiguity. However, during times of high expected ambiguity, value stocks seem to outperform relative to growth stocks.

Portfolios formed by taking long positions in dividend paying stocks and short positions in non-dividend paying stocks tend to earn positive average returns for moderate levels of expected ambiguity. Portfolios formed by taking long positions in profitable firms and short positions in unprofitable firms tend to earn higher average positive returns when facing greater ambiguity. On

average, firms with high level of earnings management underperform relative to their counterparts. This underperformance increases in times of elevated expected ambiguity.

2.5.3. Univariate Evidence

The results reported in Figure 2-3 suggest that on average, the level of expected ambiguity affects the returns of various categories of stocks. However, for understanding if ambiguity matters, we need to formally test whether ambiguity significantly affects the returns of long-short portfolio formed by the different characteristics. We proceed by regressing the returns of long-short portfolios formed by each characteristic on our expected ambiguity variable ($Ambiguity_t^E$). The results are reported in Panels A to D of Table 2-6.

$$R_{X_{it}=High,t} - R_{X_{it}=Low,t} = a + \delta Ambiguity_t^E + u_t \quad (1)$$

The expected ambiguity used in our estimation is $Ambiguity_t^E = \widehat{\ln \bar{U}_t}$ computed as described in section 2.3.2. The univariate results indicate that in the presence of greater expected ambiguity, the returns of long-short portfolios formed by firm size tend to earn greater returns. This means that when facing greater ambiguity, big firms outperform relative to small firms. Greater levels of ambiguity decrease the returns of long-short portfolios formed by firm's age and firm's risk (σ). That is, in times of increased ambiguity, younger firms tend to outperform relative to older firms. Also, safer firms seem to outperform riskier firms when ambiguity increases.

Panel B of Table 2-6 shows that in times of increased expected ambiguity, profitable firms tend to outperform relative to unprofitable firms. The results in Panel C of the same table indicate that value stocks tend to outperform relative to growth stocks in the presence of increased ambiguity. Similarly, high RD/A stocks outperform stocks with low RD/A levels in times of increased ambiguity. On the other hand, greater expected ambiguity decreases the returns of long-

short portfolios formed by PPE/A. Firms with lower asset tangibility tend to outperform those with high asset tangibility in times of increased ambiguity. Greater ambiguity also decreases the returns of long-short portfolios formed by absolute value of discretionary accruals. In other words, the greater the ambiguity, the more firms with lower earnings management outperform firms with high level of earnings management.

Overall, our univariate results so far are supportive of our first three hypotheses. They indicate that ambiguity matters when pricing different categories of stocks. In particular, we find that during periods of lower expected ambiguity, stocks that are generally hard to arbitrage and hard to value, such as stocks of firms that are small, unprofitable, risky, and stocks of growth companies tend to outperform their counterparts. On the other hand, in times of greater expected ambiguity, these stocks underperform relative to their counterparts. At the same time, during times of elevated ambiguity, stock with high information asymmetry, such as stocks of firms that are small, risky, and with high level of earnings management, underperform relative to their counterparts.

2.5.4. *Multivariate Analysis*

Next we investigate whether the expected ambiguity helps explaining the difference in returns between different categories of stocks, after controlling for macro-factors that have previously been found to help explain stock returns. More precisely, we estimate the regression in (1), while separately controlling for the Fama and French (1992) three factors or Fama and French (2016) five factors. When controlling for the market excess return, the size (*SMB*), and the value (*HML*) factors only, we estimate the regression below:

$$R_{X_{it}=High,t} - R_{X_{it}=Low,t} = a + \delta \widetilde{Ambiguity}_t^E + b (R_{M,t} - R_{F,t}) + s SMB_t + h HML_t + u_t \quad (2)$$

The expected ambiguity variable $\widetilde{Ambiguity}_t^E$ captures the degree of ambiguity that is not reflected in the *SMB* or *HML* factors. Given the strong and negative correlations between ambiguity and the size and value factors reported in Table 2-2, we first regress $Ambiguity_t^E$ from (1) on the market excess return, the size, and the value factors of Fama and French (1992), and then store the residuals as $\widetilde{Ambiguity}_t^E$. We estimate the model in (2) and report the results in Panels A to D of Table 2-6. The estimated $\hat{\delta}$ is consistent with our previous findings from the univariate setting. We find that in general, stocks with high information asymmetry and stocks that are difficult to arbitrage/value tend to underperform relative to their counterparts in times of higher expected ambiguity.

We also estimate the regression in (1), while controlling for the Fama and French (2016) five factors. That is, in addition to the market excess return, the size (*SMB*), and the value (*HML*) factors, we also consider a profitability (*RMW*) factor and an investment (*CMA*) factor. We estimate the following model:

$$R_{X_{it}=High,t} - R_{X_{it}=Low,t} = a + \delta \overline{\overline{Ambiguity}_t^E} + b (R_{M,t} - R_{F,t}) + s SMB_t + h HMLO_t + r RMW_t + c CMA_t + u_t \quad (3)$$

The variables used in model (3) have been previously introduced. However, in this particular case, *HMLO* denotes the orthogonal value factor from Fama and French (2016). In addition, $\overline{\overline{Ambiguity}_t^E}$ denotes the degree of expected ambiguity that is not captured by the other explanatory variables in the regression. $\overline{\overline{Ambiguity}_t^E}$ is measured by the residuals obtained when regressing $Ambiguity_t^E$ from (1) on the market excess return, size, (orthogonal) value, profitability, and investment factors of Fama and French (2016).

In general, the results remain consistent with our univariate findings. However, for the long-short portfolios obtained by having long positions in dividend-paying stocks and short positions in stocks not paying dividends, it seems that in times of increased expected ambiguity, the dividend payers tend to outperform non-payers. The result is significant at the 10% significance level.

2.6. Ambiguity and Market Efficiency

In this section, we investigate whether ambiguity affects the stock market reaction to firm-specific earnings announcements. In line with the theory of market efficiency, the stock market should only react to the unexpected component of the earnings announcement. We compute the announcement surprise as the difference between each firm's reported earnings per share (EPS) and the latest analyst consensus EPS forecast before the earnings announcement date, scaled by the stock price two days before the earnings announcement date (similar to Fang, Huan, and Karpoff (2016)). The earnings announcements and the analysts' earnings forecasts data are from the Institutional Brokers' Estimate System (I/B/E/S).

Table 2-7 reports the average size of negative (Panel A) and positive (Panel B) earnings surprises during times of high and low ambiguity. The earnings surprise is negative (positive) when the value of the announced earnings is below (above) its corresponding value forecasted by analysts. Ambiguity is considered low (high) when its expected value is in the bottom (top) three deciles across our sample period. The statistics indicate that on average, positive earnings surprises are not significantly different during times of high ambiguity, relative to periods of low ambiguity. Negative earnings surprises seem to be on average higher in magnitude during times of elevated ambiguity, relative to periods of low ambiguity.

2.6.1. *The Stock Market's Marginal Response to Earnings News*

A firm must have a complete set of financial variables and quarterly announcement dates to be included in our sample. Following Ball, Kothari, Shanken (1993) and Williams (2014), we eliminate observations with the price less than or equal to \$5 at the beginning of the event window to reduce the effect of market frictions. For each stock, we compute the daily abnormal return over the period of 10 days before to 60 days after each earnings release date. We estimate the market model over the period [-61, -11] days before each earnings announcement, and we use the estimated coefficients to predict the 'normal' values of return for the window [-10, +60] days around the earnings release date. We calculate abnormal return as the difference between the actual stock return and its 'normal' predicted value from the market model.

We report the average cumulative abnormal return (CAR) for 3 days [-1, +1], 5 days [-2, +2], and 11 days [-5, +5] around the release date of negative and positive earnings surprises in Panels A and B of Table 2-7. The average cumulative abnormal return around negative earnings surprises is negative and significantly lower in magnitude during times of high ambiguity, relative to periods of low ambiguity. The average cumulative abnormal return computed even over the 10 days period after the release of negative earnings surprises (i.e. $CAR[0, +10]$) is significantly lower in magnitude during high ambiguity periods, relative to periods of low ambiguity. On the other hand, the average $CAR[0, +10]$ following the announcement of positive earnings surprises is significantly higher during periods of high ambiguity relative to periods of low ambiguity.

Figure 2-4 shows the daily average abnormal return for 10 days before to 10 days after the earnings announcement date (i.e. day 0). The average abnormal return increases during the announcement day of positive earnings surprises (Panel A) and is higher in magnitude during elevated ambiguity relative to periods of low ambiguity. In contrast, the average abnormal returns

decreases during the announcement day of negative earnings surprises (Panel B) and is smaller in magnitude during high ambiguity relative to low ambiguity periods. The same pattern is followed by the average cumulative abnormal return (Figure 2-5). After negative earnings surprises, the average cumulative abnormal return is negative and smaller in magnitude during times of elevated ambiguity, relative to periods of low ambiguity. In contrast, after positive earnings surprises, the average cumulative abnormal return is higher in magnitude during times of high ambiguity relative to periods of low ambiguity.

2.6.2. *Baseline Regression*

To investigate the stock market reaction to firm-specific earnings announcements, we regress the cumulative abnormal return computed over a window surrounding the earnings release date, on the earnings surprise and controls.

$$CAR_{it} = \beta_1 SUE_{it} + Controls_t + \alpha_i + \delta_t + u_{it} \quad (4)$$

CAR_{it} is the cumulative abnormal return (CAR) of firm i , computed over a window of 3 days, 5 days, or 11 days around each earnings announcement date, while SUE_{it} refers to the standardized earnings surprise computed as described previously. The regression in (4) considers year and firm fixed effects, and controls for the size factor (SMB), the orthogonal value factor (HML), the profitability factor (RMW), and the investment factor (CMA) from Fama and French (2016). The estimated results are reported in Table 2-8 and reveal a positive and significant response coefficient for the earnings surprise. This finding is expected and indicates that an increase (decrease) in the earnings surprise leads to an increase (decrease) in the cumulative abnormal return.

To understand whether the level of ambiguity alters the stock market reaction to firm-specific earnings news, we re-estimate the regression in (4) by adding an interaction term between

SUE_{it} and a dummy variable, which identifies periods of high vs. low ambiguity. We estimate the following regression:

$$CAR_{it} = \beta_1 SUE_{it} + \beta_2 D_{Ambiguity,t} + \beta_3 SUE_{it} D_{Ambiguity,t} + Controls_t + \alpha_i + \delta_t + u_{it} \quad (5)$$

Where $D_{Ambiguity,t}$ is a dummy variable taking values of 1 when the expected ambiguity is in its top 30th percentile across our sample period, and 0 otherwise. The regression in (5) considers year and firm fixed effects and controls for the size factor (SMB), the orthogonal value factor (HML), the profitability factor (RMW), and the investment factor (CMA) from Fama and French (2016). The estimated coefficient β_3 captures the change in the stock market reaction to SUE in times of high ambiguity relative to periods of low ambiguity. The estimated results are reported in Table 2-9. In times of high ambiguity, the stock market reaction to earnings news seems to become weaker in general, as the estimated coefficient β_3 is negative and significant for the regression having as dependent variable $CAR[-1, +1]$ or $CAR[-2, +2]$.

2.6.3. *Asymmetric Reaction to Good vs. Bad Earnings News*

To understand whether the stock market responds asymmetrically to good vs. bad earnings news in times of low vs. high ambiguity, we estimate the regressions in (6) and (7) and report the estimated results in Tables 2-10 and 2-11.

$$CAR_{it} = \beta_1 GoodNews_{it} + \beta_2 BadNews_{it} + Controls_t + \alpha_i + \delta_t + u_{it} \quad (6)$$

$$CAR_{it} = \beta_1 GoodNews_{it} + \beta_2 BadNews_{it} + \beta_3 * D_{Ambiguity,t} + \beta_4 GoodNews_{it} * D_{Ambiguity,t} + \beta_5 BadNews_{it} * D_{Ambiguity,t} + Controls_t + \alpha_i + \delta_t + u_{it} \quad (7)$$

CAR_{it} is the cumulative abnormal return computed over a window of 3 days, 5 days, or 11 days around each earnings announcement date. *GoodNews* (*BadNews*) takes the value of the earnings surprise if the surprise is positive (negative), and zero otherwise. Both regressions include year

and firm fixed effects and control for the size factor (SMB), the orthogonal value factor (HML), the profitability factor (RMW), and the investment factor (CMA) from Fama and French (2016). $D_{Ambiguity,t}$ in (7) is a dummy variable which takes values of 1 when the expected ambiguity is in its top 30th percentile across our sample, and 0 otherwise.

The estimated results in Tables 2-10 and 2-11 indicate that positive earnings news has a significant and positive impact on the cumulative abnormal return, while negative earnings news has a significant and negative impact on the cumulative abnormal return (as expected). Greater ambiguity weakens the stock market reaction to bad earnings news, as indicated by the negative and significant estimated coefficient β_4 from regression (7). For good earnings news, we do not observe a significant difference in the stock market reaction to earnings surprises in times of high ambiguity relative to periods of low ambiguity. The weaker reaction of the stock market to earnings news in times of elevated ambiguity provides evidence in support of our fourth hypothesis.

