Essays in Information Economics

by

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Abstract

I present three essays on Information Economics. The first essay consists of analyzing high-frequency price dynamics around earnings announcements for the largest 1,500 U.S. stocks between 2011 and 2015. Price discovery following earnings surprises mostly occurs in the after-hours market, following the earnings announcement, and is generally complete by 10 a.m. Eighty percent of the price response to earnings surprises in the after-hours market occurs upon arrival of the first trades. Price reactions are largely explained by earnings surprises and not by order flow, consistent with the theoretical view that news can incorporate prices instantly. In the second essay, co-authored with Oliver Boguth and Vincent Grégoire, we show that in an effort to increase transparency, the Chair of the Federal Reserve now holds a press conference following some, but not all, Federal Open Market Committee announcements. Press conferences are scheduled independently of economic conditions and communicate little information. Evidence from financial markets demonstrates that investors lower their expectations of important decisions on days without press conferences, and we show that they shift attention away from these announcements. Both channels prevent effective monetary policy, as the committee is averse to surprising markets and aims to coordinate market expectations. Correspondingly, we show that announcements without press conferences convey less price-relevant information. In the third essay, co-authored with Adlai J. Fisher and Jinfei Sheng, we construct indices of media attention to macroeconomic risks including employment, growth, inflation and monetary policy. Attention rises around macroeconomic announcements and following changes in fundamentals over quarterly, annual, and business cycle horizons. The effect is asymmetric, with bad news raising attention more than good news. Increases in aggregate trade volume and volatility coincide with rising attention, controlling for announcements. Finally, changes in attention prior to the unemployment announcement predict both the announcement surprise and stock returns on the announcement day. We conclude that media attention to macroeconomic fundamentals provides useful information beyond the dates and contents of macroeconomic announcements.

Lay Summary

Public information releases from corporations and financial institutions have a significant impact on financial markets and stock prices. A long-standing issue in financial economics is to understand how fast the information gets incorporated into stock prices. This issue is often referred to the notion of price discovery. It is also important to understand how the information gets released to the public (e.g., newspaper articles, press conferences) influence price discovery. In addition, how recent technological development in financial markets influence price discovery and how it impacts the social welfare of investors is an on-going debate. This thesis sheds light on these issues and provides new empirical findings on price discovery following two public information releases, that is, earnings and macroeconomic announcements.

Preface

Chapter 2 is based solely on my own work. Chapter 3 is a co-authored project with Assistant Professor Oliver Boguth of Arizona State University and Assistant Professor Vincent Grégoire of the University of Melbourne. I initiated this project from previous research of mine. We contributed equally to the writing and to the empirical analysis. Chapter 4 is a co-authored project with my adviser Professor Adlai J. Fisher and Ph.D. colleague Jinfei Sheng. We contributed equally to the writing and to the empirical analysis.

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Among the many personal acknowledgments that I owe, the first must be my wife Natsumi Fuwa who had to go through a lot during the Ph.D. She provided me with much support and happiness. I look forward to the new stage of our lives together following the Ph.D. I must not forget to thank my parents who, despite not understanding what I do in life, always encourage me to do what I love and most importantly to work hard and not take anything for granted.

Finally, this dissertation is dedicated to my sons Alex and Sasha who both appeared in my life during the Ph.D. I owe a lot to my wife to be such a dedicated mother.

Chapter 1

Introduction

This thesis is a collection of three essays at the intersection of Information Economics. Although the topics are diverse, they share the common objective of studying the interplay between asset prices and public news events at the corporate and institutional level. In the first essay, I examine the speed at which unexpected news content of earnings announcement incorporate stock prices, i.e., price discovery, and the role of trade volume to price discovery during the after-hours market. To investigate this question, I use a unique dataset from the NASDAQ stock exchange that contain prices and signed trade volume data for U.S. stocks between 2011 and 2015. In the second essay, I investigate the impact of the Federal Open Market Committee (FOMC) announcements on financial markets and on investor attention to monetary policy when the announcement is accompanied with and without a press conference by the chairperson of the Federal Reserve. To study this question, I look at the response of asset prices and changes to different investor attention proxies before and after FOMC announcements. I then compare the response of asset prices and investor attention for FOMC announcement with and without press conferences. The third essay documents a novel channel to study the impact of the macroeconomy on asset prices through investor attention to macroeconomic risks. To measure investor attention, I use daily newspaper article counts mentioning particular macroeconomic risks from the Wall Street Journal and New York Times and study the relationship between investor attention and asset prices.

Because each essay investigates a different topic in the field of Information Economics, chapters were designed to be self-contained. I thus leave a more exhaustive discussion of the research question and contribution to the introduction specific to each chapter.

Chapter 2

How is Earnings News Transmitted to Stock Prices?

2.1 Introduction

A fundamental objective in financial economics is to understand how information is transmitted to asset prices. Fama, Fisher, Jensen, and Roll (1969) present early evidence of how stock prices adjust to firm-level news at a monthly frequency. More recent research shows how asset prices respond over short horizons to systematic news such as macroeconomic announcements (e.g., Andersen, Bollerslev, Diebold, and Vega, 2003a; Hu, Pan, and Wang, 2015a).[1] High-frequency price formation of individual stock prices around firm-level news announcements is less understood.

In this paper, I examine price discovery following earnings announcements for the largest 1,500 U.S. stocks between 2011 and 2015. This topic is difficult to study at high frequency because a large proportion of earnings announcements, which are the most important type of firm-level news, occurs outside of regular trading hours (9:30 a.m. to 4 p.m. EST). By incorporating the after-hours market into my analysis of price formation, I am able to address several important questions.[2]

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[1] Other related work on price formation following macroeconomic news includes Jones, Lamont, and Lumsdaine (1998a); Fleming and Remolona (1999a); Balduzzi, Elton, and Green (2001a); Green (2004); Andersen, Bollerslev, Diebold, and Vega (2007a); Evans and Lyons (2008); Brogaard, Hendershott, and Riordan (2014) and Chordia, Green, and Kottimukkalur (2016).

[2] Patell and Wolfson (1984) and Woodruff and Senchack (1988) were the first to document intraday prices responses to earnings surprises. More recently, Jiang, Likitapiwat, and McInish (2012) show for a sample of S&P 500 stocks that an important share of price variation occurs in the after-hours market. Santosh (2014) study the impulse response path of stock returns in business- and calendar-time units following earnings surprises in the after-hours market and over the course of five trading days. Li (2016) implements a trading strategy to take advantage of price drifts in the after-hours market following earnings announcements. I study price discovery at high frequency using a similar methodology as Andersen, Bollerslev, Diebold, and Vega (2003a) and focus on when the impact of earnings surprises on the conditional mean changes in stock returns dissipates.

I first ask how quickly earnings surprises are incorporated into stock prices. Formally, I test for horizons at which earnings surprises have *explanatory power*. I show that, for my sample, price changes are affected by earnings surprises until 10 a.m. on the first session of regular trading following the earnings announcement. After 10 a.m., I find no evidence of post-earnings announcement drifts at any frequency, including the daily horizon. This result contrasts with literature that documents slow price formation following earnings surprises.[3] It is, however, well-known that slow price formation following earnings announcements is more pronounced in small and illiquid stocks (see e.g., Hou and Moskowitz, 2005; Chordia, Goyal, Sadka, Sadka, and Shivakumar, 2009).[4]

To examine how quickly earnings surprises are incorporated into stock prices at high frequency, I utilize real-time quotations, transaction prices, and signed order flow from a limit order book exchange. I begin this analysis at the 9:30 a.m. opening of markets by comparing two sets of stocks: stocks with and without after-hours trading following earnings announcements. Indeed, for 38 percent of my sample of earnings announcements, I do not observe trades following earnings announcements in the after-hours market. I document that stocks that are small and have low analyst and media coverage, low institutional ownership, and wider bid-ask spreads have a higher probability of no after-hours trading following earnings announcements. These stocks are predicted to have slower price discovery because of poor information quality (see Brennan, Jegadeesh, and Swaminathan, 1993; Zhang, 2006). Controlling for the probability of having no after-hours trading, I find that the after-hours close-to-open returns for stocks with after-hours trading respond to earnings surprises by 40 percent more than stocks with no after-hours trading. Using a similar methodology as Andersen, Bollerslev, Diebold, and Vega (2003a, 2007a), I show that stocks with no after-hours trading have significant price discovery that lasts 30 minutes following the opening of markets. On the other hand, stocks with after-hours trading have no significant price discovery at the opening of markets,

[3]Early papers documenting slow price formation to earnings news are Ball and Brown (1968) and Bernard and Thomas (1989). More recent evidence includes Doyle, Lundholm, and Soliman (2006), Hirshleifer, Lim, and Teoh (2009), and DellaVigna and Pollet (2009).

[4]Boguth, Carlson, Fisher, and Simutin (2016) provide evidence of fast price formation of systematic news in large stocks. Bai, Philippon, and Savov (2016) show that markets have become more efficient over time and this may explain why I observe no slow price formation following earnings surprises at the daily frequency. In Section A.2 of the Appendix, I show how the post-earnings announcements drift has changed since 1984 for same sample selection criteria.

which implies that all price discovery occurs in the after-hours market.[5]

I then characterize the high-frequency dynamics of price discovery in the after-hours market. I find that more than 80 percent of the total response of stock returns to earnings surprises in the after-hours market occurs upon the arrival of the first trades. I show that the initial price adjustments to earnings surprises occur as "jumps" followed by a price drift in the same direction as the earnings surprise but the impact of earnings surprise dissipates in the after-hours market. Because earnings announcements lead to important price change in the after-hours market, this explains in part the recent findings of Bollerslev, Li, and Todorov (2016) regarding the higher risk premium attached to estimated market betas using overnight close-to-open returns.[6]

It is important to note that my results complements those of Santosh (2014).[7] Santosh uses earnings surprises as instruments in structural equations to estimate cumulative impulse response functions over five trading days following earnings announcements to test the invariance hypothesis of Kyle and Obizhaeva (2016). In its investigation, the author finds a cumulative impulse response that reflects 71 percent of the earnings news at the opening of markets and close to 90 percent for stocks with high after-hours trading. It is comforting that I find similar results using another methodology commonly used in the literature of price discovery following macroeconomic news (e.g., Andersen, Bollerslev, Diebold, and Vega, 2003a, 2007a). This methodology allows me to explicitly show when earnings surprises have no explanatory power to explain stock returns. Moreover, the methodology also allows me to investigate whether prices adjust more to earnings surprises or to order flow at the time of the announcement, which consist of the second objective of this paper.

Santosh (2014) argues that price discovery following earnings announcements occurs through the arrival of order flow consistent with classical microstructure models that suggest that transactions do affect prices because they convey information that is not common knowledge (e.g., Glosten and Milgrom, 1985; Kyle, 1985). Orders may be necessary to move prices fol-

[5]These results do not imply that price discovery occurs in the after-hours market because of actual trading. Liquidity providers can provide liquidity following earnings announcements at prices that reflects instantly the news and trading can occur even though prices already reflect the new information (see Beaver, 1968).

[6]Earnings announcements can increase stocks' market betas because earnings announcements generate systematic news (Patton and Verardo, 2012).

[7]Santosh (2014) uses TAQ data and with a larger sample of stocks that spans the time period of 2006 to 2011.

lowing public announcements when liquidity providers (who are responsible for adjusting prices) have more limited information processing abilities than some other traders (Kim and Verrecchia, 1994). On the other hand, theory of public information associates the arrival of public news with instantaneous price adjustment (e.g., Milgrom and Stokey, 1982; French and Roll, 1986). In my data, I have *signed* order flow that allows me to investigate whether prices adjust more to the actual news as predicted in French and Roll (1986) or to incoming order flow as in Kyle (1985) and Glosten and Milgrom (1985) and argued by Santosh (2014).

I follow Evans and Lyons (2002) and document the explanatory power (R^2) of earnings surprises and the net order imbalance (i.e., the difference between the total number of market-initiated buys and sells) to explain stock returns in the after-hours market following earnings announcements.[8] I find that the initial response of stock prices to earnings surprises occurs directly. The R^2 associated with the arrival of news explains ten percent of stock returns whereas net order imbalance explains only two percent. The explanatory power of earnings surprises on subsequent price changes is, however, short-lived and small, while the explanatory power of order imbalance remains sizable for the entire duration of the after-hours market. Past research in foreign exchange markets largely attributes price adjustments around macroeconomic news to order flow (see Evans and Lyons, 2008), but in the case of earnings announcements I find that the news itself largely explains the initial price adjustment. This implies that liquidity providers are capable at processing public information and incorporating news into prices without relying on order flow.[9]

The third objective of this paper is to examine how the magnitude of earnings surprises impacts high-frequency abnormal stock price volatilities, abnormal bid-ask spreads, and abnormal trade volumes. Several empirical papers linked changes in price volatilities to price discovery following the arrival of news (see e.g., Ederington and Lee, 1993; Jones, Lamont, and Lumsdaine, 1998a; Evans and Lyons, 2008). It is also important to extend the analysis to trade volume and bid-ask spreads. Microstructure theory suggests that changes in trade volume and bid-ask spreads are related to

[8] Evans and Lyons (2002) examine the impact of order imbalance and nominal interest rate (public information) on daily foreign exchange prices. I refer the reader to Evans and Lyons (2002) and the working paper version Evans and Lyons (1999) for a simple structural model motivating the empirical approach used in this paper.

[9] Chordia, Green, and Kottimukkalur (2016), Brogaard, Hendershott, and Riordan (2015), and Baldauf and Mollner (2016) also provide evidence that liquidity providers play a large role in price discovery.

price volatility and also reflect the arrival of information. I focus the analysis during regular market hours prior to and after earnings announcements.

I find significantly wider abnormal bid-ask spreads, lower abnormal stock price volatility, and lower abnormal trade volume at high-frequency on trading days prior to large earnings surprises. These results suggest that markets anticipate the magnitude of earnings surprises and further suggests that the large earnings forecast errors in some stocks are explained, in part, by poor information quality (e.g., Kasznik and Lev, 1995; Lang and Lundholm, 1996) surrounding these stocks and, in turn, implies higher information asymmetry.[10] Theory predicts that when information asymmetry is higher, trading volume may decrease before announcements because discretionary liquidity traders postpone trading after the announcement is made (e.g., Admati and Pfleiderer, 1988).

I then examine the response of price volatility, bid-ask spreads, and trade volume to earnings surprises following earnings announcements.[11] I find that large earnings surprises lead to an increase in abnormal volatility, abnormal quoted spreads, and abnormal trade volumes at the opening of markets following earnings announcements. As for the duration, the impact of earnings surprises on volatilities, spreads, and trade volumes gradually decays over the course of regular trading hours following the opening of markets, even though earnings surprises have no more impact on the adjustments on the conditional mean of prices. The dynamics portrayed by the abnormal volatility and trade volume are consistent with the theoretical findings of Banerjee and Kremer (2010). The authors argues that trade volume and volatility increases in the level of disagreement among investors on the interpretation of a public signal (i.e., agree to disagree) followed by a gradual decay with the possibility of no adjustment in the conditional mean of prices.

The last objective of this paper is to shed light on liquidity provision around earnings announcements. Liquidity provision is an important role of stock markets and matters to price discovery (O'Hara, 2003). I find that approximately 40 percent of incoming trade volume is executed against hidden

[10] These results are similar to the "calm-before-storm" effect documented in Jones, Lamont, and Lumsdaine (1998a) and Akbas (2016).

[11] An important literature documents the dynamics in trade volumes, volatilities, and spreads following earnings announcements at the daily (e.g., Beaver, 1968; Morse, 1981; Atiase and Bamber, 1994; Kandel and Pearson, 1995; Bamber, Barron, and Stober, 1997) and intraday horizon (Lee, Mucklow, and Ready, 1993). But, to my knowledge, this is the first paper that documents the intraday dynamics conditioning on the magnitude of the earnings surprises.

orders in the after-hours market following earnings announcements versus 12 percent in regular market hours.[12] This finding is significant because the acceptance of hidden orders in financial markets is not unanimous among SEC regulators and some suggest that hidden orders may deter the effectiveness of price discovery (see Shapiro, 2010). A liquidity provider may prefer hidden orders because it helps uninformed traders to mitigate the option value of limit orders that are expected to remain standing in the limit order book for a long period and, in turn, mitigate the risk of adverse selection (Harris, 1996).[13] On the other hand, Moinas (2011), Boulatov and George (2013), and Bloomfield, O'Hara, and Saar (2015) argue that informed traders may prefer hidden orders.

To understand whether hidden orders are beneficial to liquidity providers, I investigate the profitability of hidden orders versus displayed limit orders following earnings announcements in the after-hours market. If liquidity providers earn higher profits with hidden orders than with displayed orders this would suggest that abolishing hidden orders could deter liquidity provision and in turn deter price discovery following earnings announcements. I find that liquidity providers achieve profits (measured by realized spread) with displayed orders that are not statistically different from zero. But, liquidity providers that opt for hidden orders achieve significant positive profits. This finding suggests that abolishing hidden orders may deter the effectiveness of price discovery following earnings announcements because liquidity traders may be less inclined to provide liquidity without the use of hidden orders.

The remainder of this paper is organized as follows. Section I describes the data sources. In Section II, results on price discovery following earnings surprises, for both daily and intraday horizons, are presented. Price discovery in the after-hours market and the role of order flow to price discovery are presented in Section III. The results of the impact of earnings surprises on volatilities, bid-ask spreads, and trade volumes around earnings announcements are presented in Section IV. The profitability of hidden and displayed orders following earnings announcements is presented in Section V. Finally,

[12] Hidden limit orders, like displayed limit orders, have price priority but always lose on time priority against displayed limit orders. About 25 percent of incoming trade volume is executed against hidden orders in the after-hours market when there are no earnings announcements.

[13] For example, a liquidity provider who is not fast enough to cancel their limit order at the arrival of new information faces a higher risk of being "sniped" by a trader that processes new information faster with a displayed order than with a hidden order. Bessembinder, Panayides, and Venkataraman (2009) provide empirical support for the argument of Harris (1996).

Section VI concludes.

2.2 Data

2.2.1 Earnings Announcements Sample

The time coverage of this study is from January 1, 2011 to December 31, 2015. I first select from the Center for Research in Security Prices (CRSP) database stocks with NYSE, NASDAQ, or AMEX as their primary listing with share code 10 or 11. Each stock must have Compustat data, precisely total assets and market capitalization at the end of December of the previous calendar year. I use these accounting metrics to later match each stock to one of the Fama-French 25 size and book-to-market portfolios. I then rank the stocks by their market capitalization at the end of June of each year and select the largest 1,500 stocks starting from 2010. I limit my sample to the largest 1,500 stocks to minimize the computational constraint involved in processing the limit order book data, which I describe in the next section.

I identify quarterly earnings announcements for the chosen sample stocks using the announcement dates and times recorded in the Thomson Reuters I/B/E/S database. Because I/B/E/S timestamps are not always accurate (see Li, 2016; Santosh, 2014), I use the timestamps of the actual earnings news in RavenPack to improve the accuracy. I match 87 percent of the earnings announcements from I/B/E/S with the earnings news in RavenPack.[14] For the missing 13 percent, I use the timestamps in I/B/E/S.

When estimating the impact of earnings announcements on daily stock prices, announcements recorded as occurring at or after 4 p.m. on a given date are relabeled for the purpose of this empirical analysis to have the following trading day's date, to reflect the fact that reactions to such announcements are impounded in the stock's price only on the following trading day. This means that "day 0" in the event window is the trading day on which the reaction of investors to the earnings announcements trading on a U.S. exchange gets to impact the announcing firm's stock price at the daily horizon.

For each earnings announcement, I calculate the earnings surprise, defined as the scaled difference between actual and expected earnings:

$$S_{i,t} = \frac{\mathrm{EPS}_{i,t} - \widehat{\mathrm{EPS}_{i,t}}}{P_{i,t-5}}, \tag{2.1}$$

[14]RavenPack is an intraday newswire provider. In the Internet Appendix of this paper I explain how to process RavenPack data and how to merge them with CRSP.

where $\text{EPS}_{i,t}$ is the earnings per share of company i announced on day t, and $\widehat{\text{EPS}_{i,t}}$ is the forcasted earnings per share, calculated as the median consensus analyst forecast. I scale the surprise using the stock price five trading days before the announcement. I define the consensus analyst forecast as the median of all analyst forecasts issued over the 90 days before the earnings announcement date. If an analyst revises their forecasts during this interval, I use only their most recent forecasts. If a scheduled earnings announcement has no earnings forecast, the earnings announcement observation is removed from the sample. I further winsorize earnings surprises at the 1st and 99th percentile.

In this paper, I focus only on after-hours earnings announcements (between 4 p.m. and 9:30 a.m.), which represent 97 percent of the earnings announcements in my sample. The final sample is composed of 25,552 earnings announcements with an average of 1,440 firms per year and a total of 1,900 different firms between January 1, 2011 and December 31, 2015.[15] The earnings announcements are distributed as follows: 51.6 percent of the earnings announcements occur between 4 p.m. and 8 p.m., 47.1 percent occur between 4 a.m. and 9:30 a.m., and 1.3 percent occur between 8 p.m. and 4 a.m.

2.2.2 NASDAQ Limit Order Book-Level Data

Throughout the paper I use high-frequency stock prices and trade volume data from quotes and transactions from NASDAQ's TotalView-ITCH (hereafter, NASDAQ ITCH) limit order book, versions 4.1 and 5.0.[16] NASDAQ ITCH contains a series of messages that describe orders added to, removed from, and executed on NASDAQ for NASDAQ-, NYSE-, NYSE Amex-, NYSE Arca, and BATS-listed securities. I construct a message-by-message limit-order book, where the book is updated whenever there is a new message that enters the NASDAQ exchange.[17] NASDAQ ITCH data differ from the commonly used Trades and Quotes (TAQ) data provided by the NYSE. Holden and Jacobsen (2014) document that TAQ can suffer from liquidity measurement problems and errors in trade-quote matching due to insufficient timestamp granular-

[15] On any given year, the sample of stocks represents approximately 90 percent of the total U.S. stock market capitalization traded on NYSE, NASDAQ, or AMEX with share code 10 or 11.

[16] See NASDAQ (2016a,b) for the official documentation on the data.

[17] A Python code, developed in partnership with Vincent Grégoire that constructs the limit order book for NASDAQ ITCH data version 4.1 and 5.0 will be made available on the Market Empirical Analysis Toolbox for Python website http://www.meatpy.com. The code is adapted for multiprocessing.

ity. On the other hand, ITCH data are publicly available at no cost and do not suffer from liquidity measurement problems and errors in trade-quote matching. But, processing these data and constructing the limit order book are computationally costly. All trades in NASDAQ ITCH are signed, except trades against hidden (i.e., non-displayed) limit orders starting from July 14, 2014. I describe hidden orders in subsequent sections.[18] Trades are not signed in TAQ; the researcher must infer if a trade is a buy or a sell using trade classification algorithms.[19] When the empirical analysis requires signed trades, the sample period starts on January 1, 2011 and ends on July 13, 2014. Moreover, I observe every initiated trade that arrives in NASDAQ ITCH, including the NASDAQ portion of the Reg NMS Intermarket Sweep Order and odd-lot orders.[20]

After constructing the limit order book, I have for each stock an event-time midquote (the bid-ask mid point) timestamped to the nanosecond (a billionth of a second) from 9:30 a.m. to 4 p.m. I then aggregate the midquote at a lower frequency (e.g., one- or five-minute intervals) using the last observations at each interval. I also have for each stock the transaction data (price and quantity) and whether the trade was a market-initiated buy or market-initiated sell order from 4 a.m. to 8 p.m. After-hours trading on NASDAQ is from 4 p.m. to 8 p.m. and resumes from 4 a.m. to 9:30 a.m.[21]

I also observe crossing prices. Crossing prices are the price set at the opening and closing auctions (where the supply and demand curves meet at the opening and closing auction). In addition, I process the SPY Exchange Traded-Fund (ETF) that tracks the S&P 500 broad market index. I use the SPY ETF as a proxy for the intraday market return.

2.2.3 Displayed and Hidden Liquidity

Being able to distinguish between hidden and displayed limit orders is important. When a trader wishes to provide liquidity with a limit order, she has the choice to display or hide the limit order. Hidden limit orders maintain price priority but lose time priority to displayed orders at the same price. Therefore, displaying an order increases the chance of faster execution. Har-

[18] See Section A.3 in the Appendix for more institutional details surrounding hidden orders in NASDAQ ITCH.

[19] These trade classification algorithms are not flawless (see Chakrabarty, Pascual, and Shkilko, 2015). Because liquidity is largely hidden in the after-hours market, it imposes important constraints on the effectiveness of trade classification algorithms.

[20] Odd-lot orders are trades with less than 100 shares, can represent up to 60 percent of the total transactions (O'Hara, Yao, and Ye, 2014), and are not reported in TAQ.

[21] See Figure A.1 for a graphical presentation of the trading hours on NASDAQ.

ris (1996) argues that hidden orders are effective for uninformed traders who wish to mitigate the option value of limit orders that are expected to remain standing on the book for a long period and, in turn, mitigate the risk of adverse selection. On the other hand, Moinas (2011), Boulatov and George (2013), and Bloomfield, O'Hara, and Saar (2015) argue that informed traders may prefer hidden orders. In Section 2.6, I document the implication of hidden orders to price discovery following earnings announcements.

2.2.4 Summary Statistics

Table 2.1 Panel A shows the sample stocks' market capitalization at the end of June and analyst coverage breakdown by year and Panel B shows the characteristics of earnings announcements.

Table 2.1: Descriptive Statistics

This table reports descriptive statistics for the sample stocks, earnings announcements, and trading activity used in this study. Panel A reports the descriptive statistics on stock's market capitalization (MCAP) in million \$ at the end of June and analyst coverage. Panel B reports the descriptive statistics for the earnings announcements. The after-hours announcement returns are calculated between 4 p.m. prior to earnings announcements to 9:30 a.m. on the following trading day. Panel C reports the descriptive statistics for the trading activity on the NASDAQ ITCH TotalView limit order book. *Hidden* corresponds to trades executed against hidden orders (i.e., non-visible limit orders). Panel D reports the trading statistics by trade size. EA corresponds to earnings announcements, AH corresponds to after-hours, and P25, P50, and P75 stand for the 25th, 50th, and 75th percentile. The sample period is January 1, 2011 to December 31, 2015.