Tables 2-10 and 2-11 also include a test of asymmetry between the stock market response to good and bad earnings news. The results indicate a weaker reaction to bad relative to good earnings news in periods of elevated ambiguity.

2.6.4. The Marginal Response to Earnings News- By Firm Characteristics

Stocks of firms considered relatively ‘safe’ during times of high ambiguity, could react differently to earnings news compared to their counterparts. This is because during times of elevated systematic ambiguity, investors require different premiums for investing in safe relative to unsafe assets. In section 2.5, we find that ambiguity is priced in the cross-section of stock returns, and some categories of stocks tend to outperform their counterparts. In particular, we find that when ambiguity is expected to increase, stocks of firms with low information asymmetry and firms which are less difficult to value and/or arbitrage, such as firms that are bigger, less risky, profitable,

dividend payers, and firms with lower levels of earnings management, outperform relative to their counterparts.

In this sub-section, we investigate how ambiguity affects the stock market reaction to earnings news for different categories of stocks. We analyze stocks with high and low levels of the following firm-specific characteristics: number of analysts, standard deviation of analysts' forecasts, firm size, firm age, volatility of returns, property, plant, and equipment over assets (PPE/A), research and development expense over assets (RD/A), book-to-market ratio (BE/ME), and earnings management. A variable is considered to have low (high) values if it is below (above) its sample median.

We perform a similar analysis as in relation (7) for each category, and report the results in Panels A to E of Table 2-12. The results indicate that in general, stocks which underperform relative to their counterparts in times of high ambiguity experience a weaker reaction to bad earnings news. These are stocks of firms that are small, riskier, unprofitable, non-dividend payers, followed by a small number of analysts, and with a high standard deviation of analysts' forecasts.

An interesting aspect of our results is that the stocks experiencing a weaker reaction to bad earnings news in times of high ambiguity, also tend to report more bad earnings news than good news in times of elevated ambiguity, as shown in Table 2-13. In other words, firms with high information asymmetry could potentially strategically decide to release 'bad news' during periods of elevated ambiguity, as the stock market reaction to the news can be diminished. However, this is just a conjecture and a thorough analysis is beyond the scope of our paper.

2.6.5. The Magnitude of the Earnings Surprise and the Marginal Response to Earnings News

For testing our fifth hypothesis, we regress the values of positive and negative earnings surprises on the expected ambiguity at the time of the earnings release date. The results in Table 2-14 show

that greater ambiguity is associated with earnings surprises of greater magnitude. That is, analysts seem to make less accurate forecasts during times of elevated ambiguity. This provides evidence in favor of our fifth hypothesis. According to Freeman and Tse (1992), surprises of greater magnitude have in general a smaller marginal response of the stock return to the news. We investigate whether our results are consistent with these findings. We estimate the regression in (8).

$$\begin{aligned}
CAR_{it} = & \beta_1 GoodNews_{it} * D_{Small\ SUE,t}^+ + \beta_2 GoodNews_{it} * D_{Med\ SUE,t}^+ + \beta_3 GoodNews_{it} \\
& * D_{Large\ SUE,t}^+ + \beta_4 BadNews_{it} * D_{Small\ SUE,t}^- + \beta_5 BadNews_{it} * D_{Med\ SUE,t}^- \\
& + \beta_6 BadNews_{it} * D_{Large\ SUE,t}^- + Controls_t + \alpha_i + \delta_t \\
& + u_{it}
\end{aligned} \tag{8}$$

$D_{Small\ SUE,t}^+$, $D_{Med\ SUE,t}^+$, $D_{Large\ SUE,t}^+$ are dummy variables taking values of 1 when the positive standardized earnings surprise is below the 30th percentile, between the 30th and the 70th percentiles, and above the 70th percentile of positive earnings surprises in our sample. Otherwise, these dummy variables take values of 0. Similarly, $D_{Large\ SUE,t}^-$, $D_{Med\ SUE,t}^-$, $D_{Small\ SUE,t}^-$ are dummy variables taking values of 1 when the negative standardized earnings surprise is below the 30th percentile, between the 30th and the 70th percentiles, and above the 70th percentile of negative earnings surprises in our sample. Otherwise, these dummy variables take values of 0. The regression controls for the size factor (SMB), the orthogonal value factor (HML), the profitability factor (RMW), and the investment factor (CMA) from Fama and French (2016). Year and firm fixed effects are included in the regression. The estimated results in Table 2-15 show that smaller magnitude surprises have a stronger marginal impact on the stock market reaction to earnings news.

Next, we investigate whether ambiguity still affects the stock market reaction to earnings news, after controlling for the magnitude of the earnings surprise. To test this, we estimate the model in (8) with additional interaction terms between the dummies capturing the magnitude of positive and negative earnings surprises with the ambiguity dummy ($D_{Ambiguity,t}$). The estimated results reported in Table 2-16 show that ambiguity weakens the stock market reaction to bad earnings news, after controlling for the size of the surprise. In particular, this result is encountered for bad earnings news of medium and large magnitude.

2.7. Robustness Analysis

A potential concern is that our results are driven by factors other than ambiguity. To alleviate this concern, we test whether our results of a weaker stock market reaction to bad earnings news in times of high ambiguity relative to periods of low ambiguity remain robust when controlling for other potential influences. We control for the state of the business cycle, the real business conditions, the level of sentiment in the market, investor attention, the VIX, and the VIX components.

To control for different states of the business cycle, we use the NBER peak and trough dates to distinguish between expansions and recessions. We re-estimate the regression in (7) with additional interaction terms between *GoodNews* and *BadNews* with a dummy variable capturing the state of the business cycle. The results are reported in Table 2-16 and indicate that our results remain robust.

To control for the changes in the real business conditions, we include in the analysis the daily values of the Aruoba-Diebold-Scotti (ADS) business conditions index, introduced by Aruoba, Diebold and Scotti (2009). This index is computed based on real-time values of several

economic indicators, such as initial jobless claims, monthly payroll employment, industrial production, personal income less transfer payments, manufacturing and trade sales, and quarterly real GDP. Greater than 0 values of the index reveal better-than-average economic conditions, while negative values indicate worse-than-average conditions. We estimate the model in (7) with additional interaction terms between *GoodNews* and *BadNews* with the (lagged) ADS index. The results are reported in Table 2-16 as well, and are consistent with our previous findings.

An additional potential concern is that the level of sentiment in the market could affect the stock market reaction to earnings news, rather than the level of ambiguity per se. In order to address this concern, we re-estimate the model in (7) by adding interaction terms between *GoodNews* and *BadNews* with a sentiment variable. As alternative proxies for sentiment, we use the (lagged) Baker and Wurgler (2006) sentiment variable (raw and orthogonal measures). In addition, we also proxy sentiment as in Huang, Jiang, Tu, and Zhou (2015), including both their raw and orthogonal sentiment proxies. These results are reported in Table 2-17 and indicate that our results remain robust. In addition, our expected ambiguity variable is weakly correlated with the Baker and Wurgler (2006) sentiment variable (correlation coefficient of -0.18) and with the Huang, Jiang, Tu, and Zhou (2015) sentiment measure (correlation coefficient of -0.21).¹⁴

Since greater ambiguity periods can correspond to periods of greater investor attention, we need to ensure that our results still hold, while controlling for the level of attention in the stock market.¹⁵ To do so, we construct an aggregate measure of investor attention from Google Trends, by using the Google search volume (procedure similar to Da, Engelberg, and Gao, 2011) of the term ‘S&P500’ from January 2004 until December 2017. The attention measure is weakly

¹⁴ These regressions are estimated over the sample period May 2000 (the date when our expected ambiguity variable becomes available) to December 2014 (the last date when the sentiment proxies used in the regression are available).

¹⁵ Previous literature finds that limited investor attention can alter the stock market reaction to earnings news (Hirshleifer, Lim, and Teoh, 2009).

positively correlated with our expected ambiguity measure (correlation coefficient of 0.081). We re-estimate the equation in (7) by adding interaction terms between our *GoodNews* and *BadNews* variables, with the attention measure. The estimated results are reported in Table 2-18. The stock market reaction to bad earnings news is still weaker in times of elevated ambiguity, relative to periods of low ambiguity.

Similar additional robustness checks, including tests for the influence of the VIX index, the influence of the VIX components (i.e. risk aversion and stock market uncertainty computed as in section 2.1. in Bekaert, Hoerova, and Lo Duca (2013)) on the stock market's reaction to earnings news are provided in Table 2-19. Our results remain robust after using these controls.

Another potential concern could be that our results are driven by the greater investor disagreement during times of elevated ambiguity, rather than by the ambiguity measure itself. Unreported results show that the standard deviation of analysts' earnings forecasts is not significantly different during times of low vs. high expected ambiguity. Thus, it is not likely that our results are driven by greater investor disagreement during times of elevated ambiguity.

2.8. Conclusion

This paper investigates whether ambiguity has a significant effect on the cross-section of stock returns. We first construct a measure of ambiguity that is independent of risk, attitudes towards risk, and attitudes towards ambiguity based on the theoretical framework of expected utility with uncertain probabilities proposed by Izhakian (2017). We then show that ambiguity is priced in the cross-section of stocks and that investors require a premium when they are exposed to elevated ambiguity. This premium is in addition to the premium they require for bearing risk. By forming long-short portfolios based on various firm characteristics, we find that when ambiguity is expected to increase, stocks of firms with high information asymmetry and firms that are difficult

to value/arbitrage, such as firms that are smaller, riskier, and less profitable, non-dividend payers, and firms with higher levels of earnings management, underperform their counterparts.

Interestingly, our results indicate that ambiguity has an impact on the standard risk-return relation. That is, we find that during times of low ambiguity, the standard risk-return relation holds, namely riskier portfolios provide a higher return. However, when ambiguity is high, riskier portfolios provide lower returns, in violation of the standard positive risk-return relation. This finding reveals the need of extending modern portfolio theory, i.e. the mean-variance framework, to account for ambiguity as another dimension, in addition to the mean and standard deviation of returns (risk). In a portfolio optimization problem, an investor should minimize the aggregation of risk and ambiguity that he is exposed to (for a given level of expected return), rather than risk alone. It is possible that if risk and ambiguity simultaneously enter the portfolio optimization problem, the optimal portfolio might not be fully diversified. This is important for investors who are both risk-averse and ambiguity averse. We leave this investigation to be properly tested by future research.

We also show that ambiguity reduces stock market efficiency by weakening the stock market reaction to firm-specific earnings announcements. The weaker reaction is more significant for stocks of firms that have greater information asymmetry, are small, old, unprofitable, and riskier. We thus contribute to research on the relation between asset prices and firm-specific fundamentals, by showing that ambiguity is an important determinant of the market response to news, in addition to other variables such as limited investor attention, investor sentiment, the state of the economy, and market implied volatility. This finding could have implications for the persistence of the post-earnings announcement drift (PEAD) introduced by Ball and Brown (1968). The PEAD might last longer in times of elevated systematic ambiguity.

Table 2-1: Descriptive Statistics of Ambiguity and other Measures of Risk/Uncertainty

This table reports the descriptive statistics of the macro-level variables employed in the analysis. $\bar{U}^2$ denotes the level of ambiguity computed as described in section 2.3.1. in the text, while ν is the standard deviation of daily E-mini S&P 500 futures returns. The table also reports the CBOE Volatility Index (the VIX index), and the VIX components: risk aversion (RA) and stock market uncertainty (UC) computed as described in section 2.1. in Bekaert, Hoerova, and Lo Duca (2013). The sample period covered is from 10/10/1997 to 12/31/2017.

	N	Mean	Median	Std. Dev.	Skewness	Kurtosis	Maximum	Minimum
$\bar{U}^2$	5052	0.037	0.027	0.032	2.596	8.890	0.335	0.005
ν	5052	0.083	0.078	0.034	0.613	-0.156	0.203	0.016
VIX	5052	20.490	18.855	8.583	1.902	6.258	80.860	9.140
RA	5052	17.621	10.682	25.813	3.536	21.454	333.713	-117.921
UC	5052	23.505	15.537	25.100	5.744	45.792	308.923	7.573

Table 2-2: The Correlation between Ambiguity, other measures of Market Uncertainty, and Systematic Risk Factors

This table reports the Pearson correlation coefficients among the macro-variables used in our analysis: ambiguity ($\bar{U}^2$), computed as described in section 2.3.1. in the text, the expected ambiguity ($(\bar{U}^2)^E$) computed as described in section 2.3.2. in the text, the daily realized volatility (ν) of the E-mini S&P 500 futures, the CBOE Volatility Index (VIX), the VIX components: risk aversion (RA) and stock market uncertainty (UC) computed as described in section 2.1. in Bekaert, Hoerova, and Lo Duca (2013). Other macro-variables considered are the Fama and French (2016) five factors: the excess market return ($R_m - R_f$), the size factor (SMB), the value factor (HML), the profitability factor (RMW), the investment factor (CMA), and also the orthogonal version of HML (i.e. HMLO) computed as described in Fama and French (2016). The sample period covered is from 05/30/2000 to 12/31/2017. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively.