Panel A: Descriptive statistics on firm size (in million \$) and analyst coverage

	2011	2012	2013	2014	2015
MCAP min	794	721	901	1100	1199
MCAP median	2924	2576	3147	4103	4115
MCAP max	400885	547363	401730	556574	715600
Number analysts P25	5	5	4	4	4
Number analysts P50	9	9	8	8	8
Number analysts P75	14	14	14	14	14

Panel B: Descriptive statistics on earnings announcements

	2011	2012	2013	2014	2015
Number of EA	5155	5015	5136	5142	5104
% of earnings on Mond.	10	10	9	9	10
% of earnings on Tues.	23	21	23	21	22
% of earnings on Wed.	26	27	27	27	26
% of earnings on Thurs.	33	34	33	34	33
% of earnings on Frid.	5	6	6	6	6
% of EA with AH trading	71	64	61	55	57
Earnings surprises					
Mean	0.0008	0.0007	0.0006	0.0005	0.0005
St. dev.	0.0039	0.0039	0.0036	0.0033	0.0035
P25	-0.0001	-0.0002	-0.0002	-0.0002	-0.0002
P50	0.0005	0.0005	0.0004	0.0004	0.0004
P75	0.0018	0.0017	0.0015	0.0013	0.0014
AH returns around EA					
Mean	0.0000	0.0000	0.0007	0.0002	-0.0006
St. dev.	0.0507	0.0533	0.0596	0.0527	0.0570
P25	-0.0193	-0.0194	-0.0188	-0.0215	-0.0209
P50	0.0005	0.0011	0.0021	0.0019	0.0011
P75	0.0233	0.0222	0.0236	0.0264	0.0244

Panel C: Descriptive statistics on trading activity

	Market Hours			After Hours			After Hours (EA)		
	P25	P50	P75	P25	P50	P75	P25	P50	P75
Number of trades	669	1592	3679	1	3	8	4	16	104
% hidden trade	8	11	16	12	25	50	19	29	40
% hidden trade volume	8	12	18	8	25	60	21	41	59

Panel D: Descriptive statistics on trading size

	Number of shares per trade against displayed orders (%)			
	< 100	100-500	500-1,000	$> 1,000$
Market hours	32	66	1	1
After hours	33	56	7	5
After hours (EA)	30	60	6	4

	Number of shares per trade against hidden orders (%)			
	< 100	100-500	500-1,000	$> 1,000$
Market hours	27	71	2	1
After hours	27	63	7	4
After hours (EA)	22	61	8	8

	Trade size, in \$ per trade, against displayed orders (%)			
	< 1,000	1,000-5,000	5,000-50,000	> 50,000
Market hours	17	55	28	0
After hours	16	43	39	2
After hours (EA)	12	46	40	2

	Trade size, in \$ per trade, against hidden orders (%)			
	< 1,000	1,000-5,000	5,000-50,000	> 50,000
Market hours	15	52	32	1
After hours	15	39	43	3
After hours (EA)	11	36	47	6

An important aspect of the data is worth mentioning. Despite firms making earnings announcements in the after-hours market, I do not observe trades between the time of the announcement and the opening of markets at 9:30 a.m. for approximately 38 percent of the earnings announcements. I show in the following section that a lack of after-hours trading following earnings announcements indicates, in part, poor information quality surrounding these stocks, which results in slower price discovery.

Panel C of Table 2.1 shows the percentiles for the number of trades and the fraction of trades against hidden orders during regular market hours, in the after-hours market, and in the after-hours market when there is an earnings announcement across the sample of stocks. I observe that the level of trading activity increases in the after-hours market when there is an earnings announcement. Yet, the median number of trades in the after-hours market, when there is an earnings announcement, is only 15. Note that the median number of initiated trades and trade volume against hidden orders is higher when there is an earnings announcement.[22] Panel D presents the statistics on the percentage of orders, by the number of shares per trade and by trade size (in dollars), that are executed against displayed and hidden orders. Trades against hidden orders have a larger trade size than displayed orders and more so in the after-hours market. Large trade size indicates a higher likelihood of the presence of institutional traders than retail traders in the after-hours market.

[22] Chakrabarty and Shaw (2008) also find more trades initiated against hidden orders on earnings announcement days.

2.3 Price Discovery of Earnings Surprises: When is it Complete?

I now examine price discovery of earnings surprises at the daily horizon and at high frequency during regular market hours following earnings announcements.

2.3.1 Are there Daily Post-Earnings Announcement drifts?

To examine price formation at the daily horizon, I calculate for each stock in my sample the cumulative abnormal daily return starting five days before and ending 61 days after the earnings announcement. Following the same procedure as Hirshleifer, Lim, and Teoh (2009), I calculate the abnormal daily return to account for return premia associated with size and book-to-market. I deduct from stock returns the return on the size and book-to-market benchmark portfolios obtained from Ken French's website.[23] Stocks are matched to one of 25 portfolios at the end of June of every year based on their market capitalization at the end of June and their book-to-market ratio, calculated as the book equity of the last fiscal year end in the prior calendar year divided by the market value of equity at the end of December of the previous year.

I plot in Figure 2.1 the average buy-and-hold abnormal returns (BHAR) within each earnings surprises quintile and their corresponding 95 percent confidence intervals around earnings announcements.

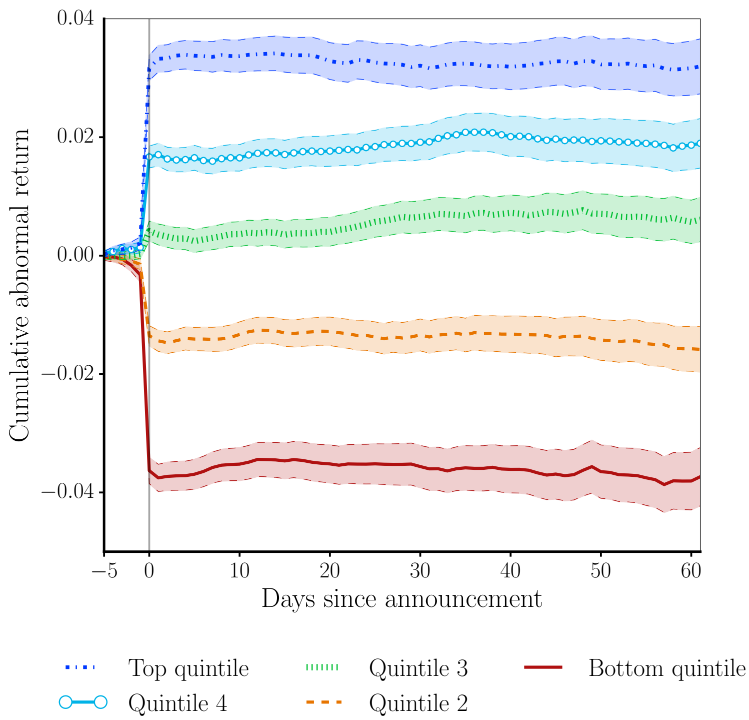
[23]Data source: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

Figure 2.1: Abnormal Daily Returns around Earnings Announcements

The figure shows the buy-and-hold cumulative abnormal returns (BHAR) around earnings announcement announced on day 0 for each earnings surprise quintile sorts. I define the BHAR for stock i from day τ to T ($\tau < T$) as:

$$BHAR[\tau, T]_i = \prod_{k=\tau}^{T}(1 + R_{i,k}) - \prod_{k=\tau}^{T}(1 + R_{p,k}),$$

where $R_{i,k}$ is the return of the stock i and $R_{p,k}$ is the return on the size and book-to-market matching Fama-French portfolio on day k. The figure represents the BHAR [-5, T] from five-days before the announcement ($\tau = -5$) to day T following the announcement where T varies from $T = -4$ to $T = 61$ trading days. The shaded areas are pointwise 95% confidence bands around the average abnormal returns. The vertical line corresponds to the earnings announcement day. The sample consists of earnings announcements from the largest 1,500 U.S. stocks between 2011 and 2015.



The first striking result is how "flat" the BHAR are following earnings announcements at day 0. Earnings surprises appear to be incorporated into the first trading day. I report in Table 2.2 Panel A the tabulated format of the abnormal returns (AR) and the BHAR over different trading day horizons following earnings announcements. The t-statistics are reported in brackets where the null is the AR and CAR are equal to zero. Panel B of Table 2.2 shows the difference in AR and BHAR between each quintile and quintile 3. Panel C shows the average AR and BHAR for the top and bottom earnings surprises decile and the difference between both deciles. Table 2.2 shows no evidence of slow price formation at the daily horizon.

Table 2.2: Cumulative Daily Abnormal Returns following Earnings Announcements

Panel A of this table reports the abnormal returns (AR) and the buy-and-hold abnormal returns (BHAR) at different horizons following earnings announcements for each earnings surprises quintile. Panel B shows the difference in the AR and the BHAR between each earnings surprises quintile and quintile 3. Panel C shows the AR and BHAR for the top and bottom earnings surprises deciles. The t-statistics where the null is zero are reported in square brackets. The AR and BHAR are calculated as follows:

$$AR[\tau]_{i,q} = R_{i,\tau} - R_{p,\tau},$$

$$BHAR[\tau, T]_{i,q} = \prod_{k=\tau}^{T}(1 + R_{i,k}) - \prod_{k=\tau}^{T}(1 + R_{p,k}),$$

where R_{ik} is the return of the stock i and R_{pk} is the return on the size and book-to-market matching portfolio on day k. The announcement date of quarter q's earnings occurs on day 0. The sample consists of earnings announcements from the largest 1,500 U.S. firms between 2011 and 2015.

Panel A: AR and CAR by earnings surprises quintile

	AR[0]	AR[1]	BHAR[2,5]	BHAR[6,30]	BHAR[31,61]	BHAR[2,61]
Top	0.03	0.002	0.001	-0.002	0.0	-0.001
	[31.2]	[4.23]	[0.94]	[-1.33]	[-0.07]	[-0.63]
Quintile 4	0.015	0.0	-0.001	0.003	0.0	0.002
	[17.99]	[1.27]	[-1.19]	[2.42]	[-0.13]	[1.05]
Quintile 3	0.004	-0.001	-0.001	0.004	0.0	0.003
	[5.19]	[-2.0]	[-2.22]	[3.92]	[-0.38]	[1.53]
Quintile 2	-0.012	-0.001	0.0	0.001	-0.002	-0.001
	[-15.53]	[-3.0]	[0.69]	[0.67]	[-1.79]	[-0.74]
Bottom	-0.033	-0.001	0.001	0.001	-0.002	0.0
	[-31.7]	[-3.34]	[1.19]	[1.01]	[-1.06]	[0.09]

Panel B: Difference in AR and CAR between each quintile and quintile 3

	AR[0]	AR[1]	BHAR[2,5]	BHAR[6,30]	BHAR[31,61]	BHAR[2,61]
Top-Q3	0.026	0.002	0.002	-0.006	0.0	-0.004
	[15.15]	[3.25]	[1.55]	[-2.51]	[0.13]	[-1.03]
Q4-Q3	0.011	0.001	0.001	-0.001	0.0	-0.001
	[7.13]	[1.62]	[0.63]	[-0.69]	[0.11]	[-0.17]
Q2-Q3	-0.016	0.0	0.001	-0.003	-0.002	-0.004
	[-10.45]	[-0.5]	[1.51]	[-1.63]	[-0.76]	[-1.1]
Bottom-Q3	-0.037	-0.001	0.002	-0.003	-0.001	-0.002
	[-20.62]	[-0.99]	[1.7]	[-1.2]	[-0.44]	[-0.61]

Panel C: AR and CAR for top and bottom earnings surprises deciles

	AR[0]	AR[1]	BHAR[2,5]	BHAR[6,30]	BHAR[31,61]	BHAR[2,61]
Top	0.034	0.002	0.001	-0.004	0.00	-0.003
Bottom	-0.037	-0.001	0.00	0.001	-0.003	-0.001
Top-Bottom	0.071	0.003	0.001	-0.005	0.003	-0.001
	[21.719]	[2.796]	[0.482]	[-1.249]	[0.642]	[-0.182]

I report in Table 2.3 the estimated coefficients of a cross-sectional regression of AR and BHAR on stock i's respective earnings surprise $S_{i,t}$.

Table 2.3: OLS Regression: Cumulative Abnormal Returns on Earnings Surprises
This table reports the results of an OLS regression of abnormal returns (AR) and cumulative abnormal returns (CAR) following earnings announcements at different horizons on earnings surprises ($S_{i,t}$). Standard errors are clustered by date and are reported in parentheses. Asterisks denote statistical significance at the 5-percent level. The sample period is January 1, 2011 to December 31, 2015.

	AR[0]	AR[1]	CAR[2,5]	CAR[6,30]	CAR[31,61]	CAR[2,61]
$S_{i,t}$	4.965*	0.293*	0.088	-0.259	0.225	0.157
	(0.165)	(0.059)	(0.094)	(0.220)	(0.251)	(0.345)
Intercept	-0.002*	-0.000	-0.000	0.002*	-0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Obs.	25552	25552	25548	25380	24088	24088
Adj-R^2	0.08	0.00	0.00	0.00	0.00	-0.00

As expected, earnings surprises positively impact abnormal returns on the earnings announcement day (AR[0]). An earnings surprise of 0.002, which is approximately the inter-quartile range between the 25th and 75th percentile of earnings surprises, increases AR[0] by one percent. Also, earnings surprises positively and significantly impact AR[1] returns. Yet, their economic magnitudes are small, at about six basis points for an earnings surprise of 0.002 with a zero percent R^2. More importantly, earnings surprises have no explanatory power on the CAR at any horizon.

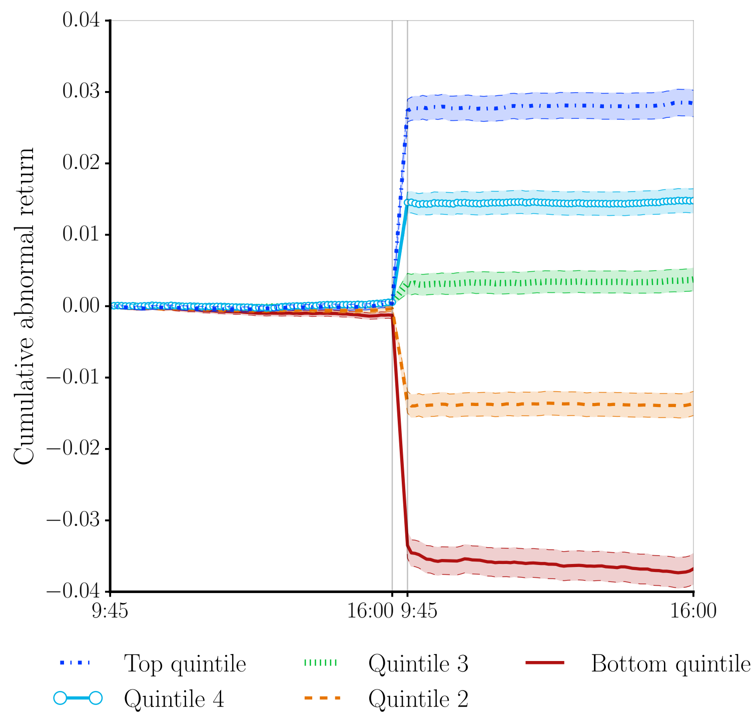
In Section A.2 of the Appendix, I show how the post-earnings announcements drift has changed since 1984 for the largest 1,500 U.S. stocks. It is obvious that markets have become more efficient at incorporating earnings surprises and only recently do we observe no strong evidence of post-earnings announcement drift at the daily horizon.

2.3.2 Are there Intraday Post-Earnings Announcement Drifts?

I now investigate at high frequency the stock return response to earnings announcements. In Figure 2.2, I plot the average cumulative abnormal log returns at a five-minute frequency for each earnings surprises quintile starting on the trading day before the earnings announcement until the closing of markets on the following trading day. The cumulative abnormal log return is the difference between the cumulative log return of the announcing firm's stock and the cumulative market log return proxied by the SPY ETF. At this stage, I ignore the returns in the after-hours trading session. The overnight (close-to-open) return is calculated using the closing price at 4 p.m. and the midquote (mid-point between the best bid and best ask price) at 9:45 a.m. on the following trading day. I use midquotes starting at 9:45 a.m. because for a small number of observations I find that midquote prices in the order book between 9:30 a.m. and 9:45 a.m., are "noisy" (i.e., the midquote is far from the previous transaction price).

Figure 2.2: Cumulative Abnormal Intraday Returns around Earnings Announcements

This figure shows the stocks' cumulative abnormal five-minute log returns beginning at 9:45 a.m. on the trading day preceding an after-hours earnings announcement until 4 p.m. the following trading day. The cumulative abnormal returns are calculated as the cumulative log returns for stock i minus the cumulative log returns of SPY ETF, a proxy for market returns. The overnight (close-to-open) return is calculated using prices at 4 p.m. preceding the earnings announcements and prices at 9:45 a.m. the following trading day. Each line represents a different quintile sort for earnings surprises. The shaded areas are pointwise 95% confidence bands around the average cumulative abnormal log returns. The sample period is January 1, 2011 to December 31, 2015.



From Figure 2.2, we see a similar picture to Figure 2.1 where there is a clear demarcation between the earnings surprises quintiles. Moreover, the CAR are also close to "flat" after the opening of markets. This suggests that most, if not all, price discovery occurs in the after-hours market.

2.3.3 The Response of After-Hours Returns to Earnings Surprises

In this section, I quantify the impact of earnings surprises on after-hours returns calculated using prices at the closing (4 p.m.) and the opening of markets (9:30 a.m.) on the trading day following the earnings announcement. More importantly, I examine whether a stock that has trading in the after-hours market following earnings announcements influences the response of after-hours returns to earnings surprises. As previously shown, I do not observe after-hours trading following earnings announcements on the NASDAQ ITCH limit order book for 38 percent of earnings announcements in my sample.[24] A stock may not have after-hours trading following earnings announcements due to factors such as stock visibility, information quality surrounding the stock, limited investor attention to the news, or that the news is too complicated to process for liquidity providers to feel confident to provide liquidity.

The dominant economic factors that explain why a stock is more likely to have after-hours trading following earnings announcements is an interesting topic meriting further understanding, but is beyond the scope of this paper. Nonetheless, important literature documents slow price formation for stocks with poor information quality.[25] I examine whether common proxies of information quality surrounding a stock influence the likelihood of observing a trade in the after-hours market following earnings announcements. I report in Table 2.4 the estimated coefficients and marginal effects from a logit regression where the dependent variable is equal to one if the stock has no after-hours trading following earnings announcements and zero otherwise. The independent variables are firm size, analyst and media coverage, institutional ownership, and average bid-ask spreads. Firm size is based on the logarithm market capitalization on the day prior to the earnings announcement. Analyst coverage is the number of analyst forecasts prior to earnings announcements, and media coverage is the log of the total num-

[24]It is possible that I may not observe a trade for a particular stock in the NASDAQ ITCH limit order book but a trade may have actually occurred on another exchange (i.e., dark pools, NYSE limit order book). Yet, as I will show, stocks with no after-hours trading on NASDAQ ITCH have slower price discovery. Therefore, this implies that price discovery did not occur on another exchange.

[25]See e.g., Brennan, Jegadeesh, and Swaminathan (1993); Hong, Lim, and Stein (2000); Hou and Moskowitz (2005); Zhang (2006), and Boguth, Carlson, Fisher, and Simutin (2016).

ber of articles in RavenPack with a relevance score of 90 or more in the 21 trading days prior to earnings announcements. Institutional ownership is the percentage of shares outstanding held by institutions from Thomson Reuters 13-F filings. The bid-ask spread is calculated using the average of the one-second quoted spread measure (i.e., bid-ask spread divided by the midquote) during regular trading hours in the 40 trading days prior to earnings announcements.[26]

[26] I provide more details on the calculation of bid-ask spreads in Section 2.5.

Table 2.4: Logit Regression: Determinants to After-Hours Trading following Earnings News

This table reports the results of a logit regression, where the dependent variable is equal to one if stock i has no trade in the after-hours market following its earnings announcement and zero otherwise. The independent variables are the stocks' log market capitalization ($Mcap_{i,t}$), the number of analyst forecasts ($Analysts_{i,t}$), the log of total number of newswire articles in RavenPack in the 21 trading days prior to earnings announcements ($Media_{i,t}$), the fraction of shares outstanding held by institutions ($Institution_{i,t}$), and the average quoted spread during regular trading hours in the 40 trading days prior to earnings announcements ($Spreads_{i,t}$). The marginal effects are evaluated at the mean. Asterisks denote statistical significance at the 5-percent level. The sample period is January 1, 2011 to December 31, 2015.

	Estimated coefficients	Marginal effects (dy/dx)
$Mcap_{i,t}$	-0.197*	-0.045*
	(0.016)	(0.004)
$Analysts_{i,t}$	-0.054*	-0.012*
	(0.003)	(0.001)
$Media_{i,t}$	-0.068*	-0.016*
	(0.015)	(0.003)
$Institution_{i,t}$	-0.965*	-0.221*
	(0.080)	(0.018)
$Spreads_{i,t}$	261.884*	59.922*
	(18.884)	(4.255)
Intercept	4.881*	
	(0.384)	
Obs.	25133	
Pseudo-R2	0.09	

As expected, Table 2.4 shows that all of the coefficients for the independent variables are statistically significant with the correct predicted signs. This result emphasizes that stocks with no after-hours trading can be explained, in part, by low information quality surrounding these stocks.

I next use the predicted values from the logit regression to investigate whether after-hours returns for stocks with a higher likelihood of after-hours trading activity are more responsive to earnings surprises. To investigate this possibility, I estimate the following regression:

$$r^{ah}_{i,t} = \alpha + \beta_1 S_{i,t} + S_{i,t} \cdot \beta_2 ProbNoTrade_{i,t} + \beta_3 ProbNoTrade_{i,t} + \epsilon_{i,t}, \quad (2.2)$$

where time t denotes the after-hours time interval that starts at 4 p.m. prior to an earnings announcement and ends at 9:30 a.m. on the next trading day. $r^{ah}_{i,t}$ denotes the log abnormal after-hours return and $S_{i,t}$ the earnings surprise for stock i. The abnormal after-hours return is calculated using the closing and opening prices from the auction if available; otherwise, I use the midquote from the limit order book.[27] I then subtract the after-hours market return using the SPY ETF. $ProbNoTrade_{i,t}$ corresponds to the predicted values of having no trades in the after-hours market from the previously estimated logit regression.[28]

I report the results in the first three columns of Table 2.5.

[27] I exclude observations with after-hours returns in the top and bottom 1/1,000th of the distribution.

[28] $ProbNoTrade_{i,t}$ is a generated regressor. The error terms from the logit regression and the regression specified in 2.2 are essentially uncorrelated (0.01); thus, adjustment for the generated regressors is minimal.

Table 2.5: OLS Regression: After-Hours Returns on Earnings Surprises

This table reports the regression results of the after-hours abnormal log return on earnings surprises. The after-hours abnormal returns are calculated using the closing price at 4 p.m. prior to earnings announcements and opening price at 9:30 a.m. on the following trading day minus the market return proxied by the SPY ETF over the same interval. $S_{i,t}$ is the earnings surprise. $ProbNoTrade_{i,t}$ is the predicted probability of having no trades in the after-hours market following earnings announcements based on the logit regression reported in Table 2.4. $NoTrade_{i,t}$ is a dummy variable equal to one if there is no trade in the after-hours market following the earnings announcement and zero otherwise. $BMO_{i,t}$ is a dummy variable equal to one if the earnings announcement occurs before the market opens (12:00 a.m. to 9:30 a.m.) and zero otherwise. $Ann_{i,t}$ is the number of earnings announcements in the after-hours market. $Friday_t$ is a dummy variable equal to one if the earnings announcement occurs on a Friday and zero otherwise. $Media_{i,t}$ is the stocks' media coverage based on the log of the total number of newswire articles in RavenPack following the earnings announcement until the opening of markets. Standard errors are clustered by date and are reported in parentheses. Asterisks denote statistical significance at the 5-percent level. The sample period is January 1, 2011 to December 31, 2015.

	(1)	(2)	(3)	(4)	(5)	(6)
$S_{i,t}$	3.850*	4.868*	4.463*	4.812*	5.475*	4.512*
	(0.108)	(0.251)	(0.132)	(0.252)	(0.367)	(0.465)
$S_{i,t} \times ProbNoTrade_{i,t}$		-2.369*		-0.873	-1.199*	-0.767
		(0.556)		(0.600)	(0.610)	(0.619)
$S_{i,t} \times NoTrade_{i,t}$			-2.016*	-1.929*	-1.823*	-1.751*
			(0.181)	(0.198)	(0.204)	(0.207)
$S_{i,t} \times BMO_{i,t}$					-0.838*	-0.865*
					(0.209)	(0.210)
$S_{i,t} \times Ann_{i,t}$					-0.001	-0.001
					(0.003)	(0.003)
$S_{i,t} \times Friday_{i,t}$					-0.215	-0.184
					(0.384)	(0.381)
$S_{i,t} \times Media_{i,t}$						0.337*
						(0.100)
$NoTrade_{i,t}$		0.005*		0.003	0.003	0.003
		(0.002)		(0.002)	(0.002)	(0.002)
$ProbNoTrade_{i,t}$			0.003*	0.002*	0.002*	0.002*
			(0.001)	(0.001)	(0.001)	(0.001)
$BMO_{i,t}$					0.000	-0.000
					(0.000)	(0.000)
$HighAnn_{i,t}$					0.002*	0.002*
					(0.001)	(0.001)
$Friday_{i,t}$					0.003*	0.003*
					(0.001)	(0.001)
$Media_{i,t}$						-0.001
						(0.000)
Intercept	-0.006*	-0.008*	-0.006*	-0.007*	-0.009*	-0.007*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Obs.	25133	25133	25133	25133	25133	25133
Adj-R^2	0.08	0.08	0.09	0.09	0.09	0.09
Year-Month FE	Y	Y	Y	Y	Y	Y

Columns (1) and (2) show a positive and significant relationship between earnings surprises and after-hours returns. In Column (1), for an increase in earnings surprises ($S_{i,t}$) of 0.002, the after-hours return increases by 77 basis points. In Column (2), I find that the after-hours return of stocks with a 100 percent probability of no after-hours trading following an after-hours earnings announcement respond 49 percent less to earnings surprises than stocks with a zero percent probability of no after-hours trading. Next, I replace $ProbNoTrade_{i,t}$ with $NoTrade_{i,t}$, which corresponds to a dummy variable equal to one if I observe no actual after-hours trading followings earnings announcements and zero otherwise. The results in Column (3) show that the impact of $NoTrade_{i,t}$ on after-hours returns is quantitatively similar to $ProbNoTrade_{i,t}$. In Column (4), I combine both the actual realization and the probability of having no trades in the after-hours market. The results in Column (4) show that, controlling for the probability of having no after-hours trading, the after-hours returns for stocks with after-hours trading respond to earnings surprises 40 percent more than stocks with no after-hours trading. In Column (5), I report the results from the previous regression by including additional control variables related to investor attention. I include an interaction variable $S_{i,t} \times BMO_{i,t}$, where $BMO_{i,t}$ equals one if the announcement occurs before the market opens (between 12:00 a.m. and 9:30 a.m.). Intuition suggests that firms that announce earnings before the market opens give investors less time to process the news than earnings announced the night before. I further interact the earnings surprise with a dummy variable, $Friday_t$, which equals one if the earnings announcement occurs on a Friday, and an additional interaction term, Ann_t, which corresponds to the total number of earnings announcements in the after-hours market on date t. Hirshleifer, Lim, and Teoh (2009) and DellaVigna and Pollet (2009) respectively show that when firms announce earnings on Fridays or on days with a high number of earnings announcements, investors are more likely to be inattentive and the price reaction to earnings surprises is weaker and subject to more persistent price drifts. I report the results in Column (5). I find no statistical significance at the five percent level for the interaction between the earnings surprises and $Friday_t$ and Ann_t.[29] But, the interaction term $S_{i,t} \times BMO_{i,t}$ is significant and negative, which indicates potential additional price discovery at the opening of markets for stocks with earnings announcements that occur before market opens.