	$\bar{U}^2$	$(\bar{U}^2)^E$	ν	VIX	RA	UC	$(R_m - R_f)$	SMB	HML	HMLO	RMW
$(\bar{U}^2)^E$	0.968***										
ν	-0.024	-0.031**									
VIX	-0.212***	-0.208***	0.680***								
RA	-0.126***	-0.126***	0.629***	0.848***							
UC	-0.021	-0.018	0.655***	0.780***	0.461***						
$(R_m - R_f)$	-0.005	-0.004	-0.073***	-0.123***	-0.219***	0.000					
SMB	-0.037**	-0.040***	0.005	-0.034**	-0.036**	-0.024	0.148***				
HML	-0.037**	-0.038**	-0.052***	-0.049***	-0.087***	-0.033**	0.117***	0.093***			
HMLO	-0.012	-0.011	-0.040***	-0.049***	-0.084***	-0.032**	0.085***	0.004	0.872***		
RMW	-0.021	-0.023	0.071***	0.089***	0.126***	0.026*	-0.451***	-0.239***	0.000	-0.077***	
CMA	-0.049***	-0.052***	-0.012	0.029*	0.047***	-0.010	-0.251***	0.084***	0.421***	-0.046***	0.251***

Table 2-3: Correlogram of $\ln(\hat{U}_t)$

This table reports the autocorrelations (AC) and the partial autocorrelation (PAC) of $\ln(\hat{U}_t)$ at different lags.

Autocorrelation	Partial Correlation	Lag	AC	PAC	$Q - Stat$	$Prob$
*****	*****	1	0.983	0.983	4885.0	0.000
*****	*	2	0.963	-0.088	9577.8	0.000
*****		3	0.942	-0.063	14064.	0.000
*****		4	0.919	-0.035	18337.	0.000
*****		5	0.897	0.019	22410.	0.000
*****		6	0.875	-0.031	26282.	0.000
*****		7	0.852	-0.016	29957.	0.000
*****		8	0.829	-0.025	33436.	0.000
*****		9	0.807	0.023	36732.	0.000
*****		10	0.785	-0.003	39856.	0.000
*****		11	0.763	-0.025	42808.	0.000
*****		12	0.743	0.018	45602.	0.000
*****		13	0.724	0.047	48256.	0.000
*****		14	0.705	-0.013	50777.	0.000
*****		15	0.687	-0.001	53173.	0.000
*****		16	0.670	-0.006	55448.	0.000
*****		17	0.653	0.022	57614.	0.000
*****		18	0.637	-0.006	59675.	0.000
*****		19	0.622	-0.008	61635.	0.000
*****		20	0.606	-0.015	63498.	0.000
*****		21	0.589	-0.039	65258.	0.000
*****		22	0.573	0.012	66923.	0.000

Table 2-4: Summary Statistics of Firm-Specific Characteristics

This table reports the summary statistics for the main firm-specific variables employed in our analysis. *Size* is the firm size computed as the market value of equity (in millions of dollars), *Age* measures the number of years since the firm's first appearance in CRSP, measured to the nearest month, *Sigma* refers to the standard deviation of daily returns over the previous 22 trading days, *PPE/A* refers to property, plant, and equipment over assets, *RD/A* captures the research and development expense over assets, while *DiscrAccruals* refers to the absolute value of discretionary accruals, computed based on the modified Jones (1991) model. Panel A reports results for the full sample period, while Panel B reports the mean and the difference in means of these firm-specific characteristics during periods of high vs. low expected ambiguity. The periods of low (high) expected ambiguity correspond to those times when the expected ambiguity is in the bottom (top) three deciles across our sample period. The accounting and the financial variables are collected from Compustat and CRSP, respectively. The sample is from 05/30/2000 to 12/31/2017.

Panel A. Descriptive Statistics-Full Sample

	<i>Size</i>	<i>Age</i>	<i>Sigma</i>	<i>PPE/A</i>	<i>RD/A</i>	<i>BE/ME</i>	<i>Discr. Accruals</i>
Mean	1220.91	16.59	0.04	0.52	0.04	0.00	0.12
Median	156.42	13.25	0.03	0.38	0.02	0.00	0.05
Min	0.01	0.08	0.00	0.00	-0.17	-0.62	0.00
Max	246672.63	91.67	4.08	16.40	63.50	1.96	90.78
Std. Dev.	4905.41	12.91	0.04	0.51	0.34	0.03	0.55
Skewness	12.38	1.91	18.45	5.33	116.21	41.75	59.10
Kurtosis	262.91	5.48	1322.63	92.85	18572.17	2691.87	6903.91

Panel B. Difference in Means between Periods of High and Low Ambiguity

	<i>Size</i>	<i>Sigma</i>	<i>PPE/A</i>	<i>RD/A</i>	<i>BE/ME</i>	<i>Discr. Accruals</i>
<i>High Ambiguity</i>	1555.7000	0.0407	0.5319	0.0452	0.00174	0.1044
<i>Low Ambiguity</i>	1076.4000	0.0447	0.5081	0.0419	0.00129	0.1198
<i>(High – Low)</i>	479.4000***	-0.0040***	0.0238***	0.0033	0.00045	-0.0154***

Table 2-5: Summary Statistics of Control Variables

This table reports the summary statistics of the main control variables used in our analysis across our entire sample period (Panel A), during periods of high (Panel B) and low expected ambiguity (Panel C). Panel D reports the difference in means of our control variables between times of high vs. low expected ambiguity. The periods of low (high) expected ambiguity correspond to those periods when the expected ambiguity is below (above) its sample median. The market excess return ($R_m - R_f$), size (SMB), value (HML), profitability (RMW), and investment (CMA) factors are the five factors in Fama and French (2016), and are obtained from Kenneth French's data library. The sample is from 05/30/2000 to 12/31/2017.

Panel A. Full Sample

	<i>Expected Ambiguity</i>	$(R_m - R_f)$	<i>SMB</i>	<i>HML</i>	<i>RMW</i>	<i>CMA</i>
Mean	0.04	0.03	0.02	0.02	0.02	0.01
Median	0.03	0.06	0.03	0.00	0.01	0.00
Min	0.00	-8.95	-3.41	-4.22	-3.03	-5.93
Max	0.27	11.35	4.48	4.83	3.16	2.41
Std. Dev.	0.03	1.21	0.57	0.66	0.50	0.42
Skewness	2.35	-0.04	0.02	0.40	0.02	-0.84
Kurtosis	6.73	8.04	3.07	8.77	4.73	15.88

Panel B. High Ambiguity

	<i>Expected Ambiguity</i>	$(R_m - R_f)$	<i>SMB</i>	<i>HML</i>	<i>RMW</i>	<i>CMA</i>
Mean	0.06	0.01	-0.02	-0.01	0.01	-0.01
Median	0.05	0.05	-0.01	-0.01	0.00	-0.01
Min	0.03	-8.95	-3.41	-4.22	-2.60	-2.40
Max	0.27	11.35	4.48	4.83	2.99	2.24
Std. Dev.	0.04	1.30	0.59	0.67	0.42	0.36
Skewness	1.99	-0.09	0.11	0.30	0.00	0.03
Kurtosis	4.17	10.77	3.96	10.03	5.89	6.66

Panel C. Low Ambiguity

	<i>Expected Ambiguity</i>	$(R_m - R_f)$	<i>SMB</i>	<i>HML</i>	<i>RMW</i>	<i>CMA</i>
Mean	0.02	0.05	0.05	0.04	0.03	0.03
Median	0.02	0.08	0.06	0.02	0.02	0.02
Min	0.00	-5.04	-3.16	-4.15	-3.03	-5.93
Max	0.03	6.89	3.62	4.75	3.16	2.41
Std. Dev.	0.01	1.11	0.55	0.65	0.56	0.47
Skewness	0.03	0.06	-0.06	0.51	0.01	-1.25
Kurtosis	-1.12	2.16	1.94	7.36	3.65	17.57

Panel D. Difference in Means between Periods of High vs. Low Ambiguity

<i>Expected Ambiguity</i>	$(R_m - R_f)$	<i>SMB</i>	<i>HML</i>	<i>RMW</i>	<i>CMA</i>
<i>(High - Low)</i>	-0.04	-0.07***	-0.04**	-0.02	-0.04***

Table 2-6: Time Series Regressions of Portfolio Returns

This table reports results of the regression of the returns on long-short portfolio returns regressed on the expected ambiguity ($Ambiguity_t^E$), the Fama and French (1992) three factors, and the Fama and French (2016) five factors respectively. The expected ambiguity, $Ambiguity_t^E$ is computed as described in the text. The long-short portfolios are formed based on firm *Size*, *Age*, risk (σ), dividends (D), profitability (E), property, plant, and equipment over assets (PPE/A), research and development expense over assets (RD/A), book-to-market ratio (BE/ME), and the absolute value of discretionary accruals ($DAccruals$). For each characteristic, we long firms in the top three NYSE deciles and short firms in the bottom three NYSE deciles. We report three sets of results for each firm characteristic. The first set of results include the estimated coefficients from the baseline regression $R_{X_{it}=High,t} - R_{X_{it}=Low,t} = a + \delta Ambiguity_t^E + u_t$. The second set of results extends the baseline model to include the excess return on the market ($R_m - R_f$), the size factor (SMB), and the value factor (HML) from Fama and French (1992). The third set of results include the excess market return ($R_m - R_f$), the size factor (SMB), the *orthogonal* value factor (HML0) computed as in Fama and French (2016), the profitability factor (RMW), and the investment factor (CMA) from Fama and French (2016). For each of the two extended models, we include an orthogonal ambiguity measure proxied by the residuals obtained from a regression of the expected ambiguity measure on the Fama and French (2016) five factors. SMB (HML) is not included as a control variable for the long-short portfolio returns formed on size (BE/ME). The sample is from 05/30/2000 to December 31, 2017. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively.

Panel A. Size, Age, and Risk

		<i>Intercept</i>	$Ambiguity_t^E$	$(R_{M,t} - R_{F,t})$	SMB_t	HML_t	RMW_t	CMA_t	$R^2(\%)$
Size	Large-Small	0.0015**	0.0011***						0.20
	Large-Small	-0.0004***	0.0010***	0.0037***		-0.0031***			31.68
	Large-Small	-0.0004***	0.0009***	0.0035***		-0.0026***	0.00114***	-0.0037***	32.09
Age	Old-Young	-0.0019**	-0.0010**						0.25
	Old-Young	-0.0001	-0.0009**	-0.0002	-0.0004*	0.0026***			5.54
	Old-Young	-0.0002**	-0.0006	0.0011***	0.0002	0.0016***	0.0046***	0.0039***	15.31
σ	High-Low	-0.0022***	-0.0012***						0.18
	High-Low	-0.0003**	-0.0008**	0.0032***	0.0040***	-0.0014***			24.10
	High-Low	-0.0001	-0.0012***	0.0018***	0.0031***	-0.0004	-0.0063***	-0.0027***	33.73

Panel B. Profitability and Dividend Policy

		<i>Intercept</i>	<i>Ambiguity</i> _t ^E	$(R_{M,t} - R_{F,t})$	<i>SMB</i> _t	<i>HML</i> _t	<i>RMW</i> _t	<i>CMA</i> _t	<i>R</i> ² (%)
E	> 0 – < 0	0.0075**	0.0044**						0.49
	> 0 – < 0	-0.0001	0.0043**	-0.0011*	-0.0043***	0.0030**			2.40
	> 0 – < 0	-0.0002	0.0044**	-0.0005	-0.0037**	0.0034**	0.0024	0.0023	2.48
D	> 0 – = 0	-0.0002	-0.0001						0.58
	> 0 – = 0	-0.0001	0.0001	0.0001	-0.0018***	0.0034***			16.77
	> 0 – = 0	-0.0003***	0.0004*	0.0015***	-0.0009***	0.0027***	0.0056***	0.0035***	35.47

Panel C. Tangibility and Growth Opportunities

		<i>Intercept</i>	<i>Ambiguity</i> _t ^E	$(R_{M,t} - R_{F,t})$	<i>SMB</i> _t	<i>HML</i> _t	<i>RMW</i> _t	<i>CMA</i> _t	<i>R</i> ² (%)
PPE/A	High-Low	-0.0032***	-0.0016***						0.38
	High-Low	-0.0004***	-0.0013***	0.0005**	-0.0001	0.0041***			9.47
	High-Low	-0.0006***	-0.0010**	0.0020***	0.0010***	0.0036***	0.0063***	0.0033***	17.78
RD/A	High-Low	0.0023***	0.0011***						0.25
	High-Low	0.0003***	0.0009**	0.0009***	0.0019***	-0.0050***			18.83
	High-Low	0.0005***	0.0006*	-0.0009***	0.0005**	-0.0047***	-0.0076***	-0.0033***	34.71
BE/ME	High-Low	0.0048	0.0031*						0.17
	High-Low	-0.0006	0.0029	-0.0022*	-0.0008				0.99
	High-Low	-0.0007	0.0034*	-0.0019*	-0.0008		0.0012	0.0069***	1.64

Panel D. Discretionary Accruals

		<i>Intercept</i>	<i>Ambiguity</i> _t ^E	$(R_{M,t} - R_{F,t})$	<i>SMB</i> _t	<i>HML</i> _t	<i>RMW</i> _t	<i>CMA</i> _t	<i>R</i> ² (%)
DAccrual	High-Low	-0.0015**	-0.0008**						0.17
	High-Low	-0.0002	-0.0008**	0.0003***	0.0009***	-0.0011***			2.00
	High-Low	-0.0001	-0.0009**	-0.0003***	0.0006***	-0.0006***	-0.0021***	-0.0018***	4.86

Table 2-7: Statistics of Earnings Surprises and Cumulative Abnormal Returns

Panels A and B report the mean of negative (Panel A) and positive (Panel B) standardized earnings surprises, computed as the difference between each firm's reported earnings per share (EPS) minus the latest analyst consensus EPS forecast before the earnings announcement date, scaled by the stock price two days before the earnings announcement date. Periods of low (high) ambiguity correspond to periods when the expected ambiguity is in the bottom (top) 30th percentile across our sample period. This table also reports the average cumulative abnormal return for different windows around the release date. The last column in each Panel reports the difference in means for each variable during periods of high relative to periods of low expected ambiguity. All values are in %. The sample period is from May 2000 to December 2017. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively.

Panel A. Negative Earnings Surprise

	High Ambiguity	Low Ambiguity	Difference (High-Low)
Size of Surprise	-3.28	-2.85	-0.43***
CAR [-1, +1]	-1.54	-2.07	0.53***
CAR [-2, +2]	-1.81	-2.29	0.49**
CAR [-5, +5]	-2.41	-2.62	0.22
CAR [0, +10]	-1.98	-2.77	0.79***

Panel B. Positive Earnings Surprise

	High Ambiguity	Low Ambiguity	Difference (High-Low)
Size of Surprise	1.51	1.52	-0.01
CAR [-1, +1]	1.52	1.46	0.06
CAR [-2, +2]	1.37	1.31	0.06
CAR [-5, +5]	0.98	0.75	0.22
CAR [0, +10]	0.86	-0.15	1.01***

Table 2-8: The Stock Market Reaction to Earnings News – Baseline Regression

The table reports the estimates for the following model: $CAR_{it} = \beta_1 SUE_{it} + Controls_t + \alpha_i + \delta_t + u_{it}$, where CAR_{it} is the cumulative abnormal return computed over a window of 3 days, 5 days, or 11 days around each earnings announcement date, while SUE_{it} refers to the earnings standardized surprise. The regression controls for the size factor (SMB), the orthogonal value factor (HML), the profitability factor (RMW), and the investment factor (CMA) from Fama and French (2016). Year and firm fixed effects are included in the regressions. The sample period covered is from May 2000 until December 2017. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively.

	<i>CAR</i> [-1, +1]	<i>CAR</i> [-2, +2]	<i>CAR</i> [-5, +5]
<i>SUE</i>	0.1689***	0.1772***	0.2037***
<i>SMB</i>	0.0080***	0.0085***	0.0080***
<i>HML</i>	-0.0015	-0.0019*	-0.0035***
<i>RMW</i>	-0.0037***	-0.0046***	-0.0050***
<i>CMA</i>	-0.0045***	-0.0020	-0.0041**

Table 2-9: The Stock Market Reaction to Earnings News in times of High Ambiguity

The table reports the estimates for the following model:

$$CAR_{it} = \beta_1 SUE_{it} + \beta_2 D_{Ambiguity,t} + \beta_3 SUE_{it} D_{Ambiguity,t} + Controls_t + \alpha_i + \delta_t + u_{it}$$

where CAR_{it} is the cumulative abnormal return computed over the windows $[-1,+1]$, $[-2,+2]$, and $[-5,+5]$, around each earnings announcement date. SUE_{it} is the standardized earnings surprise and $D_{Ambiguity,t}$ is a dummy variable taking values of 1 when the expected ambiguity is in the top 30th percentile across our sample, and 0 otherwise. The regression controls for the size factor (SMB), the orthogonal value factor (HML), the profitability factor (RMW), and the investment factor (CMA) from Fama and French (2016). The sample period is from May 2000 to December 2017. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively.

	$CAR[-1, +1]$	$CAR[-2, +2]$	$CAR[-5, +5]$
SUE_{it}	0.1889***	0.1919***	0.2176***
$D_{Ambiguity,t}$	0.0018	0.0010	-0.0019
$SUE_{it} D_{Ambiguity,t}$	-0.0844***	-0.0625*	-0.0633
<i>SMB</i>	0.0080***	0.0085***	0.0080***
<i>HML</i>	-0.0013	-0.0018*	-0.0035***
<i>RMW</i>	-0.0038***	-0.0046***	-0.0049***
<i>CMA</i>	-0.0044***	-0.0019	-0.0042**
<i>Year fixed effect</i>	Yes	Yes	Yes
<i>Firm fixed effect</i>	Yes	Yes	Yes
Overall Impact of SUE:			
$SUE+(SUE*D_{Ambiguity})$	0.1045***	0.1294***	0.1543***

Table 2-10: The Stock Market Reaction to Good vs. Bad Earnings News- Baseline Regression

The table reports the estimates for the following model: $CAR_{it} = \beta_1 GoodNews_{it} + \beta_2 BadNews_{it} + Controls_t + \alpha_i + \delta_t + u_{it}$, where CAR_{it} is the cumulative abnormal return (CAR) computed over a window of 3 days, 5 days, or 11 days around each earnings announcement date. $GoodNews_{it}$ ($BadNews_{it}$) refers to positive (negative) earnings standardized surprises, taking values of the earnings surprise if the surprise is positive (negative), and 0 otherwise. The regression controls for the size factor (SMB), the orthogonal value factor (HML), the profitability factor (RMW), and the investment factor (CMA) from Fama and French (2016). Year and firm fixed effects are included in the regressions. This table also reports a test of asymmetry that examines whether the response of stocks to good and bad earnings surprises is asymmetric. The sample period covered is from May 2000 until December 2017. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively.

	CAR[−1, +1]	CAR[−2, +2]	CAR[−5, +5]
<i>GoodNews</i>	0.2451***	0.2666***	0.3277***
<i>BadNews</i>	0.1059***	0.1034***	0.1014***
<i>SMB</i>	0.0079***	0.0084***	0.0079***
<i>HML</i>	-0.0015	-0.0019*	-0.0035***
<i>RMW</i>	-0.0038***	-0.0047***	-0.0051***
<i>CMA</i>	-0.0045***	-0.0020	-0.0041**
<i>Test of Asymmetry</i>			
<i>GoodNews – BadNews</i>	0.1392***	0.1632***	0.2263***

Table 2-11: The Stock Market Reaction to Good vs. Bad Earnings News in times of High Ambiguity

The table reports the estimates of the following model: $CAR_{it} = \beta_1 GoodNews_{it} + \beta_2 BadNews_{it} + \beta_3 * D_{Ambiguity,t} + \beta_4 GoodNews_{it} * D_{Ambiguity,t} + \beta_5 BadNews_{it} * D_{Ambiguity,t} + Controls_t + \alpha_i + \delta_t + u_{it}$, where CAR_{it} is the cumulative abnormal return (CAR) computed over a window of 3 days, 5 days, or 11 days around each earnings announcement. $GoodNews_{it}$ ($BadNews_{it}$) refers to positive (negative) earnings standardized surprises, taking values of the earnings surprise if the surprise is positive (negative), and 0 otherwise. $D_{Ambiguity,t}$ is a dummy variable taking values of 1 when the expected ambiguity ($Ambiguity_t^E = \ln \widehat{U}_t$ computed as described in section 2.3.2. in the text) is in the top 30th percentile across our sample period, and 0 otherwise. The regression controls for the size factor (SMB), the orthogonal value factor (HML), the profitability factor (RMW), and the investment factor (CMA) from Fama and French (2016). Year and firm fixed effects are included in the regressions. We also provide a test of asymmetry that examines whether the response of stocks to good and bad earnings surprises is asymmetric. The sample period covered is from May 2000 until December 2017. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively.

	CAR[-1, +1]	CAR[-2, +2]	CAR[-5, +5]
<i>GoodNews</i>	0.2523***	0.2646***	0.3232***
<i>BadNews</i>	0.1334***	0.1285***	0.1255***
<i>D_{Ambiguity}</i>	0.0012	0.0000	-0.0032
<i>GoodNews * D_{Ambiguity}</i>	-0.0422	0.0057	0.0208
<i>BadNews * D_{Ambiguity}</i>	-0.1022**	-0.0974*	-0.1033
<i>SMB</i>	0.0079***	0.0085***	0.0079***
<i>HML</i>	-0.0013	-0.0018*	-0.0035***
<i>RMW</i>	-0.0039***	-0.0047***	-0.0051***
<i>CMA</i>	-0.0044***	-0.0019	-0.0042**
<i>Test of Asymmetry</i>			
<i>GoodNews+(GoodNews*D_{Ambiguity})</i>	0.2102***	0.2703***	0.3440***
<i>BadNews+(BadNews*D_{Ambiguity})</i>	0.0312	0.0311	0.0223
<i>Difference</i>	0.1790***	0.2392***	0.3217***

Table 2-12: The Stock Market Reaction to Earnings News in times of High Ambiguity: Firm-Specific Characteristics

The table reports the estimates of the following model: $CAR_{it} = \beta_1 GoodNews_{it} + \beta_2 BadNews_{it} + \beta_3 GoodNews_{it} * D_{Ambiguity,t} + \beta_4 BadNews_{it} * D_{Ambiguity,t} + Controls_t + \alpha_i + \delta_t + u_{it}$, where CAR_{it} is the cumulative abnormal return (CAR) computed over a window of 3 days around each earnings announcement. $GoodNews_{it}$ ($BadNews_{it}$) refers to positive (negative) earnings standardized surprises, taking values of the earnings surprise if the surprise is positive (negative), and 0 otherwise. $D_{Ambiguity,t}$ is a dummy variables taking values of 1 when the expected ambiguity ($Ambiguity_t^E = \ln \bar{U}_t$ computed as described in section 2.3.2. in the text) is in its top 30th percentile, and 0 otherwise. The regression controls for the size factor (SMB), the orthogonal value factor (HML), the profitability factor (RMW), and the investment factor (CMA) from Fama and French (2016). Year and firm fixed effects are included in the regressions. We also provide a test of asymmetry that examines whether the response of stocks to good and bad earnings surprises is asymmetric. The firm-specific characteristics considered are: the number of analysts making recommendations for each stock, the standard deviation of analysts' earnings forecasts, the firm size, age, total risk (σ), property, plant, and equipment over assets (PPE/A), research and development expense over assets (RD/A), book-to-market ratio (BE/ME), and the absolute value of discretionary accruals ($D_{Accruals}$). We also consider two categorical variables: E to capture whether the firm is profitable ($E > 0$) or unprofitable ($E < 0$), and D to capture whether the firm pays dividends ($D > 0$) or not ($D = 0$). A firm characteristic has low (high) values if it is below (above) its sample median. The sample period covered is from May 2000 until December 2017. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively.

Panel A. Information Asymmetry

	<i>Nr. Analysts</i>		<i>StdDev. Forecasts</i>	
	Low	High	Low	High
<i>GoodNews</i>	0.2277***	0.2949***	0.8811***	0.1848***
<i>BadNews</i>	0.1625***	0.0904**	0.0690	0.1981***
<i>D_{Ambiguity}</i>	0.0002	0.0018	0.0016	-0.0004
<i>GoodNews * D_{Ambiguity}</i>	-0.0547	-0.0638	-0.0670	-0.0473
<i>BadNews * D_{Ambiguity}</i>	-0.1185*	-0.0802	-0.2415	-0.1393**
<i>SMB</i>	0.0069***	0.0086***	0.0081***	0.0084***
<i>HML</i>	-0.0006	-0.0019	-0.0037**	-0.0005
<i>RMW</i>	-0.0041***	-0.0039***	-0.0027	-0.0050***
<i>CMA</i>	-0.0038**	-0.0055***	-0.0055***	-0.0059***
<i>Test of Asymmetry</i>				
<i>GoodNews+(GoodNews*D_{Ambiguity})</i>	0.1729**	0.2311***	0.8141***	0.1375**
<i>BadNews+(BadNews*D_{Ambiguity})</i>	0.0440	0.010	-0.1724	0.0587
<i>Difference</i>	0.1289	0.2209**	0.9866***	0.0788

Panel B. Size, Age, and Risk

	<i>Size</i>		<i>Age</i>		σ	
	Small	Big	Young	Old	Low	High
<i>GoodNews</i>	0.2084***	0.3291***	0.2139***	0.3139***	0.4016***	0.2290***
<i>BadNews</i>	0.2144***	0.0207	0.1129***	0.1464***	0.0268	0.2453***
<i>D_{Ambiguity}</i>	0.0010	0.0011	0.0004	0.0014	0.0024	-0.0009
<i>GoodNews * D_{Ambiguity}</i>	-0.1015	0.0041	-0.0059	-0.1017	-0.0582	-0.0223
<i>BadNews * D_{Ambiguity}</i>	-0.1077*	-0.0666	-0.1116	-0.0994*	-0.0121	-0.2003**
<i>SMB</i>	0.0086***	0.0065***	0.0071***	0.0083***	0.0063***	0.0090***
<i>HML</i>	0.0009	-0.0021*	-0.0012	-0.0014	-0.0004	-0.0013
<i>RMW</i>	-0.0049***	-0.0030**	-0.0068***	-0.0012	0.0004	-0.0072***
<i>CMA</i>	-0.0014	-0.0056***	-0.0048***	-0.0035**	-0.0024	-0.0041**
<i>Test of Asymmetry</i>						
<i>GoodNews+(GoodNews*D_{Ambiguity})</i>	0.1070*	0.3332***	0.2079***	0.2122***	0.3435***	0.2067**
<i>BadNews+(BadNews*D_{Ambiguity})</i>	0.1068*	-0.0459	0.0013	0.0470	0.0147	0.0449
<i>Difference</i>	0.0002	0.3791	0.2066**	0.1652*	0.3288***	0.16178