Another factor likely to influence the response of after-hours returns to earnings surprises is media coverage. Peress (2008) finds that stocks with less media coverage have longer post-earnings announcement drifts. To proxy for media coverage, I count the total number of articles appearing in the intraday newswire database RavenPack between the time of the announcement and the opening of markets. I interact the earnings surprise with $Media_{i,t}$, which is the log of the total number of articles about stock i. I report the results in Column (6). The interaction term is positive and statistically significant at the five percent level.

Overall, the results show that stocks' after-hours returns around earnings announcements are less responsive to earnings surprises if there is no after-hours trading following the announcement. We should, therefore, expect additional and significant price discovery for these stocks at the opening of markets. Moreover, stocks with low media coverage and stocks with earnings announcements that occur before the market opens are also expected to have additional price discovery.

[29] Chakrabarty, Moulton, and Wang (2015) show that, with the advent of high-frequency tradings, the impact of limited attention on cumulative abnormal returns after earnings announcements is diminished.

2.3.4 The Dynamics of Price Discovery following Earnings Announcements at the Opening of Markets

In this section, I investigate whether any price discovery remains following earnings surprises at the time the market opens at 9:30 a.m. The empirical approach is inspired from Andersen, Bollerslev, Diebold, and Vega (2003a, 2007a).

I first construct a panel dataset for each stock i that contains the five-minute log return $r_{i,\tau}$ starting at 9:30 a.m. and ending at 10:30 a.m. (9:35 a.m. is the first five-minute observation) following earnings announcements using the first transaction price starting at 9:30 a.m., the earnings surprise $S_{i,t}$, announced in the previous after-hours trading session prior to the opening of markets, the after-hours return $r_{i,t}^{ah}$, and the five-minute market return r_{τ}^{m} using the SPY ETF. I use transaction prices to calculate the returns. Note that τ corresponds to a five-minute interval, for a total of twelve five-minute intervals between 9:30 a.m. and 10:30 a.m. I estimate the following cross-sectional ordinary least squares (OLS) regression:

$$r_{i,\tau} = \alpha + \beta_{\tau} S_{i,t} + \gamma_{\tau} r_{i,t}^{ah} + \delta r_{\tau}^{m} + \epsilon_{i,\tau}. \tag{2.3}$$

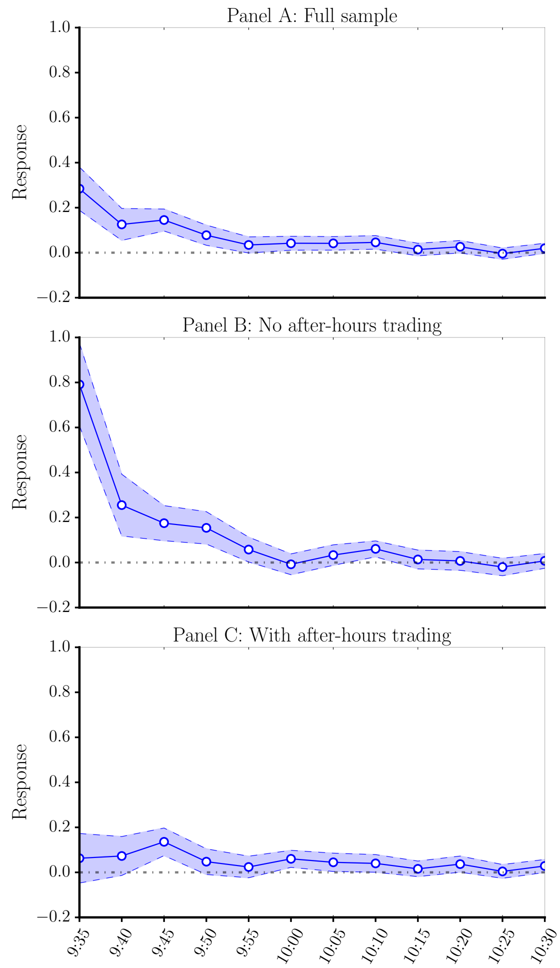
I control for after-hours return r_{it}^{ah} because it may influence how the markets respond to earnings surprises at opening. Because the model contains so many variables, it would prove counterproductive to report all of the parameters estimates. The coefficients of interest are the estimated $\hat{\beta}_{\tau}$ and are plotted in Figure 2.3 with their corresponding 95 percent confidence intervals. The standard errors are calculated using the Driscoll-Kraay extension of the Newey-West HAC estimator (Driscoll and Kraay, 1998). The Discoll-Kraay method is a generalized method of moments technique for large cross-sectional and time dimensions panel datasets. The coefficient estimates are identical to OLS estimates but the standard errors are robust to heteroskedasticity and to general forms of spatial and temporal dependence.

Figure 2.3: The Response of Stock Returns to Earnings Surprises at the Opening of Markets

This figure shows the estimated response coefficients $\hat{\beta}_\tau$ from the stock return conditional mean regression (2.3):

$$r_{i,\tau} = \alpha + \beta_\tau S_{i,t} + \gamma_\tau r_{i,t}^{ah} + \delta r_\tau^m + \epsilon_{i,\tau}.$$

τ corresponds to a five-minute interval between 9:30 a.m. and 10:30 a.m. Earnings announcements are announced in the after-hours market preceding the opening of markets at 9:30 a.m. The shaded areas are pointwise 95% confidence bands around the estimated coefficients. The standard errors are calculated using the Driscoll and Kraay (1998) method. Panel A shows the estimated coefficients for the full sample of earnings announcements and Panel B and Panel C respectively show the results for stocks with no after-hours trading and with after-hours trading following earnings announcements. The sample period is January 1, 2011 to December 31, 2015.



In Figure 2.3, Panel A shows the estimated coefficients $\hat{\beta}_\tau$ for the full sample of earnings announcements. Also, Panel B and Panel C respectively show the estimated coefficients for stocks with and without after-hours trading. I previously documented that no after-hours trading is the strongest factor influencing the response of stocks' after-hours (close-to-open) returns to earnings surprises. Prices of these stocks are less responsive to earnings surprises and therefore we should expect these stocks to have additional and significant price discovery at the opening of markets.

Panel A shows a moderate impact of earnings surprise on stock returns (a coefficient of 0.4) at the opening of markets followed by a slow decay ending around 10 a.m. For stocks with no after-hours trading, the general pattern is one of a quick mean adjustment, characterized by a jump at the opening of markets followed by a slow decay. An increase in the earnings surprise of 0.002 increases returns by 17 basis points and a total cumulative impact of 30 basis points by 10 a.m. In Panel C, we see that stocks with after-hours trading have on average small, if any, remaining price discovery when markets open. For stocks in Panel C, we must then explore price discovery in the challenging context of after-hours trading, which I undertake in the following section.

In Table 2.6 Panel A, I report in a tabulated format the estimated coefficients $\hat{\beta}_\tau$ between 9:30 a.m. and 10 a.m. of Figure 2.3. I also report the estimated coefficients for different sub-samples based on high (top quartile) and low (bottom quartile) predictability of having after-hours trading following earnings announcements, announcement time (i.e., earnings announcements before market opens or after market closes), and for high (top quartile) and low (bottom quartile) media coverage based on the total number of articles in RavenPack between the time of the announcement and the opening of markets. I also report the sum of the estimated coefficients for both $\hat{\beta}_\tau$ and $\hat{\gamma}_\tau$ between 9:30 and 10 a.m. After-hours returns may contain information about the news not captured by earnings surprises.

Table 2.6: Price Discovery following Earnings Surprises at the Opening of Markets

Panel A of this table reports the estimated response coefficients $\hat{\beta}_\tau$ and $\hat{\gamma}_\tau$ from the stock return conditional mean regression (2.4):

$$r_{i,\tau} = \alpha + \beta_\tau S_{i,t} + \gamma_\tau r^{ah}_{i,t} + \delta r^m_\tau + \epsilon_{i,\tau}.$$

$r^{ah}_{i,t}$ is the after-hours return and r^m is the market return proxied by the SPY ETF. After-hours (AH) returns are calculated using the stock price at 4 p.m. prior to earnings announcements and the stock price at 9:30 a.m. following earnings announcements. After-hours trading refers to stocks with one or more trades following the earnings announcement in the after-hours market. The probability of after-hours trading corresponds to the stocks' predicted probability of having after-hours trading based on a logit regression reported in Table 2.4. After market closes refers to earnings announcements between 4 p.m. and 11:59 p.m. and before market opens to earnings announcements between 12:00 a.m. and 9:30 a.m. Media coverage corresponds to the total number of newswire articles in RavenPack between the earnings announcement time and 9:30 a.m. Low and high respectively correspond to the to the bottom and top quartile. Standard errors are clustered by date and reported in parentheses. Asterisks denote statistical significance at the 5-percent level. Panel B shows the R^2 from two univariate regressions: (1) stock returns on earnings surprises $S_{i,t}$ and (2) stock returns on after-hours returns $r^{ah}_{i,t}$ using stock returns calculated from 9:30 a.m. to 10 a.m. and from 10 a.m to 4 p.m. The sample period is January 1, 2011 to December 31, 2015.

Panel A: The response of stock returns to earnings surprises and after-hours returns at opening of markets

	β_τ						$\sum_\tau \beta_\tau$	$\sum_\tau \gamma_\tau$
	9:30-9:35	9:35-9:40	9:40-9:45	9:45-9:50	9:50-9:55	9:55-10:00	9:30-10:00	9:30-10:00
Full sample	0.284*	0.126*	0.145*	0.078*	0.034	0.042*	0.723*	0.098*
Actual AH trading								
No AH Trading	0.791*	0.255*	0.175*	0.154*	0.058*	-0.008	1.452*	0.283*
With AH trading	0.063	0.073	0.136*	0.048	0.024	0.060*	0.412*	0.051*
Probability of AH trading								
Low	0.480*	0.248*	0.163*	0.065	0.023	0.018	1.076*	0.151*
High	0.010	-0.054	0.092	0.018	-0.045	0.056	0.068	0.041*
Announcement time								
After market closes	0.307*	0.159*	0.173*	0.126*	0.012	0.044*	0.814*	0.081*
Before market opens	0.225*	0.086*	0.125*	0.038	0.055*	0.041	0.604*	0.126*
Media coverage								
Low	0.365*	0.142	0.174*	0.111*	0.071*	0.024	0.899*	0.109*
High	0.046	0.074	0.064	-0.003	-0.010	0.063	0.257	0.072*

Panel B: Explanatory power (R^2) of earnings surprises and after-hours returns to stock returns

	9:30-10:00		10:00-4:00	
	$R^2_{Surprise}$	$R^2_{AH\ Return}$	$R^2_{Surprise}$	$R^2_{AH\ Return}$
Full sample	0.01	0.03	0.00	0.00
Actual AH trading				
No AH trading	0.05	0.11	0.00	0.00
With AH trading	0.01	0.01	0.00	0.00
Probability of AH trading				
Low	0.03	0.05	0.00	0.00
High	0.00	0.01	0.00	0.00
Announcement time				
After market closes	0.01	0.02	0.00	0.00
Before market opens	0.02	0.04	0.00	0.00
Media coverage				
Low	0.02	0.03	0.00	0.00
High	0.00	0.02	0.00	0.00

I find that stocks with a high predictability of having after-hours trading have no significant price discovery at the opening of markets. This suggests that stocks with high information quality affect the speed of price discovery. Similarly, stocks with high media coverage have no significant price discovery but I find the opposite for stocks with low media coverage. I find little difference in price discovery for stocks with earnings announcements that occur before the market opens or after the market closes. Yet, the impact of after-hours returns is greater for stocks that announce before the market opens.

In Panel B, I show the explanatory power (R^2) of a univariate regression of stock returns on earnings surprises and stock returns on after-hours returns between 9:30 to 10 a.m. and from 10 a.m. and 4 p.m. I choose a cutoff of 10 a.m. because this is where price discovery following earnings surprises is generally complete in Figure 2.3. Consistent with the results of Panel A, earnings surprises for stocks with no after-hours trading have the highest explanatory power to explain stock returns (R^2 of five percent) between 9:30 a.m. and 10 a.m. Also, the after-hours return has a high explanatory power

(R^2 of eleven percent), for stocks with no after-hours trading. Stocks with a high probability of after-hours trading have an R^2 of zero percent for earnings surprises and one percent for after-hours returns. After 10 a.m., I find that all R^2 are equal to zero for the full sample and across subgroups, which suggests that price discovery following earnings surprises and after-hours returns is generally complete by 10 a.m.

2.4 Price Discovery following Earnings Surprises in the After-Hours Market

2.4.1 Market Activity in the After Hours around Earnings Announcements

Before I examine price discovery in the after-hours market, it is worthwhile to highlight the differences in market activity across stocks in the after-hours following earnings announcements. I show in Figure 2.4 an example of stock price and trade volume (in hundreds of shares) reactions around an earnings announcement scheduled at 4:30 p.m. on October 18, 2011 for a large liquid firm, Apple Inc. (AAPL) at a one-minute frequency between 3:30 and 5:30 p.m.[30]

The figure shows little trading volume in the limit order book after the market closes at 4 p.m. At the time of the announcement (4:30 p.m.), the stock price drops following a negative earnings surprise and high trade volume occurs.

In Figure 2.5 Panel A, I show the distribution of total trades (log scale) between the time of the earnings announcement and the opening of markets at 9:30 a.m. for my sample of stocks with after-hours trading following earnings announcements.

[30] I calculate the stock price as the volume-weighted transaction price.

Figure 2.4: An Example of Price Response to Earnings Announcements at High Frequency

This figure shows the stock price and trade volume (in hundreds of shares) at a frequency of one minute between 3:30 p.m. and 5:30 p.m. for the company Apple (ticker: AAPL) around the earning announcement made at 4:30 p.m. on October 18, 2011. The black dots are the volume-weighted transaction prices. The positive blue bars are the initiated market buy orders and the negative red bars are the initiated market sell orders.

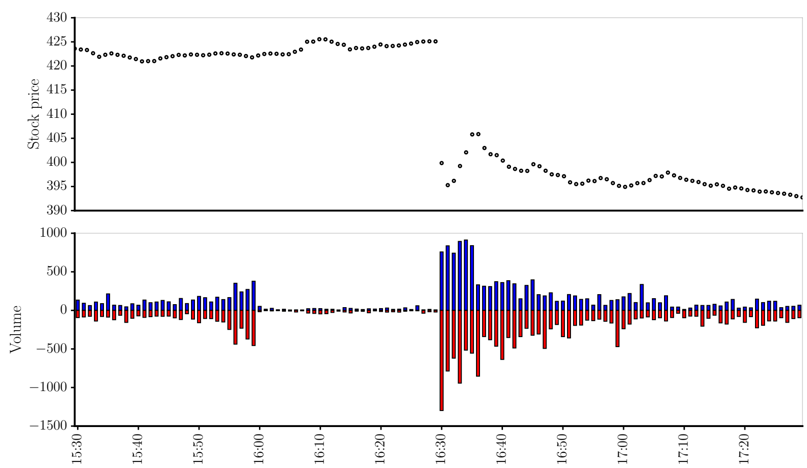
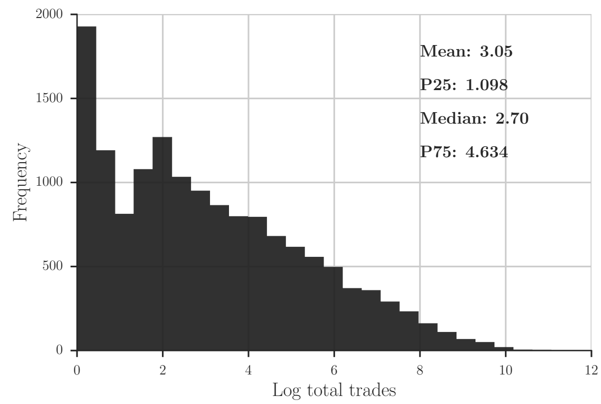


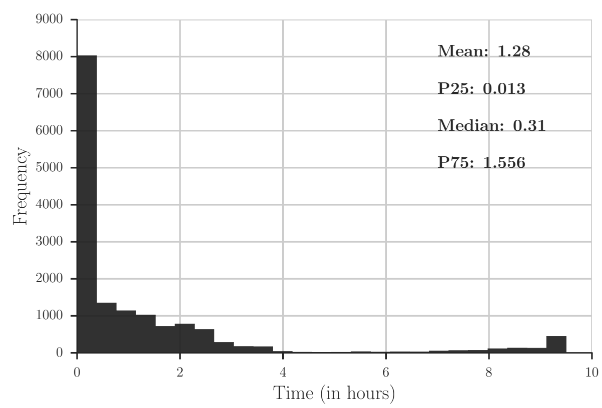
Figure 2.5: Statistics on After-Hours Trading following Earnings Announcements

This figure shows in Panel A the distribution of the total number of trades (in log scale) between the time of the earnings announcement and the opening of markets at 9:30 a.m. for all earnings announcements with after-hours trading. Panel B shows the distribution of the trading time (in hours) between the first trade following the earnings announcement and the actual earnings announcement. P25 and P75 stand for the 25th and 75th percentiles, respectively.

Panel A: Distribution of total trades in the after-hours market following earnings announcements



Panel B: Lapse time distribution between the first trade and earnings announcements



Note that the mean is 3.05 and the median is 2.70 (a total of 21 and 15 trades), suggesting that there are indeed only a few trades for more than half of the sample. But, for some earnings announcements, the total number of trades is in the thousands. In Panel B, I show the lapse of time (in hours) between the first trade and the earnings announcement. The mean and the median are 1.28 and 0.31 hours, respectively. For 25 percent of the sample, the first trade occurs within 47 seconds.[31]

Another question of interest is who is participating in the after-hours market. The NASDAQ ITCH data do not contain trader identification for each order entry in the limit order book. Barclay and Hendershott (2004) show that adverse selection risk is higher in the after-hours market, which suggests that traders who participate in the after-hours market are more likely to be informed and sophisticated. As shown in Table 2.1 Panel D and Panel E, trade size both in shares and in dollars is greater in the after-hours market than during regular market hours, consistent with the idea that large trade size is more likely to come from institutional traders than retail traders.[32]

2.4.2 The Dynamics of Price Discovery in the After-Hours Market

In this section, I examine price discovery in the after-hours market. Because no liquidity providers have the obligation to provide liquidity in the after-hours, prices are not continuous. For example, we may observe available liquidity only the bid side of the book and nothing on the ask side. During market hours, each stock has a designated market maker that provides liquidity on both sides of the book. Moreover, a large share of liquidity is hidden. Therefore, working in calendar time using midquotes to calculate returns is not feasible. To overcome this challenge, for each stock with after-hours trading I calculate returns over ten intervals denoted k using the arrival of trades to define an interval. For instance, if a firm has ten trades, each trade arrival represents a trade bin. If a firm has five trades then it has only five trade arrival bins k. If a firm has more than ten trades then I divide the number of total trades in the after-hours by ten (a fraction

[31] Even large firms can have a delay between the announcement and the first trade because of trading halts imposed by the exchange.

[32] In Section A.4 of the Appendix, I use another dataset to investigate whether high-frequency trading is predominant in the after-hours market. Compared to regular trading hours, I find that high-frequency traders are less present in the after-hours market.

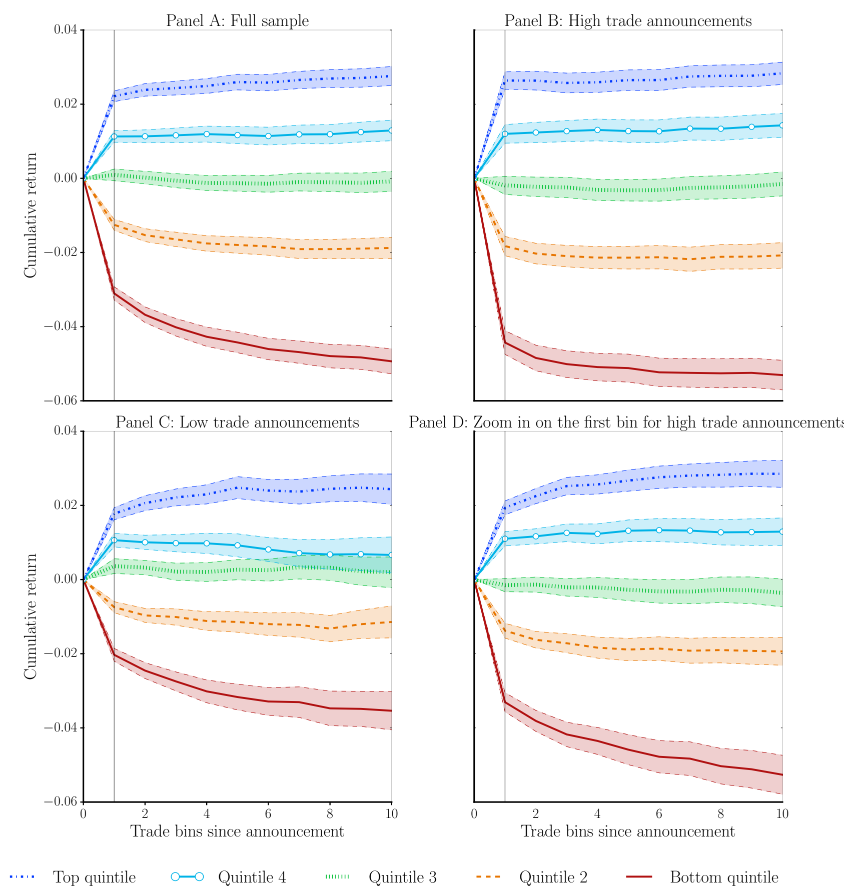
of total trades) and a trade bin k contains a fraction of the total trades.[33] Essentially, I use business-time units rather than calendar-time units to calculate stock returns. The return over a trade arrival bin is the sum of the log returns using transaction prices. I use the last trade prior to the earnings announcement to calculate returns for the first trade bin. I choose the arrival of trades and not trading volume to construct trade bins because the literature has shown that the arrival of trades has a larger impact on stock price volatility than trade volume (see Jones, Kaul, and Lipson, 1994).

Figure 2.6 shows the average cumulative return following earnings surprises at the announcement in business time in the after-hours market. Trade bin $k = 1$ is the first trade bin following the announcement.

[33]For example, if a firm has 15 trades, this represent 1.5 trades per bin. The first bin will contain the first trade following the announcement, the second bin contains the second and third trade, the third bin contains the fourth trade, and so on.

Figure 2.6: Cumulative Returns following Earnings Announcements in the After-Hours Market

This figure shows the stocks' cumulative returns following earnings announcements in the after-hours market. The x-axis corresponds to trade bins. The definition of a trade bin is described in the main text. Each line represents a different quintile sort for earnings surprises. The shaded areas are pointwise 95% confidence bands around the average returns. Panel A shows the cumulative returns for all stocks with after-hours trading following earnings announcements (EA). Panel B shows the cumulative returns for stocks with more than 20 trades in the after-hours market following EA. Panel C shows the cumulative returns for stocks with less than or equal to 20 trades following EA. Panel D zooms in on the first trade bin of Panel B and shows cumulative returns over ten trade bins following EA. The dashed vertical line is the arrival of the first trade bin following the earnings announcement. The sample period is January 1, 2011 to December 31, 2015.



Panel A shows the cumulative return for the full sample of firms with after-hours trading. The figure shows a clear demarcation between the different earnings surprises quintiles at the first trade bin. I then split the sample of firms into high trade announcements (more than 20 trades following the announcement) and low trade announcements (less than or equal to 20 trades) and plot their cumulative returns in Panels B and C respectively.[34] Panel C shows longer price drift than in Panel B and the initial price adjustment to earnings surprises is also more moderate. In Panel D, I "zoom in" on the first trade bin of Panel B. I take all trades in the first trade bin for firms with more than 20 total trades in the after-hours and once more construct ten trade bins. We now also observe price drifts for large firms at higher frequency.

I now quantify the impact of earnings surprises on stock returns on each trade bin by estimating the following model:

$$r_{i,k} = \alpha + \beta_k S_{i,t} + \epsilon_{i,k}, \tag{2.4}$$

where k defines a trade bin. Similar to Figure 2.6, I show in Figure 2.7 the estimated $\hat{\beta}_k$ for the full sample in Panel A, for the high trade announcements in Panel B, for the low trade announcements in Panel C, and zoom-in on the first trade bin ($k = 1$) for high trade announcements in Panel D.