Panel C. Profitability and Dividend Policy

	<i>E</i>		<i>D</i>	
	<i>E</i> < 0	<i>E</i> > 0	<i>D</i> = 0	<i>D</i> > 0
<i>GoodNews</i>	0.2477***	11.3124***	0.2193***	0.7442***
<i>BadNews</i>	0.1361***	-0.3879	0.1622***	0.0438
<i>D_{Ambiguity}</i>	0.0008	0.0042	0.0013	-0.0004
<i>GoodNews</i> * <i>D_{Ambiguity}</i>	-0.0602	-7.7425**	-0.0257	-0.3320**
<i>BadNews</i> * <i>D_{Ambiguity}</i>	-0.1205***	0.1823	-0.1134**	-0.1311**
<i>SMB</i>	0.0077***	0.0146	0.0082***	0.0063***
<i>HML</i>	-0.0013	0.0081	-0.0015	-0.0002
<i>RMW</i>	-0.0039***	-0.0370	-0.0058***	0.0023
<i>CMA</i>	-0.0042***	-0.0415	-0.0045***	-0.0035*
<i>Test of Asymmetry</i>				
<i>GoodNews</i> +(<i>GoodNews</i> * <i>D_{Ambiguity}</i>)	0.1875***	3.5699**	0.1936***	0.4121***
<i>BadNews</i> +(<i>BadNews</i> * <i>D_{Ambiguity}</i>)	0.0156	-0.2057	0.0489	-0.0874
<i>Difference</i>	0.1719**	3.7756*	0.1447*	0.4995***

Panel D. Tangibility and Growth Opportunities

	<i>PPE/A</i>		<i>RD/A</i>		<i>BE/ME</i>	
	Low	High	Low	High	Low	High
<i>GoodNews</i>	0.3396***	0.2918***	0.3936***	0.1652***	-0.0333	0.1680
<i>BadNews</i>	0.0124	0.1422***	0.2208***	0.1004	-0.2882*	0.1086
<i>D_{Ambiguity}</i>	0.0052	0.0052**	0.0010	0.0006	-0.0026	0.0076*
<i>GoodNews * D_{Ambiguity}</i>	-0.0217	0.0153	-0.1312	-0.0146	0.3841*	0.2243
<i>BadNews * D_{Ambiguity}</i>	0.2081*	-0.0349	-0.1675*	-0.1977	0.2641	0.0225
<i>SMB</i>	0.0092***	0.0058***	0.0103***	0.0061***	0.0174***	0.0095**
<i>HML</i>	-0.0048**	-0.0015	-0.0007	-0.0036*	-0.0039	0.0115*
<i>RMW</i>	-0.0086***	0.0000	-0.0039**	-0.0088***	-0.0001	-0.0048
<i>CMA</i>	-0.0044*	0.0001	-0.0012	-0.0085***	-0.0119	-0.0092
<i>Test of Asymmetry</i>						
<i>GoodNews+(GoodNews*D_{Ambiguity})</i>	0.3179***	0.3071***	0.2623*	0.1506**	0.3509*	0.3923**
<i>BadNews+(BadNews*D_{Ambiguity})</i>	0.2205**	0.1073	0.0533	-0.0973	-0.0241	0.1312
<i>Difference</i>	0.0974	0.1999	0.2090	0.2479*	0.3749	0.2611

Panel E. Discretionary Accruals

	<i>Discretionary Accruals</i>	
	Low	High
<i>GoodNews</i>	0.1899**	0.3102***
<i>BadNews</i>	0.1256**	0.0398
<i>D_{Ambiguity}</i>	0.0015	0.0120**
<i>GoodNews * D_{Ambiguity}</i>	0.0636	0.0781
<i>BadNews * D_{Ambiguity}</i>	-0.0842	0.0712
<i>SMB</i>	0.0063***	0.0061*
<i>HML</i>	-0.0037	-0.0041
<i>RMW</i>	-0.0084***	-0.0064*
<i>CMA</i>	0.0034	-0.0022
<i>Test of Asymmetry</i>		
<i>GoodNews+(GoodNews*D_{Ambiguity})</i>	0.2535	0.3883**
<i>BadNews+(BadNews*D_{Ambiguity})</i>	0.0414	0.1110
<i>Difference</i>	0.2121	0.2773

Table 2-13: Frequency of Good and Bad Earnings News in times of High vs. Low Expected Ambiguity

This table reports the proportion of good and bad earnings surprises for different categories of stocks, in times of low vs. high expected ambiguity. A firm-specific characteristic is considered to have high (low) values if it is above (below) the sample median during quarter t . We consider the following firm characteristics: the number of analysts making recommendations for each stock, the standard deviation of analysts' earnings forecasts, the firm *size*, *age*, total risk (σ), property, plant, and equipment over assets (PPE/A), research and development expense over assets (RD/A), book-to-market ratio (BE/ME), and the absolute value of discretionary accruals ($DAccruals$). Periods of low (high) expected ambiguity are considered those periods when the expected ambiguity is above (below) its sample median. The sample period covered is from May 2000 until December 2017.

		<i>Low Ambiguity^E</i>			<i>High Ambiguity^E</i>		
		Bad News	Zero News	Good News	Bad News	Zero News	Good News
<i>Nr. Analysts</i>	Low	46.75%	8.30%	44.95%	51.44%	6.83%	41.72%
	High	38.18%	10.97%	50.85%	43.51%	9.27%	47.22%
<i>StdDev Forecast</i>	Low	33.22%	15.31%	51.47%	35.98%	14.81%	49.22%
	High	46.23%	5.75%	48.02%	51.08%	4.91%	44.02%
<i>Size</i>	Small	45.38%	9.37%	45.25%	49.04%	8.16%	42.80%
	Big	38.76%	10.08%	51.16%	44.83%	8.35%	46.82%
<i>Age</i>	Young	40.29%	9.75%	49.96%	45.61%	8.04%	46.34%
	Old	44.13%	9.68%	46.19%	48.02%	8.49%	43.49%
σ	Low	45.21%	9.57%	45.23%	48.93%	7.78%	43.29%
	High	39.81%	9.82%	50.37%	43.89%	8.92%	47.19%
<i>PPE/A</i>	Low	35.96%	11.55%	52.49%	39.04%	10.25%	50.71%
	High	45.64%	8.65%	45.71%	49.80%	7.61%	42.59%
<i>RD/A</i>	Low	41.38%	10.79%	47.82%	46.46%	8.80%	44.74%
	High	33.57%	10.04%	56.39%	37.30%	9.01%	53.69%
<i>BE/ME</i>	Low	43.01%	6.78%	50.21%	43.41%	7.25%	49.34%
	High	55.29%	4.12%	40.59%	53.60%	5.68%	40.73%
<i>DAccruals</i>	Low	42.32%	9.38%	48.30%	47.07%	8.24%	44.70%
	High	34.70%	12.31%	53.00%	37.38%	11.31%	51.31%

Table 2-14: The Magnitude of Earnings Surprises in times of High Expected Ambiguity

This table reports the estimated coefficients obtained when regressing positive and negative standardized unexpected earnings surprises (SUE) on our expected ambiguity measure. SUE is computed as the difference between each firm's reported earnings per share (EPS) minus the latest analyst consensus EPS forecast before the earnings announcement date, scaled by the stock price two days before the earnings announcement date (as in Fang, Huang, and Karpoff (2016)). The expected ambiguity used in these regressions is $Ambiguity_t^E = \widehat{\ln \bar{U}_t}$ computed as described in section 2.3.2. in the text. Year and firm fixed effects are included in the regressions. The sample period covered is from May 2000 until December 2017. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively.

	Positive Surprise		Negative Surprise	
	Coefficient	p-value	Coefficient	p-value
$Ambiguity_t^E$	0.0027***	0.0015	-0.0144***	<.0001

Table 2-15: The Stock Market Reaction to Earnings News
(Controlling for the Magnitude of the Earnings Surprise)

The table reports the estimates of the following model: $CAR_{it} = \beta_1 GoodNews_{it} * D_{Small\ SUE,t}^+ + \beta_2 GoodNews_{it} * D_{Med\ SUE,t}^+ + \beta_3 GoodNews_{it} * D_{Large\ SUE,t}^+ + \beta_4 BadNews_{it} * D_{Small\ SUE,t}^- + \beta_5 BadNews_{it} * D_{Med\ SUE,t}^- + \beta_6 BadNews_{it} * D_{Large\ SUE,t}^- + Controls_t + \alpha_i + \delta_t + u_{it}$, where CAR_{it} is the cumulative abnormal return (CAR) computed over a window $[-1, +1]$ around each earnings announcement. $GoodNews_{it}$ ($BadNews_{it}$) refers to positive (negative) standardized earnings surprises, taking values of the earnings surprise if the surprise is positive (negative), and 0 otherwise. $D_{Small\ SUE,t}^+$, $D_{Med\ SUE,t}^+$, $D_{Large\ SUE,t}^+$ are dummy variables taking values of 1 when the positive standardized earnings surprise is below the 30th percentile, between the 30th and the 70th percentiles, and above the 70th percentile of positive earnings surprises in our sample. Otherwise, these dummy variables take values of 0. Similarly, $D_{Large\ SUE,t}^-$, $D_{Med\ SUE,t}^-$, $D_{Small\ SUE,t}^-$ are dummy variables taking values of 1 when the negative standardized earnings surprise is below the 30th percentile, between the 30th and the 70th percentiles, and above the 70th percentile of negative earnings surprises in our sample. Otherwise, these dummy variables take values of 0. The regression controls for the size factor (SMB), the orthogonal value factor (HML), the profitability factor (RMW), and the investment factor (CMA) from Fama and French (2016). Year and firm fixed effects are included in the regression. The sample period covered is from May 2000 until December 2017. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively.

	<i>Coefficient</i>	<i>P – Value</i>
$GoodNews_{it} * D_{Small\ SUE,t}^+$	-3.3751	0.1802
$GoodNews_{it} * D_{Med\ SUE,t}^+$	8.7886***	<.0001
$GoodNews_{it} * D_{Large\ SUE,t}^+$	0.2295***	<.0001
$BadNews_{it} * D_{Small\ SUE,t}^-$	12.7088***	<.0001
$BadNews_{it} * D_{Med\ SUE,t}^-$	0.6917***	<.0001
$BadNews_{it} * D_{Large\ SUE,t}^-$	0.0660***	0.0047
<i>SMB</i>	0.0072***	<.0001
<i>HML</i>	-0.0017*	0.0841
<i>RMW</i>	-0.0036***	0.0004
<i>CMA</i>	-0.0051***	<.0001
<i>Test of Difference</i>		
$GoodNews_{it} * D_{Large\ SUE,t}^+ - GoodNews_{it} * D_{Small\ SUE,t}^+$	3.6046	0.1517
$BadNews_{it} * D_{Large\ SUE,t}^- - BadNews_{it} * D_{Small\ SUE,t}^-$	-12.6428***	<.0001

**Table 2-16: The Stock Market Reaction to Earnings News in times of High Ambiguity
(Controlling for the Magnitude of the Earnings Surprise)**

The table reports the estimates of the following model: $CAR_{it} = \lambda_1 GoodNews_{it} * D_{Small\ SUE,t}^+ + \lambda_2 GoodNews_{it} * D_{Med\ SUE,t}^+ + \lambda_3 GoodNews_{it} * D_{Large\ SUE,t}^+ + \beta_1 BadNews_{it} * D_{Small\ SUE,t}^- + \beta_2 BadNews_{it} * D_{Med\ SUE,t}^- + \beta_3 BadNews_{it} * D_{Large\ SUE,t}^- + Y_1 GoodNews_{it} * D_{Small\ SUE,t}^+ * D_{Ambiguity,t} + Y_2 GoodNews_{it} * D_{Med\ SUE,t}^+ * D_{Ambiguity,t} + Y_3 GoodNews_{it} * D_{Large\ SUE,t}^+ * D_{Ambiguity,t} + \vartheta_1 BadNews_{it} * D_{Small\ SUE,t}^- * D_{Ambiguity,t} + \vartheta_2 BadNews_{it} * D_{Med\ SUE,t}^- * D_{Ambiguity,t} + \vartheta_3 BadNews_{it} * D_{Large\ SUE,t}^- * D_{Ambiguity,t} + Controls_t + \alpha_i + \delta_t + u_{it}$, where CAR_{it} is the cumulative abnormal return (CAR) computed over a window $[-1, +1]$ around each earnings announcement. $GoodNews_{it}$ ($BadNews_{it}$) refers to positive (negative) standardized earnings surprises, taking values of the earnings surprise if the surprise is positive (negative), and 0 otherwise. $D_{Small\ SUE,t}^+$, $D_{Med\ SUE,t}^+$, $D_{Large\ SUE,t}^+$ are dummy variables taking values of 1 when the positive standardized earnings surprise is below the 30th percentile, between the 30th and the 70th percentiles, and above the 70th percentile of positive earnings surprises in our sample. Otherwise, these dummy variables take values of 0. Similarly, $D_{Large\ SUE,t}^-$, $D_{Med\ SUE,t}^-$, $D_{Small\ SUE,t}^-$ are dummy variables taking values of 1 when the negative standardized earnings surprise is below the 30th percentile, between the 30th and the 70th percentiles, and above the 70th percentile of negative earnings surprises in our sample. Otherwise, these dummy variables take values of 0. $D_{Ambiguity,t}$ is a dummy variable taking values of 1 when the expected ambiguity ($Ambiguity_t^E = \ln \bar{U}_t$ computed as described in section 2.3.2. in the text) is in the top 30th percentile across our sample period, and 0 otherwise. The regression controls for the size factor (SMB), the orthogonal value factor (HML), the profitability factor (RMW), and the investment factor (CMA) from Fama and French (2016). Year and firm fixed effects are included in the regression. The sample period covered is from May 2000 until December 2017. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively.