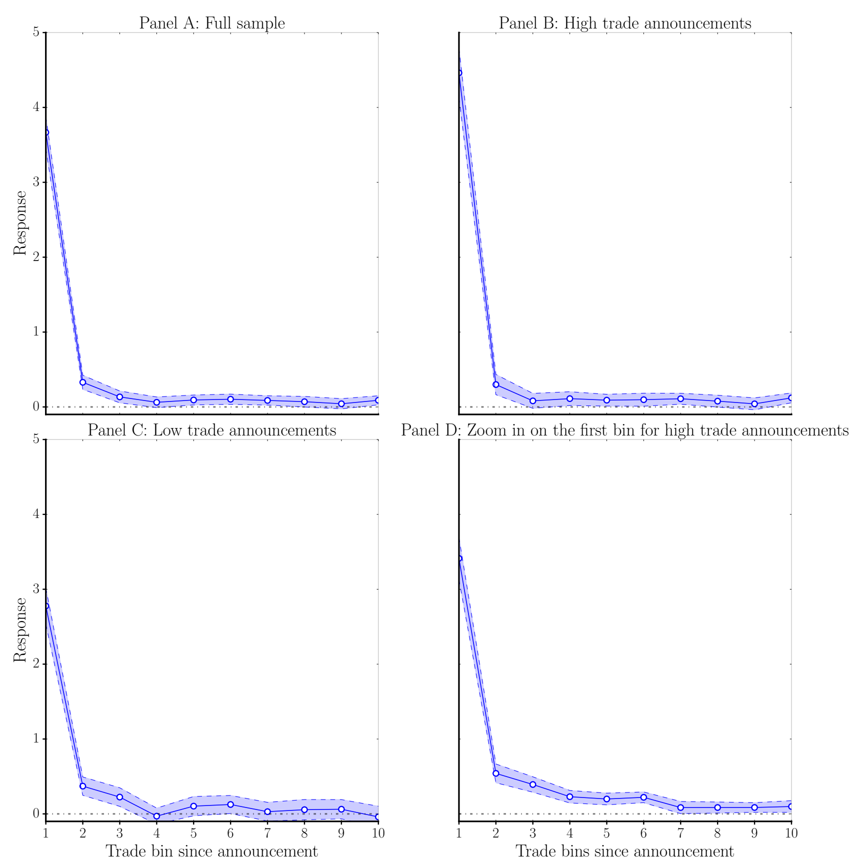
[34]The mean number of trades in the after-hours is 20, and 48 percent of firms have more than 20 trades.

Figure 2.7: The Response of Stock Returns to Earnings Surprises in the After-Hours Market

This figure shows the estimated response coefficients $\hat{\beta}_k$ of the conditional mean regression (2.4):

$$r_{i,k} = \alpha + \beta_k S_{i,t} + \epsilon_{i,k},$$

where k corresponds to trade arrival bins. The definition of a trade bin is described in the main text. The shaded areas are pointwise 95% confidence bands around the estimated coefficients. The standard errors are calculated using the Driscoll and Kraay (1998) method. Panel A shows the stock price response coefficients $\hat{\beta}_k$ for all stocks with after-hours trading following earnings announcements (EA). Panel B shows the stock price response coefficients for stocks with more than 20 trades in the after-hours market following EA. Panel C shows the stock price response coefficients for stocks with less than or equal to 20 trades following EA. Panel D zooms in on the first trade bin of Panel B and shows the stock price response coefficients over ten trade bins following EA. The sample period is January 1, 2011 to December 31, 2015.



Panel A shows that price discovery occurs over the first three trade bins. The impact of earnings surprises on returns is one of a “jump” followed by a quick decay in the remaining response of returns to earnings surprises. With an earnings surprise of 0.002, the initial jump amounts to an increase in return of 75 basis points. The initial jump represents approximately 83 percent of the total price response to earnings surprises in the after-hours market. The median completion time of the first trade bin in calendar time-units is 18 minutes. Panel B and Panel C show almost no difference in the speed of price discovery between high and low trade announcements. A reason why the speed of price discovery appears similar is because speed is measured in business-time units (e.g., arrival of trades) rather than calendar-time units, consistent with the microstructure invariance hypothesis of Kyle and Obizhaeva (2016) and with the findings of Santosh (2014). But, the speed of price discovery in calendar time is not similar between groups. Assuming that price discovery completes by the end of the third trade bin, I find that the median and mean time to completion of price discovery of earnings surprises for high (low) trade count firms is, respectively, 0.61 (1.31) and 1.84 (2.86) hours. Lastly, Panel D shows that, within the first trade arrival bin for stocks with a high trade count following announcements, we do indeed observe “slow” price discovery. Overall, the results show that a large share of price discovery for stocks with after-hours trading occurs around the arrival of the first trades.

2.4.3 How is Earnings News Transmitted to Stock Prices?

The previous results show that stock prices respond to earnings surprises almost immediately at the time of the first trades. What is not clear, however, is whether earnings surprises impact prices directly, indirectly through incoming trades (order flow), or both. French and Roll (1986) and Fleming and Remolona (1999a) argue that publicly available news may be incorporated in prices instantaneously, even without trading.

In the absence of news, it is generally assumed that asset prices primarily adjust through incoming market order flow, specifically net order imbalance. This is consistent with classic theories of intermediation (e.g., Kyle, 1985; Glosten and Milgrom, 1985). Net order imbalance is the difference between buyer-initiated and seller-initiated market orders - it is a measure of net buying pressure. Net order imbalance conveys information that liquidity providers need to aggregate into prices. If news impacts prices through order flow, then net order flow should largely explain price changes following earnings announcements and not earnings surprises.

To test whether earnings surprises (news) or order flow explain price changes following earnings announcements, I use the same methodology as Evans and Lyons (2002). These authors estimate a structural model where changes in daily foreign exchange rates are determined by public information and aggregate order imbalances. Formally, the change in log price following the arrival of news in Evans and Lyons (2002) can be stated as

$$\Delta P_t = S_t + OI_t, \tag{2.5}$$

where S_t is the surprise, OI_t is the order imbalance, and ΔP_t is the change in log price following the news over interval t. Evans and Lyons (2002, 2008) show that order imbalance, and not public macroeconomic news (e.g., changes in interest rate), is the main determinant of daily exchange rates and argue that foreign exchange dealers have limited ability to interpret the news. The model of Evans and Lyons (2002) is adaptable at high frequency and one can show whether stock prices respond primarily to news or to order flow following earnings announcements.

Similar to Evans and Lyons (2002), I study the explanatory power (R^2) of net order imbalance and earnings surprises to explain the response of stock returns following earnings announcements in the after-hours market over each trade arrival bin defined in the previous section. If the explanatory power of earnings surprises is greater than order imbalance, then prices respond primarily to news and not order flow.

I define market-initiated net order imbalance (OI) in trade bin k as:

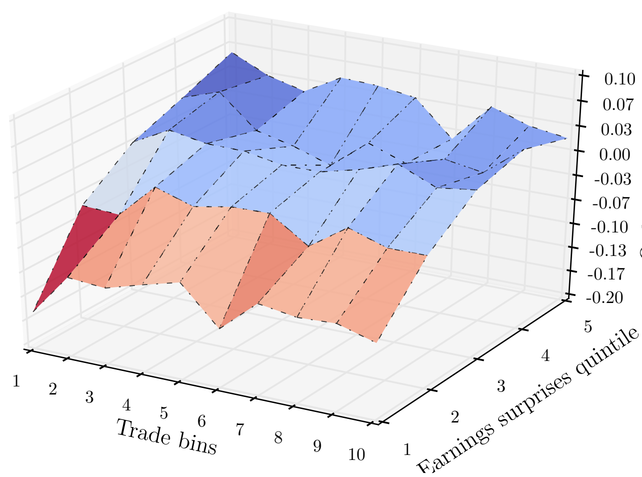
$$OI_k = \frac{B_k - S_k}{B_k + S_k}, \tag{2.6}$$

where B_k and S_k respectively correspond to trade buys and sells in shares units in trade bin k.[35] Because I observe only trades that occurs on NASDAQ, an important assumption is that at any moment in time, the OI is the same across all other trading venues. Li (2016) shows that NASDAQ has the highest fraction of trades following earnings announcements during the after hours with 44% followed by NYSE with 38%. I show in Figure 2.8 the average order imbalance across all trade bins for each earnings surprises quintile. The figure shows that negative earnings surprises lead to more selling pressure and vice versa for positive news. Also, note that the bottom earnings surprises quintile leads to greater net order imbalance (in absolute terms) than the highest earnings surprises quintile.

[35] I find quantitatively the same result in the paper using the number of buy and sell trades instead of using trade buys and sells in shares units.

Figure 2.8: Order Imbalance following Earnings Announcements in the After-Hours Market

This figure shows the average net order imbalance at each trade bin across different earnings surprises quintiles following earnings announcements for stocks with after-hours trading. The definition of a trade bin is described in the main text. Trade bin one corresponds to the first trade bin following the earnings announcement. The earnings surprises quintiles are sorted from the lowest (1) to the highest (5). The order imbalance is calculated as the difference between market-initiated buy and sell orders (in shares units) divided by the total market-initiated buys and sells orders. The sample period is January 1, 2011 to July 13, 2014.



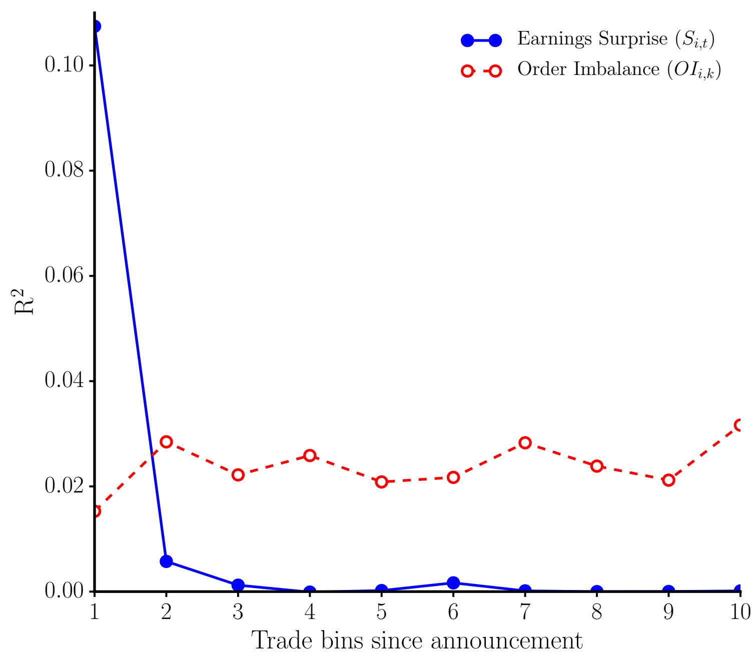
In Figure 2.9, I show the R^2 for two distinct sets of univariate regressions of stock returns on earnings surprises ($S_{i,t}$) and order imbalance (OI_k) at each trade arrival bin k following earnings announcements.[36]

The figure shows that earnings surprises explain more than ten percent of the initial stock price reaction to the arrival of news whereas order imbalance explains slightly less than two percent. After the first trade arrival bin, earnings surprises have almost no explanatory power. On the other hand, the explanatory power of order imbalance is approximately three percent.

[36] Note that the sample period ends on July 13, 2014. As previously noted, NASDAQ ITCH does not include signed trades against hidden orders from July 14, 2014.

Figure 2.9: Explanatory Power of Earnings Surprises and Order Imbalance to Stock Returns in the After-Hours Market

This figure shows the R^2 from a univariate regression of stock returns on earnings surprises (solid blue line) and stock returns on incoming net order imbalance (dotted red line) at each trade bin k following earnings announcements in the after-hours market. Net order imbalance is the difference between market-initiated buy and sell orders (in shares units) divided by the total market-initiated buy and sell orders. The x-axis units are the trade bins. The definition of a trade bin is described in the main text. The sample period is January 1, 2011 to July 13, 2014.



Because the largest share of price discovery following earnings announcements occurs at the first trade bin (approximately 80 percent) and earnings surprises explain ten percent of the initial price adjustment, we can conclude that price discovery in the after-hours market largely occurs directly from the arrival of news. Yet, order flow remains sizable for the remaining of the after-hours.

I report in Table 2.7 Panel A the results of regressions of stock returns between the earnings announcements and the opening of markets on earnings surprises and order imbalance. I also include as independent variables the log of the total number of trades ($Trd_{i,t}$), analyst dispersion ($Disp_{i,t}$), and interaction terms $S_{i,t} \times Trd_{i,k}$, $OI_{i,t} \times Trd_{i,t}$, $OI_{i,t} \times S_{i,t}$, $OI_{i,t} \times Disp_{i,t}$. Order imbalance may play a larger role if there is more trade, when the $S_{i,t}$ is negative, as depicted in Figure 2.8, or when analyst dispersion prior to earnings announcement is high (see Pasquariello and Vega, 2007). Analyst dispersion is calculated as:

$$Disp_{i,t} = \frac{\sqrt{V_{t-1}[\text{EPS}_{i,t}]}}{|E_{t-1}[\text{EPS}_{i,t}]|}, \tag{2.7}$$

where $V_{t-1}[\text{EPS}_{i,t}]$ is the variance of all the forecasts of earnings that analysts issue for company i within an interval of ninety days before the announcement. I calculate the dispersion only for companies with at least four analysts estimate prior to the earnings announcements.

Table 2.7: OLS Regression: Stock Returns on Earnings Surprises and Order Imbalance

This table reports coefficients from regressions of the log stock returns following earnings announcements in the after-hours market on earnings surprises ($S_{i,t}$) order imbalance ($OI_{i,k}$), log total number trades ($Trd_{i,k}$), and analyst dispersion ($Disp_{i,t}$). The definition of a trade bin is described in the main text. The order imbalance is calculated as the difference between market-initiated buy and sell orders (in shares units) divided by the total market-initiated buy and sell orders. Panel A shows the results for all stocks with after-hours trading over the entire after-hours period following earnings announcements. Panel B shows the results in the first trade bin ($k = 1$) and over all remaining trade bins ($k > 1$). Panel C shows the results for stocks with more than 20 trades following earnings announcements and zooms in on the first trade bin and reconstructs a new set of ten trade bins. The standard errors are clustered by date and reported in parenthesis. Asterisks denote statistical significance at the 5-percent level. The sample period is from January 1, 2011 to July, 14, 2014.

Panel A: After hours

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$S_{i,t}$	4.431*			2.518*	2.429*	2.445*	2.744*
	(0.147)			(0.254)	(0.249)	(0.249)	(0.279)
$OI_{i,t}$		0.010*	0.002*		0.002*	0.002*	0.002*
		(0.001)	(0.001)		(0.001)	(0.001)	(0.001)
$OI_{i,t} \times Trd_{i,t}$			0.005*		0.004*	0.004*	0.004*
			(0.001)		(0.001)	(0.001)	(0.001)
$S_{i,t} \times Trd_{i,t}$				0.552*	0.540*	0.537*	0.459*
				(0.088)	(0.087)	(0.087)	(0.092)
$S_{i,t} \times OI_{i,t}$						0.129	0.055
						(0.177)	(0.197)
$Disp_{i,t} \times OI_{i,t}$							0.000
							(0.003)
$Trd_{i,t}$			-0.001*	-0.002*	-0.002*	-0.002*	-0.002*
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Disp_{i,t}$							0.001
							(0.003)
Intercept	-0.005*	-0.001*	0.002*	0.000	0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Obs.	11255	11255	11255	11255	11255	11255	9555
Adj-R^2	0.10	0.01	0.03	0.11	0.12	0.12	0.12

Panel B: After hours - per trade bin

	Trade bin $k = 1$					Trade bins $k > 1$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$S_{i,t}$	3.761*	2.992*		2.922*	3.106*	0.737*	0.302		0.226	0.264
	(0.127)	(0.140)		(0.138)	(0.158)	(0.096)	(0.196)		(0.193)	(0.221)
$S_{i,t} \times Trd_{i,k}$		0.500*		0.481*	0.382*		0.119*		0.116	0.103
		(0.083)		(0.083)	(0.087)		(0.060)		(0.060)	(0.067)
$OI_{i,k}$			0.005*	0.004*	0.004*			0.002*	0.002*	0.001
			(0.000)	(0.000)	(0.001)			(0.001)	(0.001)	(0.001)
$OI_{i,k} \times Trd_{i,k}$			0.003*	0.002*	0.003*			0.003*	0.003*	0.003*
			(0.001)	(0.001)	(0.001)			(0.000)	(0.000)	(0.000)
$S_{i,t} \times OI_{i,k}$					-0.102					0.099
					(0.143)					(0.152)
$Disp_{i,t} \times OI_{i,k}$					0.002					0.001
					(0.002)					(0.003)
$Trd_{i,k}$		-0.002*	-0.001*	-0.002*	-0.002*		-0.000	-0.000	-0.000	-0.000*
		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
$Disp_{i,t}$					0.002					-0.001
					(0.002)					(0.002)
Intercept	-0.004*	-0.002*	0.001	-0.001*	-0.002*	-0.001*	-0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Obs.	11255	11255	11255	11255	9555	10040	10040	10040	10040	8570
Adj-R^2	0.11	0.12	0.02	0.13	0.13	0.01	0.01	0.03	0.03	0.03

Panel C: After hours - zoom in on the first trade bin

	Trade bin $k = 1$					Trade bins $k > 1$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$S_{i,t}$	3.448*	1.825*		1.997*	2.176*	1.278*	0.861*		0.825*	0.787*
	(0.162)	(0.551)		(0.552)	(0.599)	(0.145)	(0.190)		(0.186)	(0.208)
$S_{i,t} \times Trd_{i,k}$		0.310*		0.246*	0.220		0.157		0.140	0.104
		(0.108)		(0.109)	(0.116)		(0.088)		(0.087)	(0.097)
$OI_{i,k}$			-0.010*	-0.009*	-0.009*			0.002*	0.002*	0.001
			(0.002)	(0.002)	(0.002)			(0.001)	(0.001)	(0.001)
$OI_{i,k} \times Trd_{i,k}$			0.004*	0.003*	0.003*			0.003*	0.002*	0.002*
			(0.001)	(0.000)	(0.000)			(0.000)	(0.000)	(0.000)
$S_{i,t} \times OI_{i,k}$					0.114					-0.360*
					(0.201)					(0.174)
$Disp_{i,t} \times OI_{i,k}$					-0.003					0.007*
					(0.003)					(0.003)
$Trd_{i,k}$		-0.002*	-0.001*	-0.002*	-0.002*		-0.000	-0.000	-0.000	-0.000
		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
$Disp_{i,t}$					0.004					-0.002
					(0.003)					(0.002)
Intercept	-0.005*	0.004	0.006*	0.004	0.003	-0.003*	-0.002*	-0.001	-0.002*	-0.001
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Obs.	5480	5480	5480	5480	4832	5480	5480	5480	5480	4832
Adj-R^2	0.11	0.11	0.04	0.14	0.14	0.03	0.03	0.02	0.05	0.05

Comparing the R^2 in columns (1) and (2) shows that returns are largely explained by the news and not order flow. Column (5) shows the results with the interaction term $Trd_{i,t}$ and including order flow improves the R^2 by one percent. Columns (6) and (7) show that $OI_{i,t} \times S_{i,t}$ and $Disp_{i,t} \times OI_{i,t}$ is not different from zero and does not improve the explanatory power.

Table 2.7 Panel B reports the results of regressions of stock returns in the first trade bin and over all remaining trade bins on earnings surprises and order imbalance. In the first trade bin k, the results show that the earnings surprises largely explain returns and not order flow. I repeat the same analysis in Panel C but zoom in on the first trade bin for a sub-sample of stocks with more than 20 trades following earnings announcements and I reconstruct a new set of ten trade bins. R^2 results show that returns are driven largely by earnings surprises with an R^2 of 11% but including order flow and its interaction improve the R^2 to 14%. It seems that when there is little trading, order flow carries more information, yet earnings surprises matter more. If I extend the analysis during regular market hours for stocks with no after-hours trading, I find that order imbalance does not have any explanatory power to explain stock returns between 9:30 and 10 a.m.

The overall results suggest that prices respond directly to public information. This indicates that liquidity providers are sophisticated at processing news and largely responsible for price adjustment in response to news through limit order quote updates. This result supports the recent findings of Brogaard, Hendershott, and Riordan (2015) and Chordia, Green, and Kottimukkalur (2016), who show that price discovery largely comes from quote adjustments.

2.5 The Impact of Earnings Surprises on Volatility, Liquidity, and Trade Volume

For a more comprehensive understanding of price formation following earnings surprises, one must go beyond the study of the impact of surprises on conditional mean changes in prices. For instance, volatility in prices is equivalent to information flow in a large class of models (e.g., Ross, 1989). Several empirical papers (see e.g., Ederington and Lee, 1993; Jones, Lamont, and Lumsdaine, 1998a; Andersen, Bollerslev, Diebold, and Vega, 2003a) study the response of abnormal volatility in bond and foreign exchange prices following macroeconomic news and associate the response to price discovery.[37]

[37] Beaver (1968) argues that price changes in response to earnings news reflect changes in expectations of the market as a whole while an increase in trade volume reflects changes in

In this section, I examine how the magnitude of earnings surprises impact at high frequency the dynamics of abnormal stock price volatilities, abnormal trade volumes, and abnormal bid-ask spreads on three days around earnings announcements during regular market hours. Microstructure theory suggests that changes in trade volume and bid-ask spreads are related to price volatility and also reflect the arrival of information.

How is the magnitude in earnings surprises expected to impact volatility, trade volume, and bid-ask spreads? Stocks with large earnings surprises (i.e. large forecast error) is explained, in part, to poor information quality (e.g., Kasznik and Lev, 1995; Lang and Lundholm, 1996) surrounding these stocks. Consequently, stocks with poor information quality force investors to acquire diverse information to better interpret the news. The poorer the information quality surrounding the stock, the more diverse is information about the expectation of the news among investors. Kim and Verrecchia (1991, 1994) argue that trade volume following earnings announcements increases in the level of asymmetry among investors prior to the announcement. Moreover, at the announcement, large surprises may also lead to larger dispersion in the interpretation of the news among investors. Theory predicts that trade volume also increases in the level of disagreement in the interpretation of the news (Kandel and Pearson, 1995; Banerjee and Kremer, 2010). Kim and Verrecchia (1994) further advance that higher information asymmetry at the announcement increases trading opportunities for informed traders, which leads to an increase in bid-ask spreads. When trade volume increases, volatility also increases (Kim and Verrecchia, 1994; Banerjee and Kremer, 2010).

I do not limit my analysis solely following earnings announcements but also on trading days prior to announcements. Doing so provides an indication of whether markets anticipate the magnitude of earnings surprises similar to the "calm-before-storm" effect before anticipated news as documented in Jones, Lamont, and Lumsdaine (1998a) and Akbas (2016).

To measure abnormal intraday volatility, I estimate the following model for each stock i separately:

$$r_\tau = \alpha + \rho r_{\tau-1} + \gamma r_\tau^m + \beta_\tau S_t \cdot 1_{\{\tau \in t\}} + \epsilon_\tau, \tag{2.8}$$

where τ corresponds to a five-minute interval between 9:30 a.m. and 4 p.m.,

the expectations of individual investors. Earnings news may be neutral and not change the expectations of the market as a whole but greatly alter the expectations of individuals. In this case, we would observe no price change but there would be shifts in portfolio positions reflected in trade volume and price volatility.

r_τ is the log five-minute returns using midquotes, r_τ^m is the market return proxied by the SPY ETF, and S_t is the earnings surprise release on date t in the after-hours market. The indicator variable $1_{\{\tau \in t\}}$ takes the value one if the five-minute interval τ belongs to the earnings announcement day t. I define the idiosyncratic volatility for stock i as $|\hat{\epsilon}_\tau|$. There are in total 78 five-minute intervals in a trading day t. I pool all 40 trading days prior to an earnings announcement and the day of the announcement to estimate Equation (2.8) for each stock i separately.

Following the estimation of Equation 2.8, I sum the estimated $|\hat{\epsilon}_\tau|$ at each 30-minute interval, for a total of 13 $|\hat{\epsilon}_{\tilde{\tau}}|$, which corresponds to a 30-minute intraday volatility estimate for interval $\tilde{\tau}$ on date t.

I measure liquidity using the quoted bid-ask spread measure. For each stock i, I have the best bid and ask prices at every second interval s during regular market hours. I define the one-second quoted spread as

$$QS_{i,s,t} = \frac{Ask_{i,s,t} - Bid_{i,s,t}}{P_{i,s,t}}, \tag{2.9}$$

where $P_{i,s,t}$ is the midquote, $(Ask_{i,s,t} + Bid_{i,s,t})/2$, at the one second interval s on date t. I then average the $QS_{i,s,t}$ over a 30-minute interval to get a time-weighted quoted spread measure denoted $QS_{i,\tilde{\tau},t}$.

I calculate trade volume using the measure of turnover. Denote $V_{i,\tilde{\tau},t}$ as the total number of shares traded in a 30-minute interval $\tilde{\tau}$ for stock i on date t. I define trade turnover as

$$Turn_{i,\tilde{\tau},t} = \frac{V_{i,\tilde{\tau},t}}{Out_{i,t}}, \tag{2.10}$$

where $Out_{i,t}$ is the current shares outstanding. I further scale $Turn_{i,\tilde{\tau},t}$ by its standard deviation in the trading window (-40, -11) preceding an earnings announcement for that year. I scale by the standard deviation to control for changes in normal, non-announcement period turnover across time.

In Figure 2.10 I show the average intraday volatility, quoted spreads, and turnover 40 to 11 trading days prior to earnings announcements per earnings surprises quintile. Even if we exclude two weeks (in trading days) prior to the earnings announcement, we observe that stocks with upcoming large surprises have higher volatility and quoted spreads and lower turnover. If we compare stocks with large surprises (top or bottom quintiles) and stocks with no surprises (quintile 2) at 12 p.m., volatility is greater for stocks with large surprises by 23%. Quoted spreads are wider by 25% and turnover is 7% lower for stocks with large surprises than for stocks with no surprises.

Empirical evidence from the accounting literature suggests that stocks with upcoming large forecast errors are stocks with poor information quality, e.g., less analyst coverage and less information disclosure coming from the firm (see e.g., Kasznik and Lev, 1995; Lang and Lundholm, 1996). Stocks with poor information quality imply higher information asymmetry that leads to wider bid-ask spread (Chae, 2005) and to higher information uncertainty that leads to higher stock price volatility (Zhang, 2006).

To estimate the impact of earnings surprises on abnormal volatility, I estimate the following model:

$$|\hat{\epsilon}_{i,\tilde{\tau}}| - |\bar{\epsilon}_{i,\tilde{\tau}}| = a + b_{\tilde{\tau}}|S_{i,t}| + c\frac{\sigma_{d(t)}}{\sqrt{13}} + e_{i,\tilde{\tau}}, \tag{2.11}$$

where $|\hat{\epsilon}_{i,\tilde{\tau}}|$-$|\bar{\epsilon}_{i,\tilde{\tau}}|$ is the volatility for stock i for interval $\tilde{\tau}$ minus the average volatility in the 40 to 11 trading days prior to earnings announcements for the same interval $\tilde{\tau}$. $\sigma_{d(t)}$ is the daily volatility of the market, which is the one-day-ahead volatility forecast for day $d(t)$ from a simple daily conditionally Gaussian GARCH (1, 1) using the broad stock market index from Kenneth French's website. I estimate Equation (2.11) on three trading days around the earnings announcement. In total, I estimate 39 $\hat{b}_{\tilde{\tau}}$ (13 per trading day).

In Figure 2.11, Panel A, I plot the estimated $\hat{b}_{\tilde{\tau}}$.