	<i>Coefficient</i>	<i>P – Value</i>
$GoodNews_{it} * D_{Small\ SUE,t}^+$	2.5121	0.3178
$GoodNews_{it} * D_{Med\ SUE,t}^+$	10.4553***	<.0001
$GoodNews_{it} * D_{Large\ SUE,t}^+$	0.2583***	<.0001
$BadNews_{it} * D_{Small\ SUE,t}^-$	11.2216***	<.0001
$BadNews_{it} * D_{Med\ SUE,t}^-$	0.5332***	<.0001
$BadNews_{it} * D_{Large\ SUE,t}^-$	0.0516**	0.0341
$GoodNews_{it} * D_{Small\ SUE,t}^+ * D_{Ambiguity,t}$	5.7196	0.2640
$GoodNews_{it} * D_{Med\ SUE,t}^+ * D_{Ambiguity,t}$	-1.4691	0.1378
$GoodNews_{it} * D_{Large\ SUE,t}^+ * D_{Ambiguity,t}$	-0.0273	0.5806
$BadNews_{it} * D_{Small\ SUE,t}^- * D_{Ambiguity,t}$	-0.5811	0.7440
$BadNews_{it} * D_{Med\ SUE,t}^- * D_{Ambiguity,t}$	-0.3186*	0.0515
$BadNews_{it} * D_{Large\ SUE,t}^- * D_{Ambiguity,t}$	-0.1043**	0.0109
<i>SMB</i>	0.0079***	<.0001
<i>HML</i>	-0.0013	0.1623
<i>RMW</i>	-0.0037***	0.0001
<i>CMA</i>	-0.0042***	0.0001
R^2	37.03%	

**Table 2-17: Ambiguity Effect on the Stock Market Reaction to Earnings News
(Controlling for the Business Cycle)**

The table reports the estimates of the following model: $CAR_{it} = b_{Ambiguity} * D_{Ambiguity,t} + b_X * X_t + b_{Good} GoodNews_{it} + b_{Bad} BadNews_{it} + c_{Amb}^{Good} GoodNews_{it} * D_{Ambiguity,t} + c_{Amb}^{Bad} BadNews_{it} * D_{Ambiguity,t} + d_X^{Good} GoodNews_{it} * X_t + d_X^{Bad} BadNews_{it} * X_t + Controls_t + \alpha_i + \delta_t + u_{it}$, where CAR_{it} is the cumulative abnormal return (CAR) computed over a window of 3 days around each earnings announcement. $GoodNews_{it}$ ($BadNews_{it}$) refers to positive (negative) earnings standardized surprises, taking values of the earnings surprise if the surprise is positive (negative), and 0 otherwise. $D_{Ambiguity,t}$ is a dummy variables taking values of 1 when the expected ambiguity ($Ambiguity_t^E = \ln \bar{U}_t$ computed as described in section 2.3.2. in the text) is in its top 30th percentile, and 0 otherwise. The regression controls for the size factor (SMB), the orthogonal value factor (HML), the profitability factor (RMW), and the investment factor (CMA) from Fama and French (2016). In Panel A, X_t is dummy variable taking values of 1 during expansionary periods, and 0 during recessions. The expansion vs. recession periods are identified by using the NBER peak and trough dates. In Panel B, X_t is a control variable that accounts for the (lagged) Aruoba-Diebold-Scotti business conditions index. Year and firm fixed effects are included in the regressions. The sample period covered is from May 2000 until December 2017. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively.

	Panel A	Panel B
<i>GoodNews</i>	0.2265***	0.2624***
<i>BadNews</i>	0.1438***	0.1097***
<i>GoodNews * D_{Ambiguity}</i>	-0.0477	-0.0445
<i>BadNews * D_{Ambiguity}</i>	-0.0994**	-0.1099**
<i>GoodNews * X</i>	0.0290	0.0343
<i>BadNews * X</i>	-0.0179	-0.0490**
<i>SMB</i>	0.0077***	0.0078***
<i>HML</i>	-0.0012	-0.0013
<i>RMW</i>	-0.0039***	-0.0039***
<i>CMA</i>	-0.0040***	-0.0041***
<i>R²</i>	35.55%	35.56%

**Table 2-18: Ambiguity Effect on the Stock Market Reaction to Earnings News
(Controlling for Sentiment)**

The table reports the estimates of the following model: $CAR_{it} = b_{Ambiguity} * D_{Ambiguity,t} + b_X * X_{t-1} + b_{Good} GoodNews_{it} + b_{Bad} BadNews_{it} + c_{Amb}^{Good} GoodNews_{it} * D_{Ambiguity,t} + c_{Amb}^{Bad} BadNews_{it} * D_{Ambiguity,t} + d_X^{Good} GoodNews_{it} * X_{t-1} + d_X^{Bad} BadNews_{it} * X_{t-1} + Controls_t + \alpha_i + \delta_t + u_{it}$, where CAR_{it} is the cumulative abnormal return (CAR) computed over a window of 3 days around each earnings announcement. $GoodNews_{it}$ ($BadNews_{it}$) refers to positive (negative) earnings standardized surprises, taking values of the earnings surprise if the surprise is positive (negative), and 0 otherwise. $D_{Ambiguity,t}$ is a dummy variables taking values of 1 when the expected ambiguity ($Ambiguity_t^E = \ln \bar{U}_t$ computed as described in section 2.3.2. in the text) is in its top 30th percentile, and 0 otherwise. The regression controls for the size factor (SMB), the orthogonal value factor (HML), the profitability factor (RMW), and the investment factor (CMA) from Fama and French (2016). X_{t-1} is a control variable that accounts for sentiment. Sentiment is proxied by the Baker and Wurgler (2006) raw (BW) and orthogonal sentiment index ($BW^\perp$), and by the raw (HJTZ) and orthogonal ($HJTZ^\perp$) sentiment measure in Huang, Jiang, Tu, and Zhou (2015). Year and firm fixed effects are included in the regressions. The sample period covered is from May 2000 until December 2014. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively.

	<i>BW</i>	<i>BW</i> [⊥]	<i>HJTZ</i>	<i>HJTZ</i> [⊥]
<i>GoodNews</i>	0.2636***	0.2595***	0.2563***	0.2562***
<i>BadNews</i>	0.1393***	0.1389***	0.1356***	0.1345***
<i>GoodNews</i> * <i>D_{Ambiguity}</i>	-0.0915*	-0.0887	-0.0868	-0.0849
<i>BadNews</i> * <i>D_{Ambiguity}</i>	-0.1183**	-0.1172**	-0.1075**	-0.1080**
<i>GoodNews</i> * <i>X</i>	-0.0215	-0.0011	-0.0048	-0.0001
<i>BadNews</i> * <i>X</i>	-0.0255	-0.0271	0.0059	0.0055
<i>SMB</i>	0.0075***	0.0075***	0.0075***	0.0075***
<i>HML</i>	-0.0015	-0.0014	-0.0014	-0.0014
<i>RMW</i>	-0.0036***	-0.0035***	-0.0037***	-0.0037***
<i>CMA</i>	-0.0041***	-0.0041***	-0.0041***	-0.0041***
<i>R</i> ²	35.67%	35.67%	35.66%	35.66%

**Table 2-19: Ambiguity Effect on the Stock Market Reaction to Earnings News
(Controlling for Investor Attention)**

The table reports the estimates of the following model: $CAR_{it} = b_{Ambiguity} * D_{Ambiguity,t} + b_X * X_{t-1} + b_{Good} GoodNews_{it} + b_{Bad} BadNews_{it} + c_{Amb}^{Good} GoodNews_{it} * D_{Ambiguity,t} + c_{Amb}^{Bad} BadNews_{it} * D_{Ambiguity,t} + d_X^{Good} GoodNews_{it} * X_{t-1} + d_X^{Bad} BadNews_{it} * X_{t-1} + Controls_t + \alpha_i + \delta_t + u_{it}$, where CAR_{it} is the cumulative abnormal return (CAR) computed over a window of 3 days around each earnings announcement. $GoodNews_{it}$ ($BadNews_{it}$) refers to positive (negative) earnings standardized surprises, taking values of the earnings surprise if the surprise is positive (negative), and 0 otherwise. $D_{Ambiguity,t}$ is a dummy variables taking values of 1 when the expected ambiguity ($Ambiguity_t^E = \ln \bar{U}_t$ computed as described in section 2.3.2. in the text) is in its top 30th percentile, and 0 otherwise. The regression controls for the size factor (SMB), the orthogonal value factor (HML), the profitability factor (RMW), and the investment factor (CMA) from Fama and French (2016). X_t is a control variable that accounts for investor attention. The attention measure is obtained from Google Trends and represents the monthly Google search volume for the term ‘S&P500’ over the period January 2004 to December 2017. The regression includes year and firm fixed effects, and is estimated over the period January 2004 to December 2017. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively.

	<i>Attention</i>
<i>GoodNews</i>	0.6110***
<i>BadNews</i>	0.0782
<i>GoodNews</i> * <i>D_{Ambiguity}</i>	-0.0698
<i>BadNews</i> * <i>D_{Ambiguity}</i>	-0.0827*
<i>GoodNews</i> * <i>X</i>	-0.0088***
<i>BadNews</i> * <i>X</i>	0.0011
<i>SMB</i>	0.0082***
<i>HML</i>	-0.0010
<i>RMW</i>	-0.0008
<i>CMA</i>	-0.0063***
<i>R</i> ²	32.38%

Table 2-20: Ambiguity Effect on the Stock Market Reaction to Earnings News
(Controlling for VIX and VIX Components)

Panel A reports the estimates of the following model: $CAR_{it} = b_{Ambiguity} * D_{Ambiguity,t} + b_{VIX} * VIX_{t-1} + b_{Good} GoodNews_{it} + b_{Bad} BadNews_{it} + c_{Amb}^{Good} GoodNews_{it} * D_{Ambiguity,t} + c_{Amb}^{Bad} BadNews_{it} * D_{Ambiguity,t} + d_{VIX}^{Good} GoodNews_{it} * VIX_{t-1} + d_{VIX}^{Bad} BadNews_{it} * VIX_{t-1} + Controls_t + \alpha_i + \delta_t + u_{it}$, where CAR_{it} is the cumulative abnormal return (CAR) computed over a window of 3 days around each earnings announcement. $GoodNews_{it}$ ($BadNews_{it}$) refers to positive (negative) earnings standardized surprises, taking values of the earnings surprise if the surprise is positive (negative), and 0 otherwise. $D_{Ambiguity,t}$ is a dummy variables taking values of 1 when the expected ambiguity ($Ambiguity_t^E = \ln \hat{U}_t$ computed as described in section 2.3.2. in the text) is in its top 30th percentile, and 0 otherwise. The regression controls for the size factor (SMB), the orthogonal value factor (HML), the profitability factor (RMW), and the investment factor (CMA) from Fama and French (2016). X_t is a control variable that accounts for the level of VIX index. Panel B reports the estimates of the following model: $CAR_{it} = a + b_{Ambiguity} * D_{Ambiguity,t} + b_{RA} * RA_{t-1} + b_{UC} * UC_{t-1} + b_{Good} GoodNews_{it} + b_{Bad} BadNews_{it} + c_{Amb}^{Good} GoodNews_{it} * D_{Ambiguity,t} + c_{Amb}^{Bad} BadNews_{it} * D_{Ambiguity,t} + d_{UC}^{Good} GoodNews_{it} * UC_{t-1} + d_{UC}^{Bad} BadNews_{it} * UC_{t-1} + d_{RA}^{Good} GoodNews_{it} * RA_{t-1} + d_{RA}^{Bad} BadNews_{it} * RA_{t-1} + Controls_t + \alpha_i + \delta_t + u_{it}$, where most of the variables were previously introduced. RA_t and UC_t represent the components of VIX, namely risk aversion and the stock market uncertainty, computed as described in section 2.1. in Bekaert, Hoerova, and Lo Duca (2013). All regressions include year and firm fixed effects and are estimated over the period May 2000 to December 2017. *, **, and *** denote significance at 10 percent, 5 percent, and 1 percent levels, respectively.