Figure 2.10: Average Volatility, Quoted Spread, and Turnover prior to Earnings Announcements

This figure shows the average 30-minute volatility, quoted spread, and turnover in the 40 to 11 trading days prior to earnings announcements during regular market hours for each absolute earnings surprises quintile. Volatility is the sum of the five-minute absolute value of the residuals in Equation (2.8) estimated for each stock i seperately:

$$r_\tau = \alpha + \rho r_{\tau-1} + \gamma r_\tau^m + \beta_\tau S_t \cdot 1_{\{\tau \in t\}} + \epsilon_\tau,$$

over a 30-minute interval. Quoted spread is the average of the time-weighted one-second quoted spread defined as bid-ask spread divided by the midquote in a 30-minute interval. Turnover is the sum of total shares traded in a 30-minute interval divided by the number of shares outstanding and scaled by the standard deviation of that year. The sample period is January 1, 2011 to December 31, 2015.

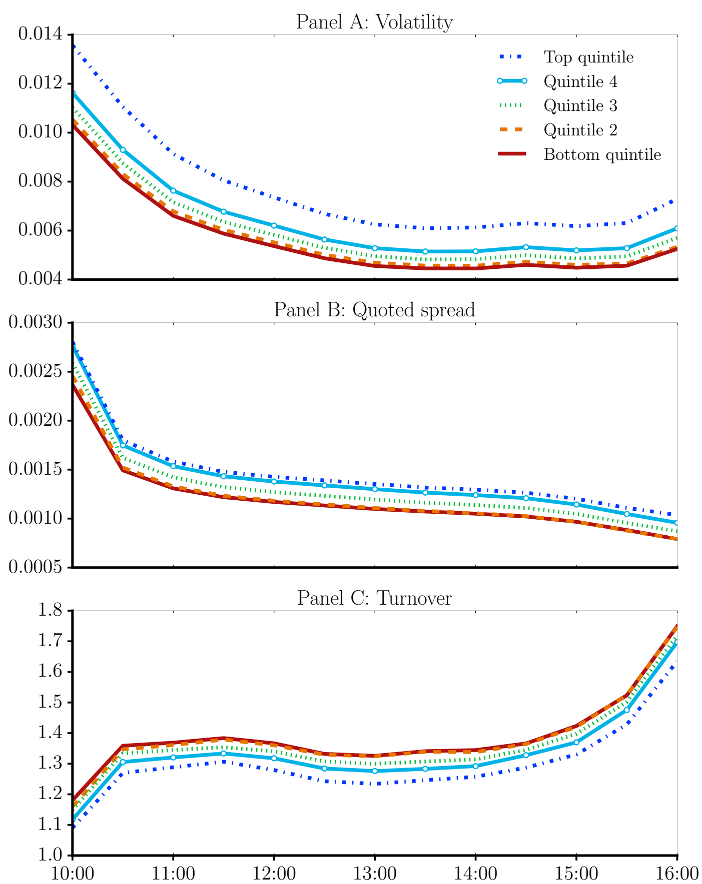


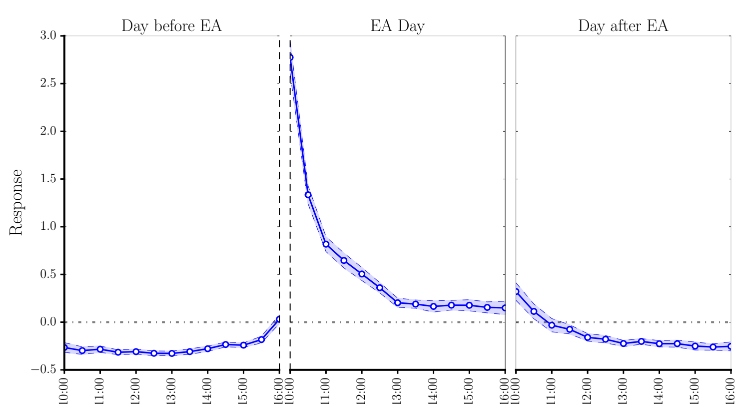
Figure 2.11: The Response of Abnormal Volatility, Abnormal Quoted Spread, and Abnormal Turnover to Earnings Surprises around Earnings Announcements

This figure shows the estimated coefficient responses of abnormal volatility, abnormal quoted spread, and abnormal turnover to absolute earnings surprises around earnings announcements at each 30-minute interval during regular trading hours. The regression specifications are described in the main text. The left pane shows the day before the earnings announcement (EA), the middle pane is the EA day, and the right pane is the day after the EA. The EA occurs in the after-hours market (between 4 p.m. and 9:30 a.m.) indicated by the straight dashed vertical lines. Volatility is the sum of the five-minute absolute value of the residuals in Equation (2.8) estimated for each stock i seperately:

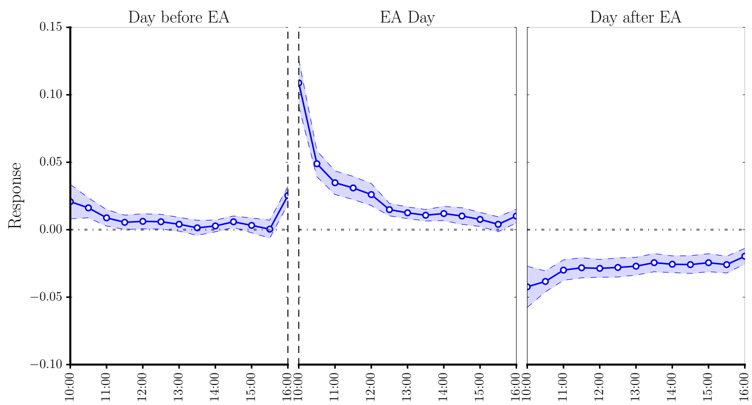
$$r_\tau = \alpha + \rho r_{\tau-1} + \gamma r_\tau^m + \beta_\tau S_t \cdot 1_{\{\tau \in t\}} + \epsilon_\tau,$$

over a 30-minute interval. Quoted spread is the average of the time-weighted one-second quoted spread defined as bid-ask spread divided by the midquote in a 30-minute interval. Turnover is the sum of total shares traded in a 30-minute interval divided by the number of shares outstanding and scaled by the standard deviation of that year. The shaded areas are pointwise 95% confidence bands around the estimated coefficients. The standard errors are calculated using the Driscoll and Kraay (1998) method.

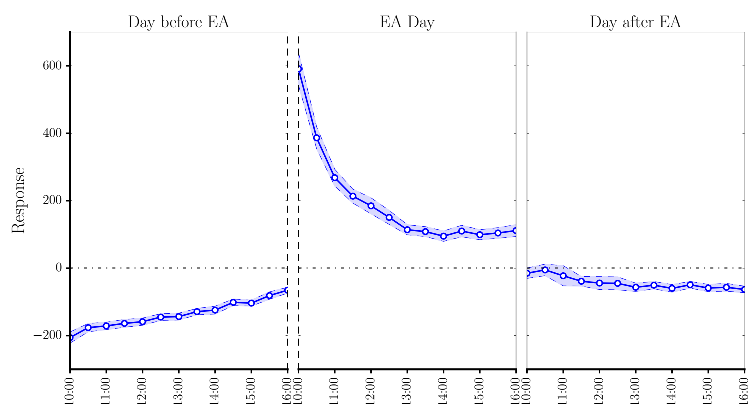
Panel A: Abnormal volatility response to earnings surprises



Panel B: Abnormal quoted spread response to earnings surprises



Panel C: Abnormal turnover response to earnings surprises



The vertical dashed lines correspond to the after-hours trading session with the earnings announcement. On the day before earnings announcements, stocks with an absolute earnings surprise of 0.003 (approximately the inter-quartile range in absolute earnings surprises) lead to a 0.075 percent decrease in abnormal volatility at the opening of markets until 2 p.m. This magnitude represents an approximate 15 percent decrease in volatility around 1 p.m. relative to the average volatility in the benchmark window

(-40, -11). On the day of the announcement, for the same magnitude of absolute earnings surprises, abnormal volatility jumps by 0.9 percent at the opening of markets followed by a gradual decay. This increase in volatility represents an approximate 82 percent increase in stock price volatility at the opening of markets relative to the benchmark window. On the following trading day, the estimated $\hat{b}_{\tilde{\tau}}$ are in general negative. This suggests that stocks with higher volatility prior to earnings announcements have their volatilities move closer to the group of stocks with smaller earnings surprises prior to earnings announcements.

I next examine the impact of earnings surprises on bid-ask spreads. I estimate Equation (2.11) with $QS_{i,\tilde{\tau}} - \overline{QS}_{i,\tilde{\tau}}$ as the dependent variable, where $\overline{QS}_{i,\tilde{\tau}}$ is the average quoted spread 40 to 11 trading days prior to earnings announcements. I plot in Panel B the estimated $\hat{b}_{\tilde{\tau}}$. I find that liquidity providers widen spreads in anticipation of large earnings surprises of approximately three percent at the opening of markets. The economic magnitude is small but as shown in Figure 2.10, stocks with large upcoming surprises already have wider bid-ask spreads many days before the announcement. On the day of the announcement, quoted spreads widen by 12 percent at the opening of markets relative to the benchmark window and the impact of earnings surprises on quoted spreads gradually decays. I show in Figure A.3 the comparison in the dynamics for stocks with and without after-hours trading. The change in dynamics for quoted spreads is largely driven by stocks with no after-hours trading.

Finally, I examine the impact of earnings surprises on trade volume. I estimate Equation (2.11) with $Turn_{i,\tilde{\tau}} - \overline{Turn}_{i,\tilde{\tau}}$ as the dependent variable, where $\overline{Turn}_{i,\tilde{\tau}}$ is the average turnover 40 to 11 trading days prior to earnings announcements. I also control for turnover in the SPY ETF to proxy for market trade volume rather than market volatility. I plot in Panel C the estimated $\hat{b}_{\tilde{\tau}}$. The impact of earnings surprises on the day prior to earnings announcements is economically large. At the opening of markets, for an absolute earnings surprise of 0.003, turnover is lower by 52 percent relative to the average turnover in the benchmark window (-41, -11). On the day of the announcement, turnover increases by 158 percent relative to the average turnover in the benchmark window. The impact of earnings surprises on turnover gradually decays on the day of the announcement.

Overall, the dynamics in volatility, bid-ask spread, and turnover leading to earnings announcements indicate that markets anticipate the magnitude of earnings surprises. The response of volatility, bid-ask spreads, and turnover to absolute earnings surprises on the earnings announcement day is more gradual than the impact of earnings surprises on the conditional mean adjustment of prices. The model of Banerjee and Kremer (2010) provides insights to this finding. In their model, the level of trade volume and volatility gradually decays following a jump because of disagreement among investors on the interpretation of public information. The decay reflects convergence in beliefs among investors on the valuation of the asset. As beliefs converges volume and volatility decreases. On the other hand, asset prices reflect the average valuation among investors and the average may not change while beliefs on the valuation among investors still differ. Yet an interesting question remain. Why is the impact of earnings news volatilities, volumes, and spreads longer-lived than its impact on prices?

2.6 Hidden Liquidity around Earnings Announcements

The last objective of this paper is to shed light on an interesting fact about liquidity following earnings announcements in the after-hours market. I find that 41 percent of the trade volume involves hidden orders following earnings announcements in the after-hours market versus only 12 percent during regular market hours and 25 percent during after hours when there is no earnings announcements. But, the acceptance of hidden orders by the SEC is still an on-going debate because hidden orders make markets less transparent (Shapiro, 2010).

What is the rational for liquidity providers to choose hidden liquidity? Harris (1996) and Bessembinder, Panayides, and Venkataraman (2009) argue that hidden orders are effective for mitigating adverse selection. On the other hand, Bloomfield, O'Hara, and Saar (2015) show in a lab experiment that informed traders may prefer hidden orders so as to not reveal how much they are willing to buy or sell and earn higher profits. Recent theoretical works suggest that hidden orders lead to deeper limit order books (Moinas, 2011), intensify competition among informed traders, and improve market efficiency (Boulatov and George, 2013). Assuming that liquidity providers that opt for hidden orders are indeed informed traders on the true fundamental price of the stock following earnings announcements, abolishing hidden orders may deter the willingness of informed liquidity providers to participate and consequently deteriorate the speed of price discovery.[38]

[38]When a trade occurs against a hidden order, market participants do learn that a trade got executed against a hidden order. For example, on NASDAQ, market participants see the message order P when a trade gets executed against a hidden order. But, starting

I now investigate the profitability of hidden orders versus displayed limit orders from the perspective of liquidity providers following earnings announcements. If, on average, the profitability associated with hidden orders is not any different from displayed orders, then abolishing hidden orders may not impact the price discovery process following earnings announcements. On the other hand, if hidden orders are associated with higher profitability, then abolishing hidden orders may deter the willingness of traders to provide liquidity and, in turn, deter price discovery.

To measure the profitability of liquidity providers, I calculate for each observed trade j across all stocks with after-hours trading following an earnings announcement the realized spread measure, $rs_{i,j}$, defined as

$$rs_{i,j} = \begin{cases} \frac{m_{i,j}-p_{i,t}}{m_{i,t-1}} * 100, & \text{if trade } j \text{ was a passive buy} \\ \frac{p_{i,t}-m_{i,j}}{m_{i,t-1}} * 100, & \text{if trade } j \text{ was a passive sell,} \end{cases} \tag{2.12}$$

where $m_{i,t}$ is the crossing price at the opening of markets if there was an auction or the midquote in the order book at 9:30 a.m if there was not. $m_{i,t-1}$ is the closing crossing price prior to the announcement if there was an auction or the midquote in the order book at 4 p.m. if there was not. [39] I also winsorized the realized spreads at the 1st and 99th percentiles. I calculate the realized spread for displayed and hidden orders separately.

To examine the profitability of liquidity provision, I estimate the following OLS regression:

$$rs^{o}_{i,k,t} = \beta_1 Displayed_{i,k,t} + \beta_2 Hidden_{i,k,t} + \epsilon_{i,k,t}. \tag{2.13}$$

$rs^{o}_{i,k,t}$ corresponds to the average realized spread across all orders of type o for stock i on earnings announcements of date t in trade bin k.[40] Order type o is either displayed or hidden orders. $Hidden_{i,k,t}$ is a dummy variable equal to one if the order type o represents hidden orders and zero otherwise.

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from July 14, 2014 market participant cannot infer from the message order P whether the trade was an initiated market buy or sell order.

[39]In the microstructure literature, calculation of the realized spread involves use of a midquote taken a few seconds or minutes after the trade but, as previously argued, one cannot use midquotes in the after-hours market. Choosing the opening price is therefore not common but remains the best choice for a wide cross-sectional analysis of realized spread in the after-hours market.

[40]An alternative regression is a cross-section regression across all trades at different trade arrival bins. The inconvenience of this regression is that it gives more weight to earnings announcement events with a large number of trades.

Similarly, $Displayed_{i,k,t}$ is a dummy variable equal to one if order type o represents a displayed orders and zero otherwise.

Table 2.8 Panel A shows the estimated coefficients estimate at different trade bins for earnings announcements with more than 20 trades and less than or equal to 20 trades.

Table 2.8: OLS Regression: Realized Spreads on Displayed and Hidden Limit Orders

This table reports coefficients from regressions of realized spreads on a dummy variable $Hidden_{i,k,t}$ equal to one if the realized spread is for hidden orders and zero otherwise, and a dummy variable $Displayed_{i,k,t}$ equal to one if the realized spread is for displayed orders and zero otherwise. The realized spread is the average realized spread for each order type (hidden or displayed) by earnings announcement dates and at each trade bin k for each stock. The definition of a trade bin is described in the main text. The regression is estimated for the first trade bin, for the second to the fifth trade bins, and for the sixth to the tenth trade bins. High (low) trade announcements correspond to earnings announcements with more than (less or equal to) 20 trades in the after-hours market. The standard errors are clustered by date and reported in parentheses. Asterisks denote statistical significance at the 5-percent level. The sample period is January 1, 2011 to July 13, 2014.

	High trade announcements			Low trade announcements		
	$k = 1$	$2 \leq k < 5$	$k \geq 5$	$k = 1$	$2 \leq k < 5$	$k \geq 5$
$Hidden_{i,k,t}$	0.23*	0.16*	0.08*	0.18*	0.24*	0.19*
	(0.04)	(0.02)	(0.02)	(0.09)	(0.06)	(0.05)
$Displayed_{i,k,t}$	-0.07	-0.06*	-0.01	0.06	0.01	-0.01
	(0.04)	(0.02)	(0.02)	(0.06)	(0.04)	(0.04)
Obs.	13100	39826	80327	6262	13083	14578
% displayed orders	66	66	66	74	71	70
% hidden orders	34	34	34	26	29	30

The results show that realized spreads for displayed orders are not statistically different from zero at the five percent level, except in the second column for high trade firms where displayed orders earn a negative profit. On the other hand, realized spreads for hidden orders are all statistically different from zero at the five percent level and much larger than displayed orders. On average, the profit for a hidden order on a $50 stock is about 7.5 cents for high trade announcements and 10 cents for low trade announcements across all trade bins.

The positive profitability associated with hidden orders can be explained, in part, by the fact that adverse selection risk for displayed orders is high and hidden orders effectively mitigate this risk or that liquidity providers are at an informational advantage on future price drift following the news. Only future research with actual data on hidden order placement can advance our knowledge as to why hidden orders are profitable. But, this result is important to policy makers that wish to abolish hidden orders to increase market transparency; it may harm price discovery following earnings announcements because some liquidity providers may only want to provide hidden liquidity.

2.7 Conclusion to Chapter 2

This paper investigates how earnings surprises are incorporated into stock prices for the largest 1,500 U.S. stocks between 2011 and 2015. This occurs due to a two-stage adjustment process. First, prices adjust sharply and directly to earnings surprises upon arrival of the first trades and more than 80 percent of the share of after-hours price discovery occurring precisely at this moment. Earnings surprises and not order flow largely explain this initial price adjustment. Second, after the initial adjustment, order flow imbalances explain the remaining price adjustment in the after-hours market. I find significant price discovery remaining at the opening of markets for stocks with no after-hours trading following earnings announcements. Around 10 a.m. following the opening of markets, earnings surprises have no explanatory power to explain stock returns.

I also find low abnormal volatility, low abnormal trade volume, and high abnormal quoted spread on the day prior to earnings announcements with large earnings surprises. This implies that markets anticipate the magnitude of earnings surprises. The positive impact of large earnings surprises on the adjustment process of price volatility, quoted spread, and trade volume following earnings announcements is more gradual and persistent than the impact of earnings surprises on prices.

Last, I show that hidden orders are widely used following earnings announcements and are more profitable than displayed orders for liquidity providers. Hidden liquidity decreases market transparency but may, in fact, improve market efficiency following the arrival of news because liquidity providers may be more inclined to supply liquidity with the use of hidden orders.

The findings of this paper shed light on existing theories on the role of order flow and liquidity provision on price discovery but also propose new avenues for future theoretical work. For instance, why is there an after-hours market? What are the economic determinants that explains why some investors trade in the after-hours market? Clearly, there is some heterogeneity among market participants, with some choosing to sit out of the active period of price formation when corporate announcements are made outside of regular trading hours, and some staying or becoming active.

Chapter 3

Shaping Expectations and Coordinating Attention: The Consequence of FOMC Press Conferences

3.1 Introduction

The Federal Open Market Committee (FOMC), the monetary policy-making body of the U.S. Federal Reserve System (Fed), meets regularly to discuss the state of the economy and set monetary policy. Because asset prices react strongly to news about macroeconomic conditions, great care is given not just to the decisions made, but also to how they are communicated to financial markets after the meetings.[41] While it was left to market participants to infer decisions from the Fed's open market operations prior to 1994, policy decisions are now announced in a press statement. In an effort to "provide additional transparency and accountability" (Bernanke, 2011), since April 2011 the FOMC publishes economic projection materials and the Chair of the Board of Governors holds a press conference (PC) following half of the announcements.Importantly, the decision to hold a PC does not depend on macroeconomic conditions, as the schedule for both announcements and PCs is released at least six months in advance.

In this paper, we study the economic consequences of having press con-

[41] A large literature documenting the response of asset prices to macroeconomic news for various asset classes includes Jones, Lamont, and Lumsdaine (1998b); Fleming and Remolona (1999b); Balduzzi, Elton, and Green (2001b); Andersen, Bollerslev, Diebold, and Vega (2003b, 2007b); Green (2004); **?**, and Hu, Pan, and Wang (2015b). Cook and Hahn (1989); Kuttner (2001); Bernanke and Kuttner (2005); Ozdagli and Weber (2015), and Bjornland and Leitemo (2009) focus their analysis on FOMC announcements. More broadly, Savor and Wilson (2013a) and Lucca and Moench (2015a) find that investors demand a large premium for macroeconomic risks, and Savor and Wilson (2014) show that this premium has important implications for asset pricing.

ferences following only some meetings. It is conceivable that the committee defers important decisions for meetings when it has the opportunity to provide explanations and context in a PC. The introduction of press conferences could therefore lead to two classes of FOMC announcements, with important announcements on days with PCs and lesser ones on days without. Such a separation would reduce the frequency at which news about the economy and monetary policy is released to financial markets, and seriously question whether PCs increase transparency.

In its official position, the Fed insists that all meetings and announcements, irrespective of press conferences, are equally important. For example, when asked if it is good *"that the market expects big news to come when you have a press conference and no news to come when you don't have one,"* Chairwoman Yellen replied that she *"would really like to strongly discourage the expectation that policy moves can only occur when there's a scheduled press conference"* (Yellen, 2014). In a similar exchange nine months later, Chairwoman Yellen insists that *"every meeting is a live meeting where the Committee can make a decision to move to change our target for the federal funds rate"* (Yellen, 2015b).

However, there is also reason to believe that PCs influence the timing of important policy decisions. For example, in June 2015 Chairwoman Yellen suggested a first interest rate raise in *"September [2015] or December [2015] or March [2016]"* (Yellen, 2015a), three FOMC meetings with scheduled press conferences. The committee would also meet in July 2015, October 2015, and January 2016, each without press conference following the announcement of their decisions. When looking at actual policy decisions, we document that only two out of eight important monetary policy announcements during our sample period were made on days without PCs, which comprise nearly half of all announcement days. Moreover, just after our sample ends, the first interest rate increase following the financial crisis was announced in December 2015, a day with PC.

Of course, it is difficult to objectively quantify the gravity of the Fed's decisions, and the small number of important policy changes prohibits a detailed statistical analysis. We therefore instead focus our analysis on the beliefs and behavior of market participants and rely on financial markets to gauge the expectations of significant monetary policy decisions. Using evidence spanning multiple asset classes, we document striking differences in both markets' expectations of and reactions to FOMC announcements with and without PCs. We first show that average returns of the S&P 500 in the 30 minutes after the FOMC announcement are large and positive on days with PCs, averaging 0.29%. This estimate is statistically significant and robust to outliers and bootstrapped small-sample statistics. In contrast, announcement returns are on average negative on days without PCs. The difference in announcement returns between PC and non-PC days is large and significant at 0.57%, and remains robust to controlling for inflation and changes to the unemployment rate, the two variables the FOMC is mandated to manage, as well as growth of gross domestic product (GDP) and past market returns.

We argue that this ex-post reaction to FOMC announcements can be used to proxy for the ex-ante market expectation of the Fed's decisions. The reasoning relies on the observation that throughout our sample similar information was revealed at both types of announcements. In particular, the Federal funds target rate, one of the main drivers of equity prices in FOMC announcements, remained unchanged at 0 to 0.25%. Since 2011, the FOMC has therefore repeatedly surprised markets positively, with the magnitude of the surprise directly proportional to ex-ante expectations of target rate increases.[42] The large market returns following announcements with PCs then correspond to large ex-ante market expectations of rate increases.

Two aspects about our analysis are important to emphasize. First, we analyze announcement returns conditional on press conferences taking place, but the returns we study do not include information revealed during the press conferences. Second, these findings are about the market reaction to FOMC announcements. They are not returns in anticipation of announcements, as in Lucca and Moench (2015a), nor do they necessarily present profitable trading opportunities. Interestingly, in our more recent sample we confirm a pre-FOMC announcement return of similar magnitude as Lucca and Moench (2015a), but only on days with PCs. In contrast, if there is no press conference, average market returns leading up to the announcement are zero.

Stock price reactions to FOMC announcements are only an indirect measure of ex-ante expectations of changes to monetary policy. To overcome this limitation, we directly measure expectations of target rate changes implied by Federal Fund Futures. On days with PCs, the probability of a rate change is on average 2.8 percentage points, or a staggering 76%, higher than on days without. The differential market assessments about probabilities of

[42] Target rate announcements are of first-order importance for equity prices (Kuttner, 2001). For example, Bernanke and Kuttner (2005) and Ozdagli and Weber (2015) estimate that a surprise decrease in the Federal funds rate of 0.25% increases stock prices by 1%, whereas the analysis in Bjornland and Leitemo (2009) suggests an even bigger impact. Gürkaynak, Sack, and Swanson (2005) confirm that rate announcements are important, but argue that the future path of policy also plays a role.

interest rate changes are not limited to the nearest FOMC announcement; rather, they persist for at least three years into the future. This confirms that markets expect more important decisions on days with press conferences.

We next investigate the effects of press conferences for monetary policy. In particular, we ask if, consistent with market expectations, the Fed makes more important announcements on days with PCs. To answer this question, we use the option-implied volatility of the S&P 500, as measured by the VIX index, to proxy for uncertainty associated with monetary policy. Consistent with findings in Beber and Brandt (2009), Savor and Wilson (2013a), and Amengual and Xiu (2015), the VIX drops sharply by 2% on average at FOMC announcements, suggesting that the Fed provides valuable information to reduce uncertainty about the economy or monetary policy. Investigating the impact of press conferences, we find that all of this decline comes on days when a PC is scheduled, where the VIX drops by over 4%. In contrast, on days without PCs, the VIX remains virtually unchanged after the announcement, and monetary policy uncertainty is not reduced.

Taken together, our findings suggest that expectations of relevant changes to monetary policy are lower on FOMC announcement days without PCs, and that the FOMC reveals less price-relevant information to markets on those days. In other words, the introduction of PCs separated FOMC announcements into important and lesser ones.

A possible concern regarding these conclusions is that really the upcoming release of the economic projection materials (EPMs), and not the scheduled PCs, are responsible for the heightened market expectations. Although the individual effects are difficult to disentangle as both events always occur on the same days, we employ a change in the timing of the release of the EPMs to show that they generally contain little information and are therefore unable to explain our findings. Crucially, even if the specific channel that separates FOMC announcements was the release of EPMs, our main findings and conclusion would not be affected. The question would then become why EPMs are not released at all meetings.

What economic channels link press conferences with market expectations and monetary policy decisions? Of course, if the Fed intended to make important monetary policy announcements only on days with PCs, and if markets understand this despite the Fed's denial, we would expect to observe both more important announcements and high market expectations on days with PCs. However, we argue that it is also possible that lowered market expectations on days without PCs impose constraints on the Fed through two related, but distinct, channels. First, if markets do not expect significant policy decisions, any announcement of such would therefore be a surprise. However, the Fed is frequently believed to be averse to surprising markets.[43] Market expectations can therefore become self-fulfilling, and this tension also increases the Fed's incentives for the kind of informal communication studied in Cieslak, Morse, and Vissing-Jorgensen (2015a).

Second, if investors now believe some meetings to be more important than others, it would be natural that they allocate more of their limited attention to these meetings.[44] But it has long been recognized that investor attention and market expectations are critical to the transmission of monetary policy (Stein, 1989; Blinder, Goodhart, Hildebrand, Lipton, and Wyplosz, 2001), and that therefore "monetary policy is more effective if it is more effective in coordinating market expectations" (Amato, Morris, and Shin, 2002, p.496).[45] Clearly, if investors pay less attention to its communication, the Fed cannot effectively coordinate market expectations and might find it optimal to delay important announcements.

We confirm that PCs indeed influence investors' allocation of attention to FOMC announcements. In particular, we show that media coverage of and interest in the FOMC is significantly higher prior to announcements with PCs than those without. The effect is large and holds both for measures typically associated with attention of institutional and retail investors. To capture attention of institutional investors, we follow Ben-Rephael, Da, and Israelsen (2016) and use Bloomberg articles and intraday newswires. Simply allowing conditional means to vary between PC and non-PC events explains

[43] For example, Stein and Sunderam (2015) model a central bank that is averse to bond-market volatility. See also Cieslak, Morse, and Vissing-Jorgensen (2015a) for a detailed discussion. In the press, a survey by the Wall Street Journal "underscores just how much work it would take for the Fed to create expectations of a rate increase at a meeting without a news conference" (Zumbrun, 2015).

[44] Press conferences can therefore serve as a coordination device when investors have limited capacity for processing information (Sims, 2003). Duffie and Sun (1990), Abel, Eberly, and Panageas (2007, 2013), and Huang and Liu (2007) show that investors optimally remain inattentive to some information if they face information acquisition costs. Similarly, in Kacperczyk, van Nieuwerburgh, and Veldkamp (2016), investors allocate scarce attention between different kinds of information and optimally focus on information about more uncertain outcomes, i.e., information that has the largest impact on prices. In both types of models, with indistinguishable FOMC announcements investors will pay equal attention to each. However, PCs designate some events to be more important than others, and they coordinate investors to pay more attention to FOMC announcements with PCs.

[45] Highlighting this importance further, Blinder (1998, p.70) states: "central banks generally control only the overnight interest rate, an interest rate that is relevant to virtually no economically interesting transactions. Monetary policy has important macroeconomic effects only to the extent that it moves financial market prices that really matter – like long-term interest rates, stock market values and exchange rates."

up to 39% of the variation in these media attention measures. Building on Fang and Peress (2009a) and Da, Engelberg, and Gao (2011a), our proxies for retail investor attention are lower-frequency measures based on articles in the print editions of major newspapers, and a broader attention measure based on Google search volume in the week prior to FOMC announcements. Just like institutional investors, retail investors also focus their attention around FOMC announcement days with press conferences. We find a similar pattern for the Bank of Canada and the Reserve Bank of New Zealand, the two other central banks that follow communication policies similar to the one of the FOMC.

The elevated investor attention leading up to FOMC announcements with press conferences could reflect an increased interest to the announcement, or novel attention paid to the actual press conference. To answer this question, we show that PCs convey little new information to markets. While the realized volatility of equities during the PC is elevated, it is not significantly higher than during the corresponding time interval following FOMC announcements without PC. Further, virtually no changes in option implied volatility indicate that PCs do not reduce uncertainty.[46] Given this evidence, it seems unlikely that press conferences themselves command the additional attention; rather, markets pay more attention because they expect more important FOMC announcements.

To answer whether the separation into important and lesser FOMC announcements might have been the Fed's intention, or an unintended consequence of having press conferences, we show that most of our findings significantly strengthen throughout our sample. While the increasing role of PCs on market expectations and investor attention could reflect slow learning of investors about a possible new regime, we also find that the amount of information released at FOMC announcements with PCs increases over time. This slow trend suggests that the Fed did not initially choose to designate FOMC meetings with PCs as more important than those without, but instead is reacting to changes in market expectations and investor attention.

Press conferences were introduced with the goal to increase transparency. Our analysis raises strong doubts about whether this goal is achieved. As we show, PCs convey little new information to markets. At the same time, our evidence suggests that the reduced information revealed at non-PC announcements decreases transparency at these intermediate times. Taken

[46]These tests measure information content only by the reaction of equity and option markets. Information that does not immediately affect market prices, either because it is not price relevant or takes longer to process, could of course still be revealed during press conferences.

together, overall transparency probably decreased as a result of having PCs after only some FOMC announcements.

The implications of this new FOMC communication policy are difficult to gauge. While transparency is frequently viewed as positive, it is less clear whether increased transparency really results in lower price volatility or in prices that better reflect fundamental values. See, for example, Amato, Morris, and Shin (2002) and Banerjee, Davis, and Gondhi (2015).

Taken to the extreme, our evidence raises the question why the FOMC meets and makes policy announcements on days without scheduled press conferences. If the objective of the FOMC is to increase transparency while simultaneously limiting market surprises and maintaining flexibility of action, it should consider following the practice of holding press conferences after every meeting, as adopted by the European Central Bank, the Bank of Japan, Sweden's Riksbank and Norway's Norges Bank.

3.2 The Federal Open Market Committee

The FOMC is the monetary policy-making body of the U.S. Federal Reserve System. It oversees the nation's open market operations, i.e., purchases and sales of U.S. Treasury and Federal Agency Securities, which affect the cost and availability of money and credit in the economy, under the statutory dual mandate of maximum employment and stable prices. The FOMC is composed of the seven members of the Board of Governors and five of the twelve Reserve Bank presidents. While the president of the Federal Reserve Bank of New York serves on a continuous basis, the presidents of the other Reserve Banks serve one-year terms on a rotating basis. By law, the FOMC must meet at least four times a year. Since 1981, however, eight regularly scheduled meetings have been held each year at intervals of five to eight weeks. Members may also be called on to participate in special meetings if circumstances require consultation or consideration of an action between these regular meetings. Prior to 1994, changes to the Federal funds rate were not announced and market participants had to infer them by observing the size and type of open market operations. In 1994, the FOMC began announcing their policy decisions in a press statement, with the announcement dates and times released to the public in June of the previous year.

Since April 2011, the Chair of the Board of Governors holds a press conference following half of the FOMC announcements. Importantly, just like the announcements themselves, PCs are scheduled at least six months in advance, and the decision to hold a PC therefore does not depend on economic or market conditions.[47] Press conferences last on average close to one hour and consist of an opening statement by the Chair of the Board of Governors followed by a question and answer session with financial journalists. Between April 2011 and January 2013, FOMC announcements with PCs were scheduled for 12:30 p.m., followed by PCs beginning at 2:15 p.m. Announcements without PCs were scheduled for 2:15 p.m. Since March 2013, FOMC announcements always occur at 2:00 p.m., and press conferences begin at 2:30 p.m..

Table 3.1 provides an overview of the FOMC announcements, their scheduled times, and the starting time of the associated press conferences. The table also reports the actual announcement times, obtained from Thomson Reuters Tick History (TRTH) as supplied by the Securities Industry Research Centre of Asia-Pacific (SIRCA). In total, our sample is comprised of 37 announcements, 19 with and 18 without press conferences. After some initial irregularities, since June 2012 press conferences now follow every other FOMC announcement.

[47] The schedule for a year is released in June of the previous year. The new communication policy was first announced on March 24, 2011, five weeks before the first meeting with a press conference.

Table 3.1: FOMC Announcement Calendar

This table shows the scheduled (Sched.) and actual (Act.) time of FOMC announcements and the scheduled time for press conferences (PCs) between April 2011 and October 2015.
Source: http://www.federalreserve.gov/monetarypolicy/fomccalendars.htm and TRTH.

Date	Sche.	Act.	PC	Date	Sched.	Act.	PC
04/27/2011	12:30	12:32	14:15	09/18/2013	14:00	14:00	14:30
06/22/2011	12:30	12:27	14:15	10/30/2013	14:00	14:00	
08/09/2011	14:15	14:18		12/18/2013	14:00	14:00	14:30
09/21/2011	14:15	14:23		01/29/2014	14:00	14:00	
11/02/2011	12:30	12:32	14:15	03/19/2014	14:00	14:00	14:30
12/13/2011	14:15	14:12		04/30/2014	14:00	14:00	
01/25/2012	12:30	12:27	14:15	06/18/2014	14:00	14:00	14:30
03/13/2012	14:15	14:15		07/30/2014	14:00	14:00	
04/25/2012	12:30	12:32	14:15	09/17/2014	14:00	14:00	14:30
06/20/2012	12:30	12:32	14:15	10/29/2014	14:00	14:00	
08/01/2012	14:15	14:13		12/17/2014	14:00	14:00	14:30
09/13/2012	12:30	12:31	14:15	01/28/2015	14:00	14:00	
10/24/2012	14:15	14:15		03/18/2015	14:00	14:00	14:30
12/12/2012	12:30	12:30	14:15	04/29/2015	14:00	14:00	
01/30/2013	14:15	14:15		06/17/2015	14:00	14:00	14:30
03/20/2013	14:00	14:00	14:30	07/29/2015	14:00	14:00	
05/01/2013	14:00	14:00		09/17/2015	14:00	14:00	14:30
06/19/2013	14:00	14:00	14:30	10/28/2015	14:00	14:00	
07/31/2013	14:00	14:00					

One challenge that arises in studying FOMC press conferences is that the number of events is quite limited. We address this issue in three ways. First, we provide bootstrapped standard errors and p-values for all our statistical tests. Second, we analyze the effect of outliers on the distribution of announcement returns. Third, we provide a test that uses information from futures market to estimate the effect of PCs going forward, effectively extending our sample by three years.

Throughout our sample, the Federal funds target range remained constant at 0 to 0.25%. Nevertheless, our sample contains some changes in monetary policy by means of quantitative easing (QE) to help revive the U.S. economy following the financial crisis. We now list some of the key FOMC announcements since 2011.

June 22, 2011 (PC): the Fed announces the end of QE2.

September 21, 2011 (no PC): the Fed announces Operation Twist, which consists of purchasing $400 billion of Treasuries with long maturities and selling an equal amount with shorter-term maturities.

June 20, 2012 (PC): the Fed announces that it will continue Operation Twist.

September 13, 2012 (PC): the Fed announces QE3.

December 12, 2012 (PC): the Fed announces the expansion of QE3.

June 19, 2013 (PC): During the PC, Chairman Bernanke suggests a gradual moderation of the pace of bond purchases could begin in the months to come.[48]

September 18, 2013 (PC): the Fed decides to hold off on "tapering".

October 29, 2014 (no PC): the Fed announces the halt of bond purchases.

3.3 Financial Markets around FOMC Announcements

In this section, we investigate whether the schedule of press conferences affects financial markets and has any consequences for the Fed and monetary

[48]Equity and fixed income markets reacted strongly to this information. Interestingly, on May 22, 2013, one month before this press conference, Chairman Bernanke made a statement using similar language in a testimony to Congress.

policy. Rather than attempting to measure the gravity of monetary policy decisions, we use evidence from equity and derivative markets to show that the introduction of PCs has significantly affected market behavior around FOMC announcements. First, PCs influence the perceived importance of FOMC announcements as only events with PCs are associated with large expectations of important monetary policy decisions. Second, on days without PCs, FOMC announcements do not resolve uncertainty about monetary policy, suggesting that the news is viewed as less momentous. Lastly, we show that the pre-FOMC announcement drift, a robustly positive stock market return prior to FOMC announcements documented by Lucca and Moench (2015a), prevails in our sample, but is limited to announcement days with press conferences.

3.3.1 Press Conferences and Market Expectations

We use two measures of stock market expectations of changes in monetary policy. First, we argue that ex-post stock market announcement returns proxy for ex-ante expectations if the total information content in announcements, expected and unexpected, is constant throughout the sample. Second, we obtain a more direct measure of true ex-ante implied probabilities of target rate changes from Federal Funds Futures.

Stock Market Announcement Returns

We begin our analysis by showing that stock market reactions to FOMC announcements differ across days with and without press conferences. If markets are efficient, these returns measure the unexpected component of the announcements. We argue that, specific to our sample, these surprises can also be used to proxy for the expected part of the announcements. Our identification relies on the observation that there is little variation in the total information content, expected and unexpected, of announcements in our sample. In particular, the Federal funds target rate, the single most closely watched number associated with FOMC announcements, has remained at its lower bound of 0 to 0.25%. Any decisions regarding this rate can therefore be thought of as binary: rates can either remain unchanged or increase.[49]

[49] In practice, unconventional monetary policies such as large-scale asset purchases can be used to effectively overcome the zero lower bound (Swanson, 2015). On the other end, target rates could increase by more than 0.25%.

Since unexpected rate increases typically lead to a drop in equity prices (Kuttner, 2001; Bernanke and Kuttner, 2005), in this scenario prices should rise when the Fed announces that rates remain low. The magnitude of the rise, however, depends on the markets' ex-ante expectations that rates would increase. For example, if markets are certain that rates will not change, an announcement of no increase should not affect prices. If on the other hand markets have a large expectation of a rate increase, any announcement of constant rates should be considered a large positive surprise, and stock prices should therefore increase significantly.

We focus on the liquid and arguably mostly efficient equity market, in particular the shortest maturity E-mini S&P 500 Futures (E-MINI), obtained from TRTH. We define the E-MINI price as the midpoint of the best outstanding bid and ask quotes, and convert this time-series of prices into one-second midquote returns. We further restrict our sample to regular equity markets trading hours, i.e., 9:30 a.m. to 4:00 p.m. EST.

Figure 3.1 plots the average cumulative E-MINI return around FOMC announcements, starting 2.5 hours before and ending 1.5 hours after the announcement. The time interval is chosen to avoid potential effects from overnight returns. As shown in Table 3.1, prior to 2013 announcements with PCs were made no earlier than 12:27 p.m., or 2 hours and 57 minutes after market open, and between August 2011 and January 2013 announcements without PCs were made no later than 2:23 p.m., or 1 hour and 37 minutes before market close. Returns are normalized to zero at the time of the announcement.

Panel A groups all FOMC announcements from April 2011 to October 2015. Consistent with the conjecture that FOMC announcements throughout our sample contained good news for equity markets, there is a small return of around 0.10% in the hour after the announcement. The 95% confidence interval, plotted in gray, suggests that this effect is not statistically significant.

A striking pattern emerges in Panel B, where we separate FOMC announcements into ones with and without press conferences. When there is a PC (blue solid line), prices increase by an economically large and statistically significant 0.40% after the announcement. In contrast, FOMC announcements without PCs (red dashed line) are accompanied by a drop in prices of about 0.20% during a volatile period following the announcement.

In Table 3.2, we formally test the main insights from Figure 3.1. The table provides estimates of moments and associated statistical tests of announcement returns, which we define as the cumulative E-MINI return in the 31-minute event window starting one minute before the announcement.

Table 3.2: FOMC Announcement Returns

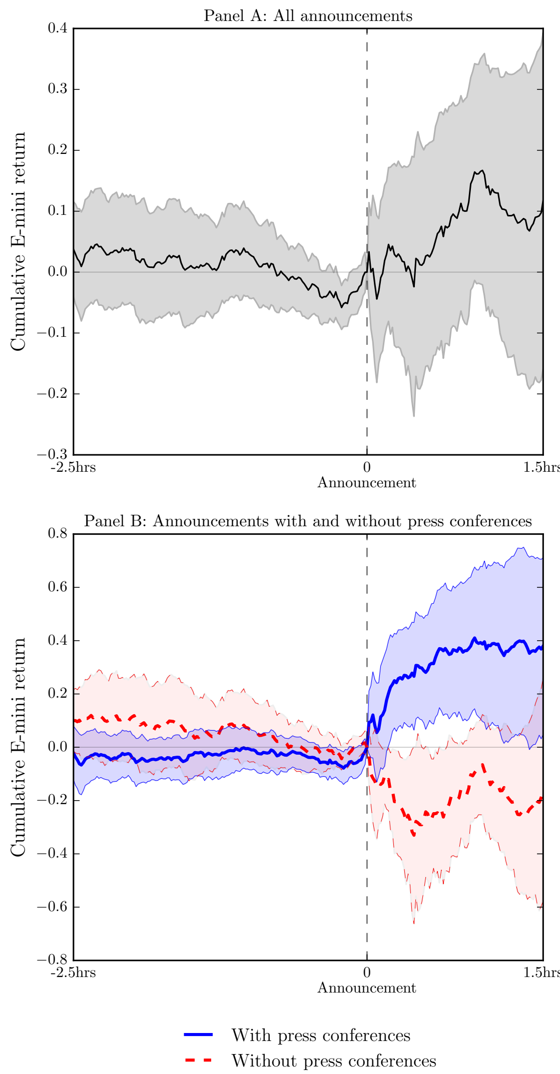
This table reports selected moments and percentiles of log returns of the shortest maturity S&P 500 E-mini Futures, in %, over the 31-minute intervals starting one minute before FOMC announcements. Values are reported for the whole sample, as well as samples split into days with and without press conferences (PCs) and their difference. Asymptotic and bootstrapped standard errors are presented in parenthesis and square brackets, respectively, and bootstrapped p-values in italics. N denotes the number of observations. Panel A is based on the whole sample, while Panel B repeats the analysis on trimmed samples that omit the smallest and largest observation. The sample period is April 2011 to October 2015.

	Panel A: Full Sample				**Panel B: Trimmed Sample**			
	All	PC	No PC	Diff.	All	PC	No PC	Diff.
Mean	0.015	0.292	-0.277	0.569	0.051	0.295	-0.181	0.476
Std. Error (asympt.)	(0.10)	(0.11)	(0.15)	(0.19)	(0.07)	(0.09)	(0.08)	(0.12)
Std. Error (bootstr.)	[0.10]	[0.11]	[0.15]	[0.18]	[0.07]	[0.09]	[0.08]	[0.12]
p-value (bootstr.)	*0.92*	*0.01*	*0.08*	*0.00*	*0.48*	*0.00*	*0.03*	*0.00*
Std. Deviation	0.623	0.478	0.636		0.432	0.371	0.327	
Minimum	-2.450	-0.711	-2.450		-0.959	-0.267	-0.959	
25th Percentile	-0.182	0.081	-0.369		-0.169	0.090	-0.350	
Median	0.080	0.274	-0.104		0.080	0.274	-0.104	
75th Percentile	0.293	0.502	0.076		0.283	0.453	0.069	
Maximum	1.238	1.238	0.356		1.052	1.052	0.221	
Proportion <0	0.405	0.211	0.611		0.400	0.176	0.625	
N	37	19	18		35	17	16	

We begin our announcement window one minute prior to the event to ensure that our findings are not affected by either information leakage before the announcement or possible data errors with regard to the exact FOMC announcement time. The choice of end time follows Ozdagli and Weber (2015), and further ensures that announcement returns are not affected by information released during the press conferences.

Figure 3.1: Cumulative E-mini Return around FOMC Announcements

This figure shows the average cumulative log return, in %, of the shortest maturity S&P 500 E-MINI futures around FOMC announcements. Returns are normalized to zero at the time of the announcement. Panel A shows results for the whole sample, while Panel B separates announcements into those with press conferences (blue solid line) and those without (red dashed line). The shaded areas are pointwise 95% confidence bands around the average returns. The sample period is April 2011 to October 2015.



The full sample results in Panel A show an average announcement return of 0.02%. On days with PCs, this figure rises to 0.29%, while it is -0.28% on days without. Based on the asymptotic distribution, the mean return for all announcements is insignificant. Announcement returns on days with PCs are both significantly positive and significantly larger than those on days without. Returns on days with PCs range from -0.71% to 1.24%, with only 4 out of 19 observations (21%) negative.

Our evidence is based on a rather small sample containing only 19 (18) observations for PC (non-PC) events. We address concerns about the sample distribution of the test statistic and the effect of possible outliers in two ways. First, we also provide bootstrapped standard errors (in brackets) and p-values (in italics). All bootstrapped results are based on 1,000,000 samples. The bootstrapped standard errors closely resemble the asymptotic ones, and the p-values confirm the previous findings.

Second, to investigate the potential impact of outliers, Panel B repeats the analysis on a trimmed sample that excludes both the largest and smallest announcement return observations in each group. Point estimates for the means are, with one exception, little affected. Only on non-PC days, average returns rise from -0.27% to -0.18%, the minimum increases from -2.45% to -0.96%, and the standard deviation declines from 0.64% to 0.33%. This implies that the sample was affected by one very large negative observation. Crucially, even in the trimmed sample, the statistical inference remains unchanged. Announcement returns on days with PCs are significantly positive, and larger than those on days without.

We test whether the announcement return differences between PC and non-PC days can be explained by different economic environments in Table 3.3. The first two specifications regress announcement returns on indicator variables for PC and non-PC days. These two tests confirm the results from Table 3.2 under the additional assumptions ordinary least square regressions impose on the error distribution. Just allowing for differences in averages between PC and non-PC days explains 19% of the variation in announcement returns.

In the third specification, we add monthly log changes in seasonally adjusted consumer price index (ΔCPI) and unemployment (ΔUE) to control for the economic environment. These variables are the most natural candidates to influence expected monetary policy, as they correspond to the FOMC's target measures under its dual mandate. Data are obtained from the U.S. Bureau of Labor Statistics, and we always use the most recently announced data. We complement these with GDP growth (ΔGDP) from the U.S. Bureau of Economic Analysis. In the fourth specification, we further

Table 3.3: FOMC Announcement Returns: Regressions

This table reports coefficients from regressions of FOMC announcement returns on a press-conference indicator PC, equal to one if a meeting is followed by a press conference and zero otherwise, non-$PC = 1 - PC$, and control variables. Announcement returns are the log returns of the shortest maturity S&P 500 E-mini Futures, in %, over the 31-minute intervals starting one minute before FOMC announcements. ΔCPI, ΔUE, and ΔGDP are log changes in, respectively, the consumer price index, the unemployment rate, and the gross domestic product. $R_{\text{S\&P}}$ is the S&P 500 log return over the 21-day interval ending 3 days before the announcement. Asymptotic heteroscedasticity robust and bootstrapped standard errors are presented in parenthesis and square brackets, respectively, and bootstrapped p-values in italics. Adjusted R^2 and the number of observations N are also reported. The sample period is April 2011 to October 2015.

	Announcement Returns			
	(1)	(2)	(3)	(4)
Intercept		-0.277	-0.292	-0.391
		(0.15)	(0.23)	(0.24)
		[0.13]	[0.19]	[0.18]
		0.01	*0.10*	*0.02*
PC	0.292	0.569	0.589	0.592
	(0.11)	(0.18)	(0.17)	(0.16)
	[0.12]	[0.18]	[0.18]	[0.16]
	0.03	*0.00*	*0.00*	*0.00*
non-PC	-0.277			
	(0.15)			
	[0.13]			
	0.01			
ΔCPI			-0.185	-0.235
			(0.36)	(0.33)
			[0.37]	[0.34]
			0.57	*0.46*
ΔUE			-0.814	-1.546
			(0.57)	(0.77)
			[0.78]	[0.77]
			0.28	*0.05*
ΔGDP			-0.019	-0.025
			(0.05)	(0.05)
			[0.06]	[0.06]
			0.75	*0.66*
$R_{\text{S\&P}}$				0.058
				(0.05)
				[0.02]
				0.01
Adjusted R^2	0.192	0.192	0.146	0.253
N	37	37	37	37

control for the cumulative log return of the S&P 500 Total Return Index over the 21 trading days ending three days before the event, $R_{\text{S\&P}}$, from TRTH. The specific window is chosen to avoid overlap with both the current and the previous FOMC meetings.

Of the control variables, changes in the unemployment rate are significantly negatively and the prior 21-day S&P 500 returns significantly positively related to announcement returns. The signs are consistent with our interpretation of the dependent variable. Following improvements in the state of the economy, such as a decrease in the unemployment rate or rising stock prices, markets increase their expectation of a tightening in monetary policy. Announcements to keep policy unchanged therefore result in large positive surprises. Importantly, none of the control variables have any impact on the coefficient on the PC indicator. The marginal impact of PCs on announcement returns is very stable across specifications, ranging from 0.57% to 0.59%, and highly statistically significant.

Ex-Ante Implied Probabilities of Target Rate Changes

Announcement returns are ex-post measures that might be affected by the content of the announcement, and might be a noisy measure of ex-ante expectations if the total information content of announcements varies throughout the sample. We now validate these results using a pure ex-ante measure from derivative markets that directly captures the expected gravity of FOMC announcements.

We measure the ex-ante probabilities of target rate changes using Federal Funds Futures (FF), for which we obtain settlement prices from TRTH. These contracts are listed for the first 36 calendar months and derive their price from the realized Federal funds overnight rate. Specifically, the settlement price is 100 minus the average daily transaction-volume-weighted Federal funds overnight rate for the delivery month. Futures prices thus reflect market expectations of the average daily Federal funds effective rate (FFER), which is published by the Federal Reserve Bank of New York each day.

To extract probabilities of rate movements from FF prices, we follow the methodology used by the CME Group.[50] The expected target rate change

[50] Alternatively, it is possible to use these contracts to estimate the announcement surprise following Kuttner (2001). However, to obtain surprises and therefore expectations, Kuttner's approach requires the use of FF prices from the end of the announcement day. This is not suitable for our purposes, as the end-of-day prices contain information revealed during the press conference. For more details on the construction of probabilities

in month m is computed as

$$\mathbb{E}(\Delta r_m) = \widehat{FFER}_m - \widehat{FFER}_{m-1}, \tag{3.1}$$

where $\widehat{FFER}_m$ is the futures-implied FFER at the end of month m. It is important to note that these expected target rate changes can be negative even though the Federal funds target rate is at its zero lower bound. This is because rates are targeted to stay within an interval, in our case 0 to 0.25%, rather than at a specific number, whereas the FF settlement price is based on realized market rates.