	Panel A	Panel B
<i>GoodNews</i>	0.2749***	0.2646***
<i>BadNews</i>	-0.0002	0.0685**
<i>GoodNews * D_{Ambiguity}</i>	-0.0413	-0.0449
<i>BadNews * D_{Ambiguity}</i>	-0.1111**	-0.1250***
<i>GoodNews * VIX_{t-1}</i>	-0.0011	-
<i>BadNews * VIX_{t-1}</i>	0.0058***	-
<i>GoodNews * UC_{t-1}</i>	-	0.0002
<i>BadNews * UC_{t-1}</i>	-	0.0016**
<i>GoodNews * RA_{t-1}</i>	-	-0.0010
<i>BadNews * RA_{t-1}</i>	-	0.0009
<i>SMB</i>	0.0075***	0.0075***
<i>HML</i>	-0.0019**	-0.0018**
<i>RMW</i>	-0.0035***	-0.0034***
<i>CMA</i>	-0.0044***	-0.0043***
<i>R²</i>	35.59%	35.59%

Figure 2-1. Ambiguity and other Measures of Risk/Uncertainty

This figure illustrates the evolution of our ambiguity measure computed as described in section 2.3.1. in the text, together with the evolution of the daily realized volatility of the E-mini S&P 500 futures, the VIX Index, and the Variance Risk Premium. The sample period covered is from 10/10/1997 to 12/31/2017.

Figure 2-2. Expected Ambiguity

This figure summarizes the expected ambiguity computed as described in section 2.3.2. in the text. The first observation for this variable is available on May 30, 2000.

Figure 2-3. Two-Way Sorted Average Stock Returns

This figure contains two-way sorted average stock returns by firm characteristics and by our expected ambiguity measure. At the end of each quarter we form 3 portfolios according to the NYSE breakpoints on firm *size* and *age*, total risk (σ), dividends (D), profitability (E), property, plant, and equipment over assets (PPE/A), research and development expense over assets (RD/A), book-to-market ratio (BE/ME), and discretionary accruals ($DAccruals$). As breakpoints for our portfolios, we use the 30th and the 70th percentiles of each firm characteristic. We form long-short equally-weighted portfolios by taking a long position in stocks with a high level of firm-specific characteristics, and short positions in those with low levels of firm-specific characteristics. We rebalance the portfolios every quarter. The grey bars denote the average return of long-short portfolios formed by firm-specific characteristics, for periods of low ambiguity, i.e. when the expected ambiguity is in the lowest three deciles across our sample period. Blue bars denote the average return of long-short portfolios during periods of high ambiguity, i.e. when the expected ambiguity is in the highest three deciles across our sample period. Black bars denote the average return for moderate ambiguity, ambiguity is between the lowest three deciles and the highest three deciles across our sample period. The sample period covered is from June 2000 until December 2017.

Figure 2-3- Contd.

Figure 2-4. Average Abnormal Returns during Periods of Low vs. High Expected Ambiguity

This figure reports the average abnormal stock returns around firm-specific earnings announcements, computed for firms with positive (Panel A) and negative (Panel B) earnings surprises. The earnings surprise is calculated as the firm's actual earnings per share (EPS) minus the latest analyst consensus EPS forecast before the earnings announcement date (both from I/B/E/S), scaled by the firm's stock price two days before the earnings announcement date (similar to Fang, Huang, and Karpoff (2016)). Abnormal returns are computed as described in section 2.6 in the text. Panels A and B compare the average cumulative returns for periods of low and high expected ambiguity. The expected ambiguity is high (low) when it is in the top (bottom) three deciles across our sample period. The sample period covered is May 2000 to December 2017.

Panel A. Positive Earnings Surprises

Panel B. Negative Earnings Surprises

Figure 2-5. PEAD during Periods of Low vs. High Expected Ambiguity

This figure reports the average cumulative abnormal return over the period of 60 days after positive (Panel A) and negative (Panel B) firm-specific earnings surprises. The earnings surprise is calculated as the firm's actual earnings per share (EPS) minus the latest analyst consensus EPS forecast before the earnings announcement date (both from I/B/E/S), scaled by the firm's stock price two days before the earnings announcement date (similar to Fang, Huang, and Karpoff (2016)). Abnormal returns are computed as described in section 2.6 in the text. Panels A and B compare the average cumulative returns for periods of low and high expected ambiguity. The expected ambiguity is high (low) when it is in the top (bottom) three deciles across our same period. The sample period covered is from May 2000 to December 2017.

LIST OF REFERENCES

- Acharya, V. V., & Pedersen, L. H. (2005). Asset pricing with liquidity risk. *Journal of Financial Economics*, 77(2), 375-410.
- Almeida, A., Goodhart, C., & Payne, R. (1998). The effects of macroeconomic news on high frequency exchange rate behavior. *Journal of Financial and Quantitative Analysis*, 33(3), 383-408.
- Amihud, Y., & Mendelson, H. (1986). Asset pricing and the bid-ask spread. *Journal of Financial Economics*, 17(2), 223-249.
- Andersen, T. G., Bollerslev, T., Diebold, F. X., & Vega, C. (2003). Micro effects of macro announcements: Real-time price discovery in foreign exchange. *American Economic Review*, 93(1), 38-62.
- Andersen, T. G., Bollerslev, T., Diebold, F. X., & Vega, C. (2007). Real-time price discovery in global stock, bond and foreign exchange markets. *Journal of International Economics*, 73(2), 251-277.
- Andersen, T. G., Bollerslev, T., & Diebold, F. X. (2007). Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility. *The Review of Economics and Statistics*, 89(4), 701-720.
- Andersen, T. G., Bollerslev, T., Diebold, F. X., & Ebens, H. (2001). The distribution of realized stock return volatility. *Journal of Financial Economics*, 61(1), 43-76.
- Anderson, E. W., Ghysels, E., & Juergens, J. L. (2009). The impact of risk and uncertainty on expected returns. *Journal of Financial Economics*, 94(2), 233-263.
- Andrei, D., & Hasler, M. (2014). Investor attention and stock market volatility. *The Review of Financial Studies*, 28(1), 33-72.
- Aruoba, S. B., Diebold, F. X., & Scotti, C. (2009). Real-time measurement of business conditions. *Journal of Business & Economic Statistics*, 27(4), 417-427.
- Avramov, D., Chordia, T., Jostova, G., & Philipov, A. (2009). Dispersion in analysts' earnings forecasts and credit rating. *Journal of Financial Economics*, 91(1), 83-101.
- Au, A. S., Doukas, J. A., & Onayev, Z. (2009). Daily short interest, idiosyncratic risk, and stock returns. *Journal of Financial Markets*, 12(2), 290-316.
- Bai, J., & Perron, P. (2003). Critical values for multiple structural change tests. *The Econometrics Journal*, 6(1), 72-78.

- Beber, A., & Brandt, M. W. (2009). When it cannot get better or worse: The asymmetric impact of good and bad news on bond returns in expansions and recessions. *Review of Finance*, 14(1), 119-155.
- Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, 131(4), 1593-1636.
- Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance*, 61(4), 1645-1680.
- Balduzzi, P., Elton, E. J., & Green, T. C. (2001). Economic news and bond prices: Evidence from the US Treasury market. *Journal of Financial and Quantitative Analysis*, 36(4), 523-543.
- Ball, R., Kothari, S. P., & Shanken, J. (1995). Problems in measuring portfolio performance An application to contrarian investment strategies. *Journal of Financial Economics*, 38(1), 79-107.
- Ball, R., & Brown, P. (1968). An empirical evaluation of accounting income numbers. *Journal of Accounting Research*, 159-178.
- Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, 9(1), 3-18.
- Barsky, R. B., & Kilian, L. (2002). Do We Really Know that Oil Caused the Great Stagflation? A Monetary Alternative. In *NBER Macroeconomics Annual 2001*, 16, 137-198. MIT Press.
- Barsky, R. B., & Kilian, L. (2004). Oil and the macroeconomy since the 1970s. *Journal of Economic Perspectives*, 18(4), 115-134.
- Basistha, A., & Kurov, A. (2015). The impact of monetary policy surprises on energy prices. *Journal of Futures Markets*, 35(1), 87-103.
- Basu, S. The Investment Performance of Common Stocks in Relation to Their Price-Earnings Ratios: A Test of the Efficient Market Hypothesis. *The Journal of Finance*, 32(3), 663-682.
- Baumohl, B. (2013). The secrets of economic indicators: hidden clues to future economic trends and investment opportunities. 3rd edition, *Pearson Education, Inc.*
- Bawa, V. S., Brown, S. J., & Klein, R. W. (1979). Estimation risk and optimal portfolio choice. No. 3 in *Studies in Bayesian Econometrics*, North Holland, Amsterdam.
- Beechey, M. J., & Wright, J. H. (2009). The high-frequency impact of news on long-term yields and forward rates: Is it real?. *Journal of Monetary Economics*, 56(4), 535-544.
- Bekaert, G., Hoerova, M., & Duca, M. L. (2013). Risk, uncertainty and monetary policy. *Journal of Monetary Economics*, 60(7), 771-788.
- Berger, D., & Turtle, H. J. (2012). Cross-sectional performance and investor sentiment in a multiple risk factor model. *Journal of Banking & Finance*, 36(4), 1107-1121.

- Bernanke, B. S., & Kuttner, K. N. (2005). What explains the stock market's reaction to Federal Reserve policy?. *The Journal of Finance*, 60(3), 1221-1257.
- Blanchard, O. J. (1981). Output, the stock market, and interest rates. *The American Economic Review*, 71(1), 132-143.
- Blinder, A. S. (2014). Federal Reserve policy before, during, and after the fall. In: Baily, M. N., Taylor, J. B. (eds.), *Across the great divide: New perspectives on the financial crisis*, Stanford: Hoover Institution Press, 89-102.
- Blinder, A. S., Ehrmann, M., Fratzscher, M., De Haan, J., & Jansen, D. J. (2008). Central bank communication and monetary policy: A survey of theory and evidence. *Journal of Economic Literature*, 46(4), 910-45.
- Bossaerts, P., Ghirardato, P., Guarnaschelli, S., & Zame, W. R. (2010). Ambiguity in asset markets: Theory and experiment. *The Review of Financial Studies*, 23(4), 1325-1359.
- Boudoukh, J., Richardson, M., Shen, Y. J., & Whitelaw, R. F. (2007). Do asset prices reflect fundamentals? Freshly squeezed evidence from the OJ market. *Journal of Financial Economics*, 83(2), 397-412.
- Boyd, J. H., Hu, J., & Jagannathan, R. (2005). The stock market's reaction to unemployment news: Why bad news is usually good for stocks. *The Journal of Finance*, 60(2), 649-672.
- Brennan, M. J. (1970). Taxes, market valuation and corporate financial policy. *National Tax Journal*, 23(4), 417-427.
- Brenner, M., & Izhakian, Y. Y. (2017). Asset pricing and ambiguity: Empirical evidence. *Journal of Financial Economics*, Forthcoming.
- Brogaard, J., & Detzel, A. (2015). The asset-pricing implications of government economic policy uncertainty. *Management Science*, 61(1), 3-18.
- Caballero, R. J., & Krishnamurthy, A. (2008). Collective risk management in a flight to quality episode. *The Journal of Finance*, 63(5), 2195-2230.
- Campbell, J. Y. (1987). Stock returns and the term structure. *Journal of Financial Economics*, 18(2), 373-399.
- Campbell, J. Y., & Cochrane, J. H. (1999). By force of habit: A consumption-based explanation of aggregate stock market behavior. *Journal of Political Economy*, 107(2), 205-251.
- Campbell, J. Y., & Hentschel, L. (1992). No news is good news: An asymmetric model of changing volatility in stock returns. *Journal of Financial Economics*, 31(3), 281-318.
- Cao, H. H., Wang, T., & Zhang, H. H. (2005). Model uncertainty, limited market participation, and asset prices. *The Review of Financial Studies*, 18(4), 1219-1251.

- Chang, B. Y., & Feunou, B. (2014). Measuring uncertainty in monetary policy using implied volatility and realized volatility. *Bank of Canada Review*, Spring 2014, 32-41.
- Chatrath, A., Miao, H., & Ramchander, S. (2012). Does the price of crude oil respond to macroeconomic news?. *Journal of Futures Markets*, 32(6), 536-559.
- Chen, Z., & Epstein, L. (2002). Ambiguity, risk, and asset returns in continuous time. *Econometrica*, 70(4), 1403-1443.
- Chordia, T., & Shivakumar, L. (2002). Momentum, business cycle, and time-varying expected returns. *The Journal of Finance*, 57(2), 985-1019.
- Coles, J. L., & Loewenstein, U. (1988). Equilibrium pricing and portfolio composition in the presence of uncertain parameters. *Journal of Financial Economics*, 22(2), 279-303.
- Cook, T., & Korn, S. (1991). The reaction of interest rates to the employment report: The role of policy anticipations. *Economic Review*, Federal Reserve Bank of Richmond, September-October, 3-12.
- Corsi, F. (2009). A simple approximate long-memory model of realized volatility. *Journal of Financial Econometrics*, 7(2), 174-196.
- Cooper, M. J., Gutierrez, R. C., & Hameed, A. (2004). Market states and momentum. *The Journal of Finance*, 59(3), 1345-1365.
- Cutler, D. M., Poterba, J. M., & Summers, L. H. (1989). What moves stock prices?. *Journal of Portfolio Management*, 15, 4-12.
- Huang, D., Jiang, F., Tu, J., & Zhou, G. (2015). Investor sentiment aligned: A powerful predictor of stock returns. *The Review of Financial Studies*, 28(3), 791-837.
- Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. *The Journal of Finance*, 66(5), 1461-1499.
- David, A., & Veronesi, P. (2013). What Ties Return Volatilities to Fundamentals and Price Valuations?. *Journal of Political Economy*, 121, 682-746.
- Dechow, P. M., Sloan, R. G., & Sweeney, A. P. (1995). Detecting earnings management. *The Accounting Review*, 193-225.
- DellaVigna, S., & Pollet, J. M. (2009). Investor inattention and Friday earnings announcements. *The Journal of Finance*, 64(2), 709-749.
- Diether, K. B., Malloy, C. J., & Scherbina, A. (2002). Differences of opinion and the cross section of stock returns. *The Journal of Finance*, 57(5), 2113-2141.
- Doukas, J. A., Kim, C. F., & Pantzalis, C. (2002). A Test of the Errors-in-Expectations Explanation of the Value/Glamour Stock Returns Performance: Evidence from Analysts' Forecasts. *The Journal of Finance*, 57(5), 2143-2165.