To convert expected rate changes to probabilities, we assume that target rates can only change by 0.25% at any given meeting and compute

$$P(\updownarrow) = \left|\mathbb{E}(\Delta r_m)\right| / 0.25, \tag{3.2}$$

$$P(\uparrow) = \max\left[\mathbb{E}(\Delta r_m), 0\right] / 0.25. \tag{3.3}$$

The calculation of $\widehat{FFER}_m$ depends on whether there is another FOMC meeting scheduled in month $m+1$. If there is, we estimate

$$\widehat{FFER}_{m-1} = 100 - FF_{m-1} \tag{3.4}$$

$$\widehat{FFER}_m = \frac{1}{N-M}\left[N(100 - FF_m) - M(100 - FF_{m-1})\right] \tag{3.5}$$

where FF_m is the price of the future expiring in month m, N is the number of calendar days in month m, and M is the calendar day of the FOMC meeting minus 1. If there is no meeting scheduled in the following month, we instead estimate

$$\widehat{FFER}_{m-1} = \frac{1}{M}\left[N(100 - FF_m) - (N-M)(100 - FF_{m+1})\right] \tag{3.6}$$

$$\widehat{FFER}_m = 100 - FF_{m+1}. \tag{3.7}$$

To test whether press conferences affect the probability of rate changes, we obtain for each FOMC meeting the FF implied probability computed on the previous day. We then regress meeting-to-meeting changes in the FF implied probability onto changes in an indicator variable for press conferences and control variables.

Our findings are summarized in Table 3.4. In the first three columns, the dependent variable is based on the probability of changes in interest

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of rate movements, see http://www.cmegroup.com/trading/interest-rates/countdown-to-fomc.html.

rates. The first specification only contains an intercept and changes in the PC indicator variable, ΔPC, which can take one of three values: one if the announcement has a PC while the previous did not, minus one for the opposite case, and zero if both the current and prior announcement were followed by or not followed by PCs. It shows that, on average, the probability of rate changes is 2.8 percentage points higher on days with press conferences than on those without. The estimate is statistically significant and economically large compared to the sample average of the probability of rate changes of 5.1%. The estimate thus suggests that meetings with press conferences are associated with a $(5.1+2.8/2)/(5.1-2.8/2)-1 = 76\%$ increased probability of a change in target rates relative to those without.

When adding control variables in specifications (2) and (3), the coefficient on ΔPC is unaffected, and press conferences remain associated with a higher probability of rate changes. Of the control variables, only the past S&P 500 return is significant. The negative coefficient suggests that changes in market prices reflect the altered probabilities of interest rate changes.

Since the target rate has been at its zero lower bound throughout our sample, we also perform the tests on the narrower probability of target rate increases. The results, shown in columns (4)-(6) of Table 3.4, confirm the previous findings. On days with press conferences, the probability of a rate increase is 3.3 percentage points higher than on days without press conferences. Relative to the unconditional average of a rate increase of 3.3% in our sample, this corresponds to a three-fold increase in probability on press conference days relative to non-PC days.

Federal Funds Futures are listed for the next 36 calendar months, providing a rich source of information regarding long term expectations of rate changes. To investigate the effects of press conferences on the term structure of market expectations, we first compute the probability of a rate change for each FOMC meeting from 2011 to 2016 using FF settlement prices at the end of the first trading day of each calendar year. Results are presented in Figure 3.2, where full circles identify meetings with PCs while hollow dots identify those without.

In the plot for 2011, the probabilities of rate changes are smoothly increasing over the next eight FOMC announcements. The plot is based on data from January 3, 2011, and the introduction of press conferences had not yet been announced. Therefore, not surprisingly, press conferences do not affect the probabilities. In the following years, we see a clear separation between meetings with PCs and those without. Probabilities of interest rate changes are consistently higher for meetings associated with PCs.

Next, we formally test the main insights from Figure 3.2. For this test, we

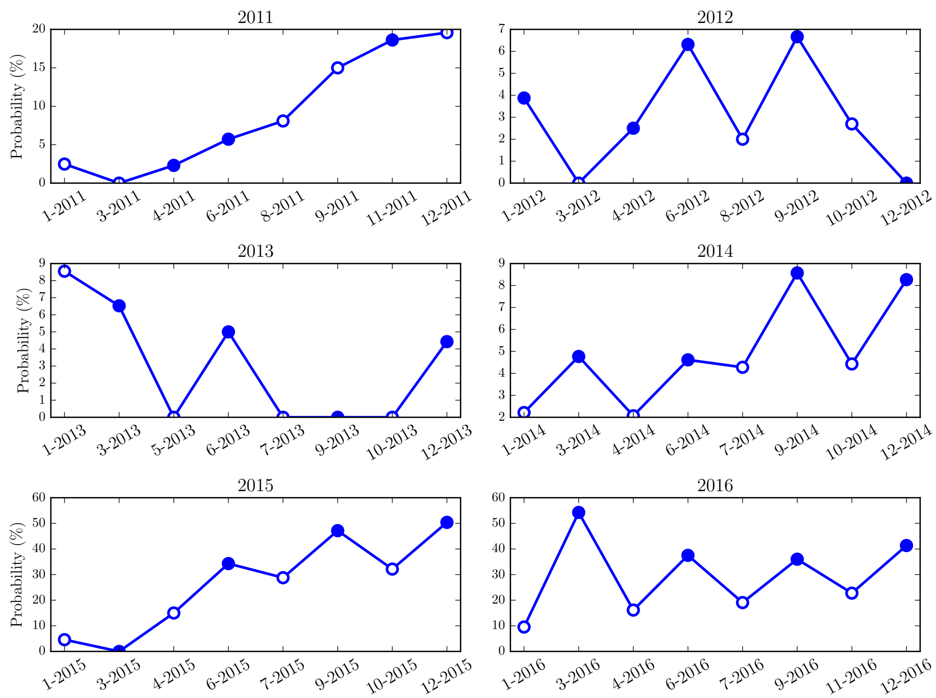
Table 3.4: Probability of Interest Rate Changes before FOMC Announcements

This table reports coefficients from regressions of meeting-to-meeting changes in the probability of interest rate changes, in %, on changes ΔPC of an indicator variable equal to one if a meeting is followed by a press conference and zero otherwise, and control variables. Probabilities of changes, $\Delta P(\updownarrow)$, or increases, $\Delta P(\uparrow)$, in Federal funds rates are derived from Federal Funds Futures as measured one day prior to each FOMC meeting. ΔCPI, ΔUE, and ΔGDP are log changes in, respectively, the consumer price index, the unemployment rate, and the gross domestic product. $R_{\text{S\&P}}$ is the S&P 500 log return over the 21-day interval ending 3 days before the announcement. Asymptotic heteroscedasticity robust and bootstrapped standard errors are presented in parenthesis and square brackets, respectively, and bootstrapped *p*-values in italics. Adjusted R^2 and the number of observations N are also reported. The sample period is April 2011 to October 2015. Detailed information on the construction of implied probability measures is provided in the text.

	$\Delta P(\updownarrow)$			$\Delta P(\uparrow)$		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.078	0.817	2.439	0.090	0.337	1.427
	(1.15)	(1.48)	(1.52)	(1.04)	(1.16)	(1.12)
	[1.16]	[2.26]	[2.01]	[1.04]	[2.02]	[1.92]
	0.95	*0.72*	*0.22*	*0.94*	*0.87*	*0.45*
ΔPC	2.825	2.795	2.926	3.262	3.204	3.292
	(1.25)	(1.27)	(1.09)	(1.10)	(1.11)	(1.04)
	[1.21]	[1.21]	[1.04]	[1.08]	[1.08]	[1.00]
	0.02	*0.02*	*0.00*	*0.00*	*0.00*	*0.00*
ΔCPI		-2.209	-1.553		-0.436	0.004
		(4.48)	(4.24)		(3.89)	(3.81)
		[5.01]	[4.33]		[4.48]	[4.15]
		0.66	*0.73*		*0.92*	*0.99*
ΔUE		3.211	14.911		6.180	14.039
		(10.37)	(7.68)		(9.00)	(6.81)
		[10.26]	[9.48]		[9.17]	[9.08]
		0.75	*0.12*		*0.50*	*0.12*
ΔGDP		-0.098	-0.017		0.159	0.213
		(0.82)	(0.66)		(0.77)	(0.67)
		[0.86]	[0.74]		[0.77]	[0.71]
		0.91	*0.98*		*0.84*	*0.77*
$R_{\text{S\&P}}$			-0.949			-0.638
			(0.29)			(0.28)
			[0.27]			[0.26]
			0.00			*0.02*
Adjusted R^2	0.106	0.029	0.250	0.177	0.110	0.211
N	36	36	36	36	36	36

Figure 3.2: Term Structure of the Probability of Target Rate Changes

This figure shows the implied probability of an interest rate change at each of the eight annual FOMC meetings. Implied probabilities are computed from settlement prices of Federal Fund Futures on the first trading day of each calendar year. Full circles identify meetings followed by press conferences while hollow dots identify those without. Detailed information on the construction of probability measures is provided in the text.



look at meetings after June 2012, when the regular pattern of quarterly PCs was announced.[51] Using settlement prices from after the announcement on

[51]The regular pattern allows investors to forecast dates of future press conferences. While the calendar of FOMC meetings is released in June of the previous year, the approximate dates are generally predictable from past meetings. For this test, we assume that participants knew the true meeting dates going forward, using the actual FOMC calendar up to 2017. We supplement this with the following expected meetings dates for 2018: January 31, March 14 (PC), May 2, June 13 (PC), August 1, September 19 (PC), October 31 and December 12 (PC).

each FOMC meeting date, we infer the probability of an interest rate change for the following 22 meetings. For each observation date, we then compute the change in the probability of an interest rate change $\Delta P(\updownarrow)$ between each consecutive future meeting pair along with the associated ΔPC indicator. This gives us of a total of 567 observations: 21 meeting pairs for each of the 27 observation dates. We then run the following panel regression:

$$\Delta P(\updownarrow)_{t,i} = \alpha + \sum_{i=1}^{21} \beta_{\Delta PC_i} \Delta PC_{t,i} + \varepsilon_{t,i} \tag{3.8}$$

where t represents the observation date and i represents the ith pair of consecutive future meetings. Regression results are presented in Figure 3.3. Blue squares indicate coefficient estimates $\beta_{\Delta PC_i}$ while errors bars indicate the 95% confidence interval from standard errors clustered by observation date and meeting pair. All 21 coefficient estimates are positive, and all but two are statistically significant at the 5% level. This suggests that markets expect more important decisions on days with press conferences not only for the upcoming FOMC meeting, but for at least three years into the future.

Overall, the prices of Federal Fund Futures, combined with the reactions of equity markets to FOMC announcements, paint a clear picture that markets expect big changes in monetary policy only following FOMC meetings with press conferences, and view the remaining announcements as less important.

3.3.2 Resolution of Uncertainty at FOMC Announcements

Having established that markets view FOMC announcements on days with press conferences as more important than those without, we now ask if the Fed reveals more information on these days. To quantify the amount of information revealed, we follow Beber and Brandt (2009), Savor and Wilson (2013a), and Amengual and Xiu (2015) and use the option implied volatility index, VIX, as proxy for uncertainty associated with monetary policy. With the arrival of new information, we generally expect uncertainty to decrease.[52] But volatility would change little if announcements merely confirm what markets already expected, or if announcements provide little price-relevant

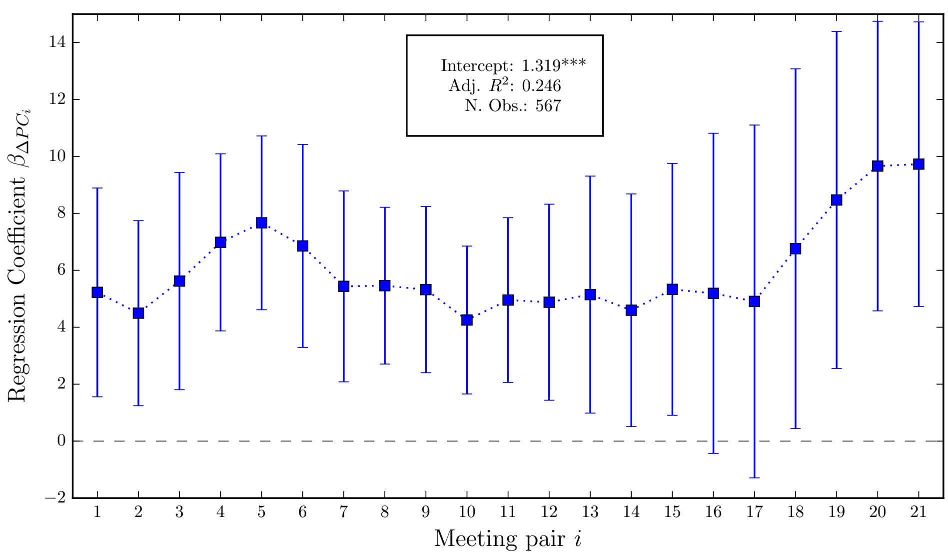
[52] Beber and Brandt (2009) and Savor and Wilson (2013a) show a general link between resolution of macroeconomic uncertainty and changes in the VIX index. Amengual and Xiu (2015) are specifically interested in large downward jumps in the VIX, and argue that in addition to resolving uncertainty, the Fed usually intervenes in hard times, effectively providing a put option to markets. For our purpose, the distinction between both interpretations is secondary.

Figure 3.3: Term Structure of the Probability of Target Rate Changes: Regression

This figure shows estimates from the panel regression:

$$\Delta P(\updownarrow)_{t,i} = \alpha + \sum_{i=1}^{21} \beta_{\Delta PC_i} \Delta PC_{t,i} + \varepsilon_{t,i},$$

where t represents the observation date and i represents the ith pair of consecutive future meetings. Observation dates are FOMC meetings dates from July 2012 to October 2015. Using settlement prices from FOMC announcement days, we infer the probability of an interest rate change for the following 22 meetings. For each observation date, we then compute the change in the probability of an interest rate change $\Delta P(\updownarrow)$, in %, between each consecutive future meeting pair. Blue squares indicate coefficient estimates $\beta_{\Delta PC_i}$ while errors bars indicate the 95% confidence interval from standard errors clustered by observation date and meeting pair. Detailed information on the construction of probability measures is provided in the text.



information. If on the other hand uncertainty in markets was large, and the announcement resolves this uncertainty, we expect large declines in the VIX.

Figure 3.4 shows cumulative changes in the VIX around the FOMC announcement, starting 2.5 hours prior and ending 1.5 hours after. The intraday VIX data is provided by TRTH. Across all FOMC announcements (Panel A), the VIX exhibits the expected pattern. There is little time-series variation prior to the announcement, but the VIX drops sharply by about 2% when the new information arrives. The release of the Fed's monetary policy decisions clearly reduces uncertainty.

A striking contrast emerges in Panel B, which separates FOMC announcements into ones that are followed by a PC (blue solid line) and ones that are not (red dashed line). While announcements with PCs see an average drop of over 4% in the volatility index, uncertainty remains virtually unaffected by FOMC announcements without PCs.

Table 3.5 formally tests this finding. We first regress log changes in VIX from one minute prior to 30 minutes after the announcement on indicator variables for PC and non-PC days. Regression (1) shows that the VIX decreases by a statistically and economically highly significant 4.3% on days with PCs, and remains unchanged on days without. Including control variables further increases the economic magnitude and the statistical significance of the impact of press conferences.

The large decrease in option-implied volatility suggests that a significant amount of uncertainty in equity markets is resolved at the time of the announcement on days with PCs. In contrast, when there is no PC, uncertainty does not change around FOMC announcements. In turn, this implies that FOMC announcements communicate price-relevant information only on PC days, and markets correctly expect no relevant monetary policy changes on days without PCs.

A potential confounding effect stems from the publication of economic projection materials (EPMs), which contain the economic projections of Federal Reserve Board members and the Federal Reserve Bank presidents about growth, unemployment, inflation, and future policy. Prior to 2013, these materials were not released until the beginning of the press conferences, and therefore after the time window of our analysis ends. Since 2013, however, they are made public simultaneously with the FOMC announcement. While the relevance of these materials is often debated in the media, they nonetheless represent additional information that can potentially contribute to the reduction in uncertainty. We address this issue in three ways.

First, we introduce an indicator variable $\mathbb{1}_{EPM}$ equal to one for the time period in which EPMs are released concurrently with the FOMC announcements (2013-2015), and zero otherwise. Regressions (5)-(7) extend

Table 3.5: Returns of VIX at FOMC Announcements

This table reports coefficients from regressions of returns in VIX around FOMC announcements on a press conference indicator PC, equal to one if a meeting is followed by a press conference and zero otherwise, non-$PC = 1 - PC$, and control variables. VIX announcement returns are the log changes in the VIX, in %, over the 31-minute intervals starting one minute before FOMC announcements. ΔCPI, ΔUE, and ΔGDP are log changes in, respectively, the consumer price index, the unemployment rate, and the gross domestic product. $R_{\text{S\&P}}$ is the S&P 500 log return over the 21-day interval ending 3 days before the announcement. $\mathbb{1}_{EPM}$ is an indicator variable equal to one for events between 2013 and 2015, and zero otherwise. Asymptotic heteroscedasticity robust and bootstrapped standard errors are presented in parenthesis and square brackets, respectively, and bootstrapped p-values in italics. Adjusted R^2 and the number of observations N are also reported. The sample period is April 2011 to October 2015.

	ΔVIX						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept		0.264	0.353	0.702	1.592	1.709	1.619
		(0.83)	(1.36)	(1.35)	(1.48)	(2.06)	(1.53)
		[0.95]	[1.38]	[1.38]	[1.54]	[1.73]	[1.68]
		0.78	*0.80*	*0.61*	*0.30*	*0.32*	*0.34*
PC	-4.338	-4.601	-4.855	-4.867	-3.957	-4.195	-3.099
	(1.02)	(1.31)	(1.27)	(1.26)	(1.82)	(1.94)	(1.55)
	[0.92]	[1.32]	[1.25]	[1.23]	[2.04]	[1.96]	[2.01]
	0.00	*0.00*	*0.00*	*0.00*	*0.05*	*0.03*	*0.12*
PC x $\mathbb{1}_{EPM}$					-1.415	-1.379	-3.139
					(2.50)	(2.51)	(2.36)
					[2.58]	[2.48]	[2.63]
					0.58	*0.58*	*0.23*
non-PC	0.264						
	(0.83)						
	[0.95]						
	0.78						
ΔCPI			3.141	3.317		2.036	2.193
			(2.37)	(2.37)		(2.55)	(2.53)
			[2.62]	[2.57]		[2.53]	[2.45]
			0.23	*0.20*		*0.42*	*0.37*
ΔUE			10.064	12.641		9.824	13.325
			(4.41)	(5.04)		(5.01)	(6.22)
			[5.53]	[5.84]		[5.24]	[5.50]
			0.07	*0.03*		*0.06*	*0.02*
ΔGDP			0.228	0.251		0.198	0.183
			(0.43)	(0.43)		(0.43)	(0.43)
			[0.46]	[0.45]		[0.44]	[0.43]
			0.62	*0.58*		*0.65*	*0.66*
$R_{\text{S\&P}}$				-0.204			-0.280
				(0.24)			(0.21)
				[0.17]			[0.17]
				0.23			*0.10*
$\mathbb{1}_{EPM}$					-1.993	-1.770	-0.764
					(1.75)	(1.95)	(1.40)
					[1.89]	[1.82]	[1.87]
					0.29	*0.33*	*0.69*
Adjusted R^2	0.225	0.225	0.247	0.252	0.274	0.281	0.305
N	37	37	37	37	37	37	37

regressions (2)-(4) by interacting PC with $\mathbb{1}_{EPM}$. The interaction term is not significant in any of the specifications, suggesting that our results are not driven by this simultaneous release of economic projection materials.

Second, we confirm in untabulated results that the changes in VIX around the release of EPMs in 2011 and 2012, which occured at the beginning of the PC, do not suggest that EPMs reduce uncertainty. The mean log changes in VIX from one minute prior to 30 minutes after the release of the EPMs is not statistically significantly different from zero, with only two out of eight observations negative.

Third, we look at the effect of summary of economic projections (SEPs) in the period prior to our sample. Quarterly SEPs, which were subsumed by the more detailed EPMs in 2011, were first introduced following the October 2007 meeting and released simultaneously with the meeting minutes. From October 2007 to March 2011 there are 28 FOMC meetings, 14 of them with SEPs. For those meetings, we regress in untabulated results the daily change in VIX on the day of the release of FOMC minutes on an SEPs dummy which is equal to one if SEPs were released at the same time or zero otherwise. The coefficient on the SEPs dummy is both positive and insignificant, which further suggests that SEPs do not reduce uncertainty.

Taken together, these tests suggest that the information contained in economic projection materials does not cause our results, since their release does not affect uncertainty. Even if that was the case, the conclusions and implications of this paper would remain, but the specific channel would be unclear. Nonetheless, our evidence suggests that it is the mere presence of a PC, and possibly the scheduled release of EPMs, that drives our results and not the potential information they communicate to the market.

Taken together, these tests cast doubt on the value of economic projection materials as a source of information for markets. In particular, since the release of the EPMs does not affect uncertainty, these materials can not be responsible for our findings. Importantly, even if it was the case that EPMs are responsible for the patterns in market expectations we attribute to press conferences, the conclusions and implications of our findings would remain unchanged. Only the specific channel that coordinates expectations would be different. Nonetheless, our evidence suggests that it is the mere presence of a PC, and possibly the scheduled release of EPMs, that drives our results and not the potential information they communicate to the market.

The argument that important monetary policy decisions should reduce uncertainty in markets is general and, in contrast to the evidence using stock market announcement returns, does not require that total information revealed at the announcement is constant in the sample. This allows us to investigate if the segregation of FOMC announcements is a new effect caused by press conferences, or if historically some announcements have always implicitly carried a higher weight. Since most press conferences (15 out of 19) are scheduled following the second FOMC meeting in each calendar quarter, we test if FOMC announcements at quarter ends have always had a larger impact on uncertainty.

Figure 3.5 shows changes in the VIX around FOMC announcements from January 2006 to March 2011, separately for the first (dashed red line) and second (solid blue line) announcements in each calendar quarter. In short, there is no difference. Therefore, there is no evidence to suggest that the timing of press conferences simply reflects a previously existing pattern. Instead, the separation into important and less important FOMC announcements seems to be caused by the advent of press conferences.

3.3.3 The Pre-FOMC Announcement Drift

In this section, we revisit the pre-FOMC announcement drift of Lucca and Moench (2015a, "LM") in the recent sample and its relation to press conferences. If important FOMC monetary policy announcements are associated with high anticipatory returns, we expect the magnitude of the pre-FOMC announcement drift to be related to the importance of the announcements.

LM find that in the period from September 1994 to March 2011, the S&P 500 index has on average increased by 49 basis points in the 24 hours prior to FOMC announcements. This return has proven difficult to explain, and one might wonder if this anomaly was specific to the chosen sample or if it is a robust effect. Our sample begins in April 2011, and therefore does not overlap with the original study.

Figure 3.6 shows average cumulative E-MINI log returns for the 2-days window ending on FOMC announcement days. Panel A shows average returns in the April 2011 to October 2015 sample (brown solid line) and for reference also shows the findings from November 1997 to March 2011 (black dotted line). While this latter sample slightly differs from the one in LM due to data availability, the cumulative returns are very similar. Panel B separates announcements from the April 2011 to October 2015 sample into those with press conference (blue solid line) and those without (red dashed line). Vertical dashed lines indicate the three announcement times throughout the sample period: 12:30 p.m. (PC 2011-2012), 2:00 p.m. (all announcements from March 2013), and 2:15 p.m. (non-PC until January 2013).

Interestingly, we observe a statistically significant pre-FOMC announcement return, but only for meetings that are followed by press conferences.

The cumulative return from opening on the day prior until the announcement is approximately 50 bp, nearly identical to the one in the earlier sample. While market prices in the LM sample smoothly increase from about 24 hours prior to the FOMC announcement until the actual announcement, we observe the returns occurring in two waves. Prices first increase on the morning of the previous day, and then jump further overnight. While studying the causes of these excess returns is beyond of the scope of this paper, a potential explanation is that the shift in timing is due to investors trying to front-run the return documented by LM.

In a stark contrast, average returns prior to FOMC announcement without PC are flat. While it is hard to explain those pre-FOMC announcements returns, it is nonetheless striking that an important pattern previously associated with FOMC meetings is now only observable around those with PCs.

3.4 Investor Attention to FOMC Announcements

In this section, we study investor attention before FOMC meetings. If investors have limited resources and information is costly to acquire or process, investors will optimally choose to focus their attention on information with larger impact on prices (see, e.g., Sims, 2003; Abel, Eberly, and Panageas, 2013; Huang and Liu, 2007; Kacperczyk, van Nieuwerburgh, and Veldkamp, 2016). If investors truly expect big changes in monetary policy only following FOMC meetings with press conferences, they should therefore be more attentive to those meetings.

Using different proxies for the attention of institutional and retail investors, in particular media coverage spanning multiple media outlets and frequencies and Google search volume, we show that interest in the FOMC is higher prior to announcements with press conferences. We argue that we measure additional attention to the FOMC announcements rather than attention to the press conferences themselves, as PCs reveal little new information to markets and therefore do not command attention. In an out-of-sample test, we show that similar results obtain in Canada and New Zealand, the two other countries where central banks follow a comparable communication policy.

3.4.1 Institutional Investor Attention

We begin our analysis with a proxy for institutional investors' attention based on articles published on the Bloomberg (BB) terminal platform (Ben-Rephael, Da, and Israelsen, 2016). To construct a news intensity measure, we first obtain the daily number of articles related to the U.S. Federal Reserve and then average these over the three business days prior to each announcement.[53]

Historical levels of BB are presented in Panel A of Figure 3.7, where full circles identify meetings with PCs while hollow dots identify those without. After early 2012, we see a clear separation between meetings with PCs and those without. Those with PCs draw more attention, and this is also apparent in the other measures of attention that we describe later.

Our findings for BB are summarized in Panel A of Table 3.6, where the dependent variable is the meeting-to-meeting log change in BB news intensity. Performing our test on changes rather than levels avoids concerns that variables might be non-stationary in-sample. The first specification within each group contains only an intercept and changes in the PC indicator variable, ΔPC. It shows that, on average, Bloomberg coverage increases by 27% on days with PCs relative to days without. This estimate is not only economically meaningful, but also statistically significant based on both the asymptotic and the bootstrapped distributions. The indicator variable alone explains 26% of the total variation in BB news intensity.

[53] The total article count is retrieved from the Bloomberg Terminal using the search word "Federal Reserve". While also based on BB, our attention measure differs from the one used by Ben-Rephael, Da, and Israelsen (2016) because their proxy is only available for individual equities and not institutions such as the Federal Reserve.

Figure 3.4: Cumulative VIX Return around FOMC Announcements

This figure shows the average cumulative log return, in %, of VIX around FOMC announcements. Returns are normalized to zero at the time of the announcement. Panel A shows results for the whole sample, while Panel B separates announcements into those with press conference (blue solid line) and those without (red dashed line). The shaded areas are pointwise 95% confidence bands around the average returns. The sample period is April 2011 to October 2015.