- Drechsler, I. (2013). Uncertainty, time-varying fear, and asset prices. *The Journal of Finance*, 68(5), 1843-1889.
- Drechsler, I., Savov, A., & Schnabl, P. (2018). A model of monetary policy and risk premia. *The Journal of Finance*, 73(1), 317-373.
- Duffie, D., Gârleanu, N., & Pedersen, L. H. (2002). Securities lending, shorting, and pricing. *Journal of Financial Economics*, 66(2-3), 307-339.
- Easley, D., Hvidkjaer, S., & O'Hara, M. (2002). Is information risk a determinant of asset returns?. *The Journal of Finance*, 57(5), 2185-2221.
- Ederington, L. H., & Lee, J. H. (1995). The short-run dynamics of the price adjustment to new information. *Journal of Financial and Quantitative Analysis*, 30(1), 117-134.
- Ellsberg, D. (1961). Risk, ambiguity, and the Savage axioms. *The Quarterly Journal of Economics*, 75(4), 643-669.
- Epstein, L. G., & Schneider, M. (2008). Ambiguity, information quality, and asset pricing. *The Journal of Finance*, 63(1), 197-228.
- Ehrmann, M., & Fratzscher, M. (2005). Exchange rates and fundamentals: new evidence from real-time data. *Journal of International Money and Finance*, 24(2), 317-341.
- Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance*, 47(2), 427-465.
- Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1), 3-56.
- Fama, E. F., & French, K. R. (2016). Dissecting anomalies with a five-factor model. *The Review of Financial Studies*, 29(1), 69-103.
- Fang, V. W., Huang, A. H., & Karpoff, J. M. (2016). Short selling and earnings management: A controlled experiment. *The Journal of Finance*, 71(3), 1251-1294.
- Faust, J., Rogers, J. H., Wang, S. Y. B., & Wright, J. H. (2007). The high-frequency response of exchange rates and interest rates to macroeconomic announcements. *Journal of Monetary Economics*, 54(4), 1051-1068.
- Freeman, R. N., & Tse, S. Y. (1992). A nonlinear model of security price responses to unexpected earnings. *Journal of Accounting Research*, 30(2), 185-209.
- French, K. R., Schwert, G. W., & Stambaugh, R. F. (1987). Expected stock returns and volatility. *Journal of Financial Economics*, 19(1), 3-29.
- Ghirardato, P., Klibanoff, P., & Marinacci, M. (1998). Additivity with multiple priors. *Journal of Mathematical Economics*, 30(4), 405-420.

- Gilboa, I., & Schmeidler, D. (1989). Maxmin expected utility with non-unique prior. *Journal of Mathematical Economics*, 18, 141-153.
- Greenspan, A. (2003). Opening Remarks at ‘Monetary Policy under Uncertainty,’ symposium sponsored by the Federal Reserve Bank of Kansas City. *Jackson Hole, Wyoming*, 284.
- Guidolin, M., & Rinaldi, F. (2013). Ambiguity in asset pricing and portfolio choice: A review of the literature. *Theory and Decision*, 74(2), 183-217.
- Guo, H., & Whitelaw, R. F. (2006). Uncovering the risk–return relation in the stock market. *The Journal of Finance*, 61(3), 1433-1463.
- Gürkaynak, R. S., Sack, B. P., & Swanson, E. T. (2007). Market-based measures of monetary policy expectations. *Journal of Business & Economic Statistics*, 25(2), 201-212.
- Hansen, L., & Sargent, T. J. (2001). Robust control and model uncertainty. *American Economic Review*, 91(2), 60-66.
- Hansen, L. P., Sargent, T. J., & Tallarini Jr, T. D. (1999). Robust permanent income and pricing. *Review of Economic Studies*, 66(4), 873-907.
- Hanson, S. G., & Stein, J. C. (2015). Monetary policy and long-term real rates. *Journal of Financial Economics*, 115(3), 429-448.
- Harvey, C. R. (2001). The specification of conditional expectations. *Journal of Empirical Finance*, 8(5), 573-637.
- Hautsch, N., & Hess, D. (2001). What’s Surprising about Surprises? The Simultaneous Price and Volatility Impact of Information Arrival. *Manuscript, Center for Finance and Econometrics, University of Konstanz, Germany*.
- Herron, R., & Izhakian, Y. Y. (2018). Ambiguity, Risk, and Dividend Payout Policy. *Working Paper*.
- Hirshleifer, D., Lim, S. S., & Teoh, S. H. (2009). Driven to distraction: Extraneous events and underreaction to earnings news. *The Journal of Finance*, 64(5), 2289-2325.
- Hong, H., Lim, T., & Stein, J. C. (2000). Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *The Journal of Finance*, 55(1), 265-295.
- Hou, K., & Moskowitz, T. J. (2005). Market frictions, price delay, and the cross-section of expected returns. *The Review of Financial Studies*, 18(3), 981-1020.
- Hsu, M., Bhatt, M., Adolphs, R., Tranel, D., & Camerer, C. F. (2005). Neural systems responding to degrees of uncertainty in human decision-making. *Science*, 310(5754), 1680-1683.
- Husted, L. F., Rogers, J. H., & Sun, B., (2016). Measuring monetary policy uncertainty: the Federal Reserve, January 1985-January 2016. *IFDP Notes, Board of Governors of the Federal Reserve System*.

- Hutton, A. P., Marcus, A. J., & Tehranian, H. (2009). Opaque financial reports, R2, and crash risk. *Journal of Financial Economics*, 94(1), 67-86.
- Inekwe, N. J. (2016). Financial uncertainty, risk aversion and monetary policy. *Empirical Economics*, 51(3), 939-961.
- Izhakian, Y. (2012). Capital asset pricing under ambiguity. *Working Paper*.
- Izhakian, Y. (2017). Expected utility with uncertain probabilities theory. *Journal of Mathematical Economics*, 69, 91-103.
- Izhakian, Y., & Yermack, D. (2017). Risk, ambiguity, and the exercise of employee stock options. *Journal of Financial Economics*, 124(1), 65-85.
- Izhakian, Y., Yermack, D., & Zender, J. F. (2016). Ambiguity and the Tradeoff Theory of Capital Structure (No. w22870). *National Bureau of Economic Research*.
- Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, 48(1), 65-91.
- Jones, J. J. (1991). Earnings management during import relief investigations. *Journal of Accounting Research*, 29(2), 193-228.
- Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review*, 99(3), 1053-69.
- Kilian, L., & Vega, C. (2011). Do energy prices respond to US macroeconomic news? A test of the hypothesis of predetermined energy prices. *Review of Economics and Statistics*, 93(2), 660-671.
- Klibanoff, P., Marinacci, M., & Mukerji, S. (2005). A smooth model of decision making under ambiguity. *Econometrica*, 73(6), 1849-1892.
- Knight, F. H., 1921. Risk, uncertainty and profit. Boston, MA: Houghton Mifflin Company.
- Kurov, A., & Gu, C. (2016). Monetary Policy and Stock Prices: Does the ‘Fed Put’ Work When It Is Most Needed?. *Journal of Futures Markets*, 36(12), 1210-1230.
- Kurov, A., Sancetta, A., Strasser, G., & Wolfe, M. (2016). Price drift before US macroeconomic news: private information about public announcements?. *ECB Working Paper No. 1901*.
- Lapp, J. S., & Pearce, D. K. (2012). The impact of economic news on expected changes in monetary policy. *Journal of Macroeconomics*, 34(2), 362-379.
- Merton, R. C. (1973). An intertemporal capital asset pricing model. *Econometrica: Journal of the Econometric Society*, 867-887.
- Mian, G. M., & Sankaraguruswamy, S. (2012). Investor sentiment and stock market response to earnings news. *The Accounting Review*, 87(4), 1357-1384.

- Mitchell, M. L., & Mulherin, J. H. (1994). The impact of public information on the stock market. *The Journal of Finance*, 49(3), 923-950.
- Mitchell, M., Pulvino, T., & Stafford, E. (2002). Limited arbitrage in equity markets. *The Journal of Finance*, 57(2), 551-584.
- Nave, J. M., & Ruiz, J. (2015). Risk aversion and monetary policy in a global context. *Journal of Financial Stability*, 20, 14-35.
- Neely, C. J. (2015). Unconventional monetary policy had large international effects. *Journal of Banking & Finance*, 52, 101-111.
- Orphanides, A. (1992). When good news is bad news: Macroeconomic news and the stock market. *Board of Governors of the Federal Reserve System. Working paper*.
- Pástor, L., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy*, 111(3), 642-685.
- Pástor, L., & Veronesi, P. (2013). Political uncertainty and risk premia. *Journal of Financial Economics*, 110(3), 520-545.
- Pericoli, M., & Veronese, G. (2015). Forecaster heterogeneity, surprises and financial markets. *Bank of Italy Temi di Discussione. Working Paper, No 1020*.
- Richardson, V. J. (2000). Information asymmetry and earnings management: Some evidence. *Review of Quantitative Finance and Accounting*, 15(4), 325-347.
- Roll, R. (1988). R^2 . *Journal of Finance*, 43, 541-566.
- Rosa, C. (2014). The high-frequency response of energy prices to US monetary policy: Understanding the empirical evidence. *Energy Economics*, 45, 295-303.
- Rothschild, M., & Stiglitz, J. E. (1970). Increasing risk: I. A definition. *Journal of Economic Theory*, 2(3), 225-243.
- Savage, L. J. (1954). *The Foundations of Statistics*, Wiley, New York, USA.
- Schipper, K. (1989). Earnings management. *Accounting Horizons*, 3(4), 91-102.
- Scholes, M., & Williams, J. (1977). Estimating betas from nonsynchronous data. *Journal of Financial Economics*, 5(3), 309-327.
- Scholtus, M., van Dijk, D., & Frijns, B. (2014). Speed, algorithmic trading, and market quality around macroeconomic news announcements. *Journal of Banking & Finance*, 38, 89-105.
- Schmeidler, D. (1989). Subjective Probability and Expected Utility without Additivity. *Econometrica*, 57(3), 571-587.

Siklos, P. L. (2017). *Central Banks into the Breach: From Triumph to Crisis and the Road Ahead*. Oxford University Press.

Sloan, R. G. (1996). Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings?. *The Accounting Review*, 71(3), 289-315.

So, R. H., Driouchi, T., & Trigeorgis, L. (2016). Option Market Ambiguity, Excess Returns and the Equity Premium. *Working Paper*.

Subrahmanyam, A. (2010). The Cross-Section of Expected Stock Returns: What Have We Learnt from the Past Twenty-Five Years of Research?. *European Financial Management*, 16(1), 27-42.

Swanson, E. T., & Williams, J. C. (2014). Measuring the effect of the zero lower bound on medium-and longer-term interest rates. *American Economic Review*, 104(10), 3154-85.

Ulrich, M. (2013). Inflation ambiguity and the term structure of US Government bonds. *Journal of Monetary Economics*, 60(2), 295-309.

Veronesi, P. (1999). Stock market overreactions to bad news in good times: a rational expectations equilibrium model. *The Review of Financial Studies*, 12(5), 975-1007.

Wang, J., & Yang, M. (2009). Asymmetric volatility in the foreign exchange markets. *Journal of International Financial Markets, Institutions and Money*, 19(4), 597-615.

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica: Journal of the Econometric Society*, 817-838.

Williams, C. D. (2015). Asymmetric responses to earnings news: A case for ambiguity. *The Accounting Review*, 90(2), 785-817.

Wu, M. T. (2014). Unconventional monetary policy and long-term interest rates. *International Monetary Fund. Working Paper No. 14-189*.

Wurgler, J., & Zhuravskaya, E. (2002). Does arbitrage flatten demand curves for stocks?. *The Journal of Business*, 75(4), 583-608.

Yu, F. F. (2008). Analyst coverage and earnings management. *Journal of Financial Economics*, 88(2), 245-271.

Zhou, J. (2015). The Good, the Bad, and the Ambiguous: The Aggregate Stock Market Dynamics around Macroeconomic News. Harvard University, *Working Paper*.