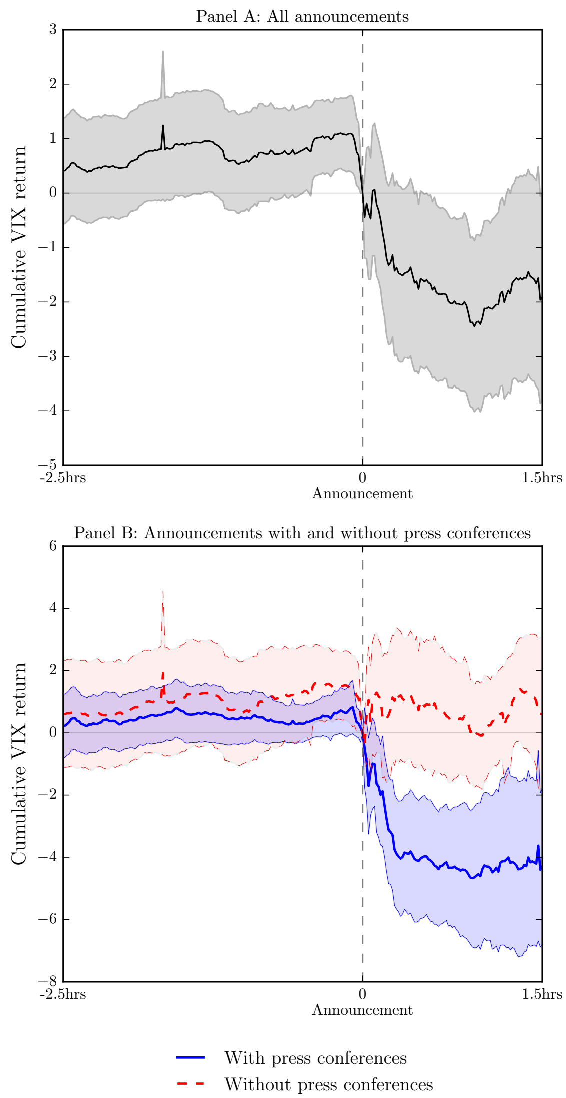


Figure 3.5: Cumulative VIX Return around FOMC Announcements (2006-2011)

This figure shows the average cumulative log return, in %, of VIX around FOMC announcements. VIX returns are normalized to zero at the announcement. Events are separated into the first (red dashed line) and second (blue solid line) announcements in each calendar quarter. The shaded areas are pointwise 95% confidence bands around the average returns. The sample contains 42 events from January 2006 to March 2011.

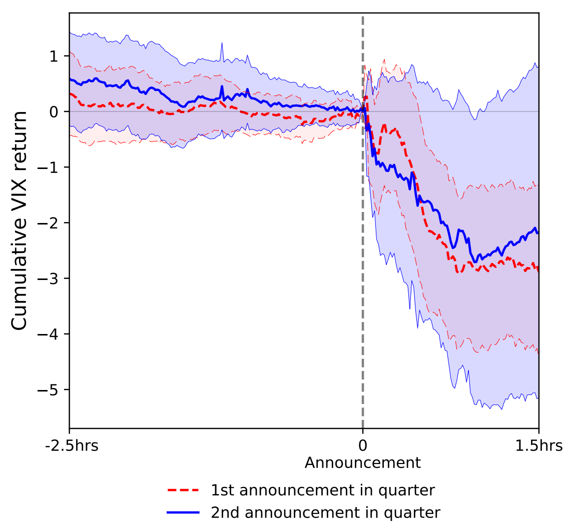


Figure 3.6: FOMC Pre-Announcement Drift and Press Conferences

This figure shows the average cumulative log return, in %, of the shortest maturity S&P 500 E-MINI futures in the 2-day window ending on FOMC announcement days. Panel A shows the results for the November 1997 to March 2011 (black dotted line) and the April 2011 to October 2015 (brown solid line) samples, while Panel B separates announcements in the latter sample into those with press conference (blue solid line) and those without (red dashed line). The shaded areas are pointwise 95% confidence bands around the average returns. Vertical dashed lines indicate the three FOMC announcement scheduled times throughout the sample period.

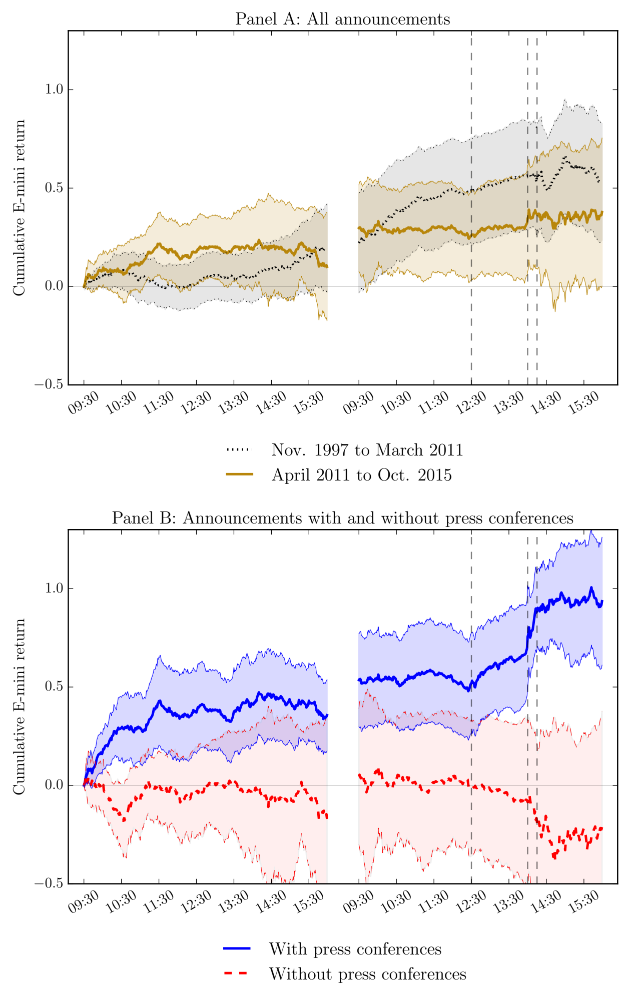


Figure 3.7: Attention Level Before FOMC Announcements

This figure shows the level of attention measures prior to each FOMC announcement. Full circles identify meetings followed by press conferences while hollow dots identify those without. The sample period is April 2011 to October 2015. Detailed information on the construction of attention measures is provided in the text.

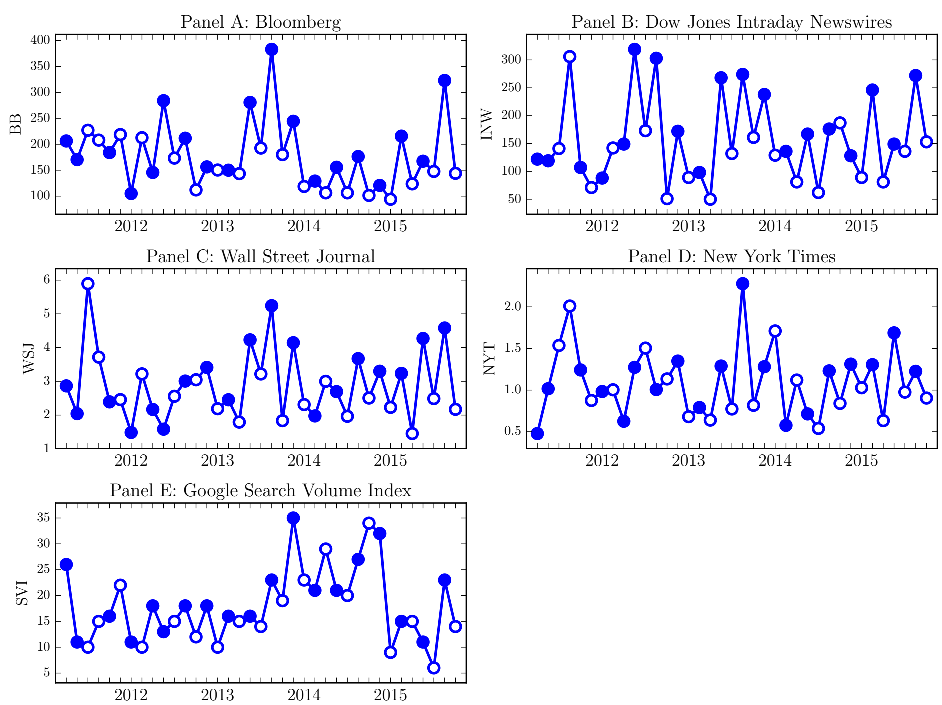


Table 3.6: Attention before FOMC Announcements

This table reports coefficients from regressions of meeting-to-meeting log changes in measures of attention, in %, on changes ΔPC of an indicator variable equal to one if a meeting is followed by a press conference and zero otherwise, and control variables. The measures of media attention are based on articles published on the Bloomberg terminal platform (BB), the Dow Jones intraday newswires (INW), or printed in the Wall Street Journal (WSJ), and the New York Times (NYT). The weekly Search Volume Index (SVI) is obtained from Google Trends for searches for "FOMC" and related terms. ΔCPI, ΔUE, and ΔGDP are log changes in, respectively, the consumer price index, the unemployment rate, and the gross domestic product. $R_{\text{S\&P}}$ is the S&P 500 log return, over the 21-day interval ending 3 days before the announcement. Asymptotic heteroscedasticity robust and bootstrapped standard errors are presented in parenthesis and square brackets, respectively, and bootstrapped p-values in italics. Adjusted R^2 and the number of observations N are also reported. The sample period is April 2011 to October 2015. Detailed information on the construction of media attention measures is provided in the text.

	Panel A: ΔBB			Panel B: ΔINW			Panel C: ΔWSJ			Panel D: ΔNYT			Panel E: ΔSVI		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Intercept	-0.259	14.531	23.398	2.026	13.269	21.609	-0.184	8.570	20.412	2.288	-0.349	7.977	-1.135	-12.321	-9.917
	(6.74)	(8.97)	(7.08)	(9.66)	(11.47)	(10.69)	(8.42)	(17.22)	(14.46)	(8.76)	(17.92)	(17.04)	(7.41)	(11.20)	(11.23)
	[6.74]	[12.43]	[11.07]	[9.60]	[18.01]	[17.52]	[8.46]	[16.27]	[14.40]	[8.70]	[16.67]	[16.06]	[7.38]	[13.85]	[14.13]
	0.97	*0.24*	*0.03*	*0.82*	*0.46*	*0.22*	*0.97*	*0.62*	*0.15*	*0.79*	*0.98*	*0.62*	*0.88*	*0.37*	*0.49*
ΔPC	26.633	26.759	27.474	50.286	50.716	51.389	21.150	21.636	22.592	18.510	19.366	20.038	21.047	22.006	22.200
	(7.04)	(7.00)	(5.85)	(10.03)	(9.37)	(8.73)	(8.97)	(8.93)	(7.45)	(9.02)	(8.55)	(8.20)	(7.50)	(7.03)	(6.84)
	[7.03]	[6.65]	[5.76]	[10.02]	[9.64]	[9.12]	[8.83]	[8.71]	[7.50]	[9.08]	[8.92]	[8.36]	[7.71]	[7.41]	[7.36]
	0.00	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.02*	*0.01*	*0.00*	*0.04*	*0.03*	*0.02*	*0.01*	*0.00*	*0.00*
ΔCPI		-57.685	-54.101		-69.728	-66.356		-32.783	-27.995		-13.330	-9.964		3.464	4.436
		(23.39)	(22.66)		(35.48)	(33.21)		(27.92)	(26.13)		(26.49)	(23.52)		(29.24)	(30.02)
		[27.59]	[23.94]		[39.92]	[37.80]		[36.12]	[31.12]		[36.94]	[34.65]		[30.72]	[30.52]
		0.04	*0.02*		*0.08*	*0.08*		*0.37*	*0.37*		*0.73*	*0.77*		*0.93*	*0.90*
ΔUE		-13.524	50.422		-44.163	15.984		-52.632	32.769		-90.319	-30.275		-100.061	-82.726
		(46.39)	(49.53)		(74.73)	(84.39)		(59.40)	(55.92)		(73.80)	(75.60)		(41.56)	(45.39)
		[56.53]	[52.33]		[81.85]	[82.77]		[73.97]	[68.10]		[75.77]	[75.94]		[62.91]	[66.74]
		0.81	*0.33*		*0.59*	*0.85*		*0.48*	*0.63*		*0.24*	*0.69*		*0.11*	*0.21*
ΔGDP		-4.385	-3.942		-3.287	-2.870		-4.490	-3.898		-1.696	-1.280		1.035	1.156
		(4.04)	(3.86)		(6.21)	(6.41)		(6.08)	(5.32)		(6.31)	(5.88)		(4.74)	(4.85)
		[4.73]	[4.10]		[6.85]	[6.49]		[6.19]	[5.34]		[6.34]	[5.94]		[5.28]	[5.24]
		0.35	*0.33*		*0.63*	*0.66*		*0.47*	*0.47*		*0.79*	*0.83*		*0.85*	*0.83*
$R_{\text{S\&P}}$			-5.188			-4.880			-6.928			-4.871			-1.406
			(1.48)			(2.19)			(1.61)			(1.41)			(2.20)
			[1.50]			[2.38]			[1.95]			[2.18]			[1.92]
			0.00			*0.04*			*0.00*			*0.03*			*0.45*
Adjusted R^2	0.264	0.282	0.443	0.394	0.390	0.435	0.112	0.060	0.280	0.077	0.029	0.119	0.147	0.141	0.126
N	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36

In the second and third specifications, we add control variables. Of these, only changes in CPI and S&P 500 returns are significant. The negative coefficient on returns suggests that interest in the Fed is higher after bad stock market realizations, consistent with well documented investor behavior, for example under prospect theory (Kahneman and Tversky, 1979). Importantly, none of the control variables affects the coefficient of interest. ΔPC remains economically large and statistically significant in all specifications.

We next move to a high-frequency measure of institutional investor attention that is based on intraday newswires (INW) in the hours before FOMC announcements. From RavenPack's global macroeconomic news database, we collect a comprehensive sample of news stories from the Dow Jones News Wire. We keep only intraday news that are classified as full-article, and are timestamped in the 24-hour window ending 1 minute before FOMC announcements. To capture the predominance of the entities mentioned, RavenPack assigns to each news a relevance score between 0 and 100. We select news articles with a minimum relevance score of 90 for either the Federal Reserve or the Federal Open Market Committee.

Our findings are summarized in Panel B of Table 3.6. As with Bloomberg news, the coefficient estimate on ΔPC is positive, highly significant, and unaffected by control variables. We find that on days with PCs the number of articles related to the FOMC in the intraday Dow Jones newswires increases by 50%. Nearly 40% of the variation in the number of intraday newswire articles on FOMC announcement days can be attributed to PCs taking place.

3.4.2 Retail Investor Attention

We next turn to proxies for retail investors' attention, which are based on low-frequency printed news in the Wall Street Journal (WSJ) and the New York Times (NYT) around FOMC announcements. To measure daily news intensity, we follow Fisher, Martineau, and Sheng (2016) and divide the number of articles related to the FOMC or monetary policy by the total number of articles published in the morning editions of each newspaper.[54] We then average daily intensity over windows that start three business days before the announcement and end with the morning edition on the announcement day. Fisher, Martineau, and Sheng (2016) provide a detailed overview of the construction of macroeconomic media attention indices and their statistical properties.

[54] In particular, we search FACTIVA for the following key words: ((federal reserve OR federal open market committee OR fomc) AND (interest rate OR monetary OR inflation OR economy OR economic OR unemployment)).

Our findings are summarized in Panels C (WSJ) and D (NYT) of Table 3.6. As with our measures of institutional investor attention, the coefficient estimate on ΔPC is positive, highly significant, and unaffected by control variables. We find that on days with PCs, media attention in the WSJ increases by 21%. The regression R^2 suggests that 11% of the variation in the number of printed news articles prior to FOMC announcement days can be attributed to PCs taking place. A similar picture emerges for our media attention measure for the NYT.

3.4.3 Google Search Volume

We conclude the attention analysis with the search volume index (SVI) from Google Trends, which measures the frequency of searches in Google for given keywords. Data obtained from Google Trends have previously been used to study the effects of investor attention (Da, Engelberg, and Gao, 2011a) and to obtain broad sentiment measures (Da, Engelberg, and Gao, 2015). In particular, the weekly SVI is calculated by dividing the number of searches for specific keywords ("FOMC" and related terms), by the total number of searches in a geographic area ("global"), and rescaling the resulting series so that the maximum is 100.

In contrast to our previous measures, the search volume index proxies for the overall level of interest among Google's users. Google is often used as a universal shortcut to websites. We posit that the SVI is a proxy for web traffic to the FOMC and other related websites, and therefore quantifies investor attention. We use the SVI in the last full week prior to each FOMC meeting, and again analyze meeting-to-meeting log changes.[55]

The findings in Panel E of Table 3.6 mirror the previous ones. Search volume for "FOMC" is 21% higher prior to announcements with PCs than before those without. Overall, there is strong evidence that both media and investors attention has shifted since the introduction of FOMC press conferences. Rather than equally spreading their attention over all eight FOMC announcements per year before PCs were introduced in 2011, investors now put more emphasis on the four announcements that are accompanied by press conferences.

[55]Given that the SVI is based on calendar weeks, concerns might arise if some FOMC announcements are later in the week than others. In our sample, the vast majority of announcements fall on a Wednesday, only three on a Tuesday and two on a Thursday. Since the two Thursday announcements are followed by PCs while the three Tuesday announcements are not, a possible bias would work against our findings.

3.4.4 The Information Content of Press Conferences

Increased attention prior to FOMC announcements with press conferences by itself does not need to be surprising. If press conferences themselves communicate information that investors pay attention to, our findings would not represent increased attention to FOMC announcements, but rather incremental attention to PCs. We now demonstrate that press conferences reveal little new information to equity markets, and therefore do not command the extra attention.

In efficient markets, the release of price relevant new information induces prices to move instantly. Consequently, in a large class of models, information flow is equivalent to volatility (e.g., Ross, 1989). We estimate high-frequency measures of realized volatility during PCs to proxy for the information revealed. While realized market volatility is generally high during PCs, this is due to the preceding FOMC announcements. In particular, we show that realized volatility is not significantly higher during actual PCs than during the same time frame following FOMC announcements without PCs. Similarly, the VIX index is largely unchanged during PCs, suggesting that possible information revealed during PCs does not reduce monetary policy uncertainty.

We define realized volatility during PCs as the square root of mean squared one-minute E-MINI log returns, expressed in percent per year, in the 60-minute window starting with the press conference. Panel A of Table 3.7 shows that realized volatility during PCs is around 15.9%. Crucially, the point estimate for average realized volatility is not larger than the one for the control sample, estimated during the times when PCs would take place on non-PC days. To the contrary, volatility in the control sample is slightly larger at 17.2%. The bootstrapped standard errors closely resemble the asymptotic ones, and the p-values confirm the findings. Overall, there is no indication that volatility during actual press conferences might be higher than at the same time on days without PCs.

Basing conclusions of this test on the entire sample induces a possible bias. In 2011 and 2012, FOMC announcements with PC were held earlier in the day than those without (see Table 3.1), and PCs started 1.75 hours after announcements. This implies that the time window for hypothetical PCs in the control group comprises of the first trading hour of the next trading day, and volatility is known to vary throughout the day.

Panel B shows the results for the reduced sample from March 2013 to October 2015 that is unaffected by differences in announcement times. The realized volatility during PCs is 17.6%, higher than the 13.6% in the control

Table 3.7: Realized Volatility during Press Conferences

This table reports the realized volatility (RV) of the shortest maturity S&P 500 E-mini Futures returns during FOMC press conferences (PCs). RV is defined as the annualized mean of squared one-minute midquote log returns, in %, during the 60-minute interval starting at the press conference. The ratio of this RV relative to the announcement RV, estimated between 1 minute prior and 30 minutes after the announcement, is also reported. On days without PCs, RV is estimated during the corresponding event-time in which PCs would take place. Asymptotic and bootstrapped standard errors are presented in parenthesis and square brackets, respectively, and bootstrapped p-values in italics. N denotes the number of observations. The sample period is April 2011 to October 2015.

	RV			RV relative to announcement RV		
	PC	No PC	Difference	PC	No PC	Difference
Panel A: Full Sample						
Mean	15.92	17.18	-1.26	0.64	0.63	0.01
Std. Error (asympt.)			(3.09)			(0.07)
Std. Error (bootstr.)			[3.00]			[0.06]
p-value (bootstr.)			*0.65*			*0.82*
N	19	18		19	18	
Panel B: March 2013 to October 2015						
Mean	17.61	13.55	4.06	0.62	0.56	0.06
Std. Error (asympt.)			(2.85)			(0.08)
Std. Error (bootstr.)			[2.72]			[0.08]
p-value (bootstr.)			*0.14*			*0.43*
N	11	11		11	11	

sample. The difference has a p-value of 0.14, suggesting that PCs do not convey important information. This conclusion remains when we control for the information content of FOMC announcements. Volatility estimates during both actual PCs and in the control group are nearly identical relative to those estimated between one minute before and 30 minutes after FOMC announcements. Since realized volatility spikes immediately after announcements and then declines slowly, our evidence indicates that high volatility during PCs is driven by news revealed at the FOMC announcement, and not the press conferences themselves.[56]

Overall, the evidence based on realized volatility does not suggest that important price-relevant information is revealed during press conferences. We also confirm in untabulated results that the average change in VIX from the beginning to the end of the PC is zero, corroborating our conclusion that press conferences provide little additional information to markets.

3.4.5 International Evidence

We now look at evidence from other countries as out-of-sample evidence for our findings. Most central banks hold press conferences following each of their regular meetings, for example the European Central Bank, the Bank of Japan, Sweden's Riksbank and Norway's Norges Bank. We are aware of only two central banks that follow a pattern similar to the one adopted by the FOMC: the Reserve Bank of New Zealand and the Bank of Canada.[57]

Since March 1999, the Reserve Bank of New Zealand holds eight regular annual meetings, and every other meeting is followed by a press conference. Our sample ends in August 2016 and contains 141 meetings, 70 of which had PCs. The Bank of Canada follows the same pattern, but only started PCs in January 2013. Until July 2016, there were 29 meetings, 15 of which were followed by a PC.

Since not all our previous tests are applicable to an international setting, we repeat only the analysis using Bloomberg news intensity and Google search volume in these two countries.[58] We first obtain historical Bloomberg

[56] Persistence in realized volatility following macroeconomic news is well documented in Andersen, Bollerslev, Diebold, and Vega (2003b), and investigating its causes is beyond the scope of our paper.

[57] Two additional central banks hold PCs only after only some announcements. The Bank of England's Monetary Policy Committee holds monthly meetings, and issues a quarterly *Inflation Report* that is followed by a PC. However, until August 2015, the inflation report was released about one week after the monetary policy announcement. The Swiss National Bank hold quarterly meetings and semi-annual PCs.

[58] The Wall Street Journal, the New York Times, and the intraday newswires are US-

news intensity for announcements of both central banks considered, and the Google SVI based on searches in the respective home country from Google Trends.[59]

Our findings are summarized in Table 3.8. Our main attention results are confirmed for both central banks considered. On days with PC, the attention in Bloomberg news coverage increases by 31% in Canada and 20% in New Zealand. Similarly, Google search intensity increases by 24% in Canada and 13% in New Zealand. These findings suggest that the shift in attention induced by post-announcement press conferences is not unique to the FOMC but present for all central banks that have adopted similar communication patterns.

3.5 Shaping Expectations and Coordinating Attention

In this section, we investigate the economic mechanism underlying our findings. In particular, we want to understand why market expectations and investor attention are higher on days with PCs, and why the Fed makes decisions that reduce monetary policy uncertainty only on these days.

It is conceivable that the Fed instituted press conferences with the intention to defer important decisions for meetings when it has the opportunity to provide explanations and context in a PC. This is a natural and convincing argument, even though it was not mentioned when a possible introduction of press conferences was originally discussed, and Chairwoman Yellen maintains that all FOMC meetings are equally important.[60]

Alternatively, it is also possible that the shifts in market expectations and investor attention are unintended consequences of the press conferences.

based media with sparse international coverage. In addition, Brusa, Savor, and Wilson (2016) show that, while FOMC decisions impact international stock markets, those markets do not react significantly to decisions of their domestic central bank. Consequently, we do not expect foreign financial markets to react as the U.S. market does.

[59] We adjust the timezone settings in Bloomberg prior to obtaining news count for the Reserve Bank of New Zealand to avoid capturing news published after the announcement. Google Trends provides weekly data for a maximum time range of 5 years, and we therefore follow our original sample and obtain weekly Google Trends data for 2011 to 2015.

[60] Press conferences were first mentioned during a FOMC conference call on October 15, 2010. The discussion revolved about what other central banks do, about providing "a little more clarity", and that it "dovetails with some of the concerns about interpretations" (Bernanke, 2010). It is also acknowledged that "communicating what we are doing will be challenging", that PCs "would probably become obligatory on a regular basis", and that it "would be quite a commitment".

Table 3.8: Attention before Announcements in Canada and New Zealand

This table reports coefficients from regressions of meeting-to-meeting log changes in Bloomberg news count (BB) and the Google Search Volume Index (SVI), in %, on changes ΔPC of an indicator variable equal to one if a meeting is followed by a press conference and zero otherwise, for interest rate announcements of the Bank of Canada and the Reserve Bank of New Zealand. Asymptotic heteroscedasticity robust and bootstrapped standard errors are presented in parenthesis and square brackets, respectively, and bootstrapped p-values in italics. Adjusted R^2 and the number of observations N are also reported. The sample period is January 2013 to July 2016 for Canada, March 1999 to August 2016 for Bloomberg on New Zealand and January 2011 to December 2015 for Google on New Zealand. Detailed information on Bloomberg news and the SVI is provided in the text.

	Canada		New Zealand	
	ΔBB	ΔSVI	ΔBB	ΔSVI
	(1)	(2)	(3)	(4)
Intercept	-1.968	0.797	-1.398	0.241
	(10.36)	(6.90)	(3.03)	(5.34)
	[10.35]	[6.90]	[3.03]	[5.31]
	0.85	*0.93*	*0.65*	*0.96*
ΔPC	31.166	23.532	20.190	13.111
	(10.36)	(6.90)	(3.09)	(5.34)
	[10.37]	[6.91]	[3.06]	[5.31]
	0.00	*0.00*	*0.00*	*0.01*
Adjusted R^2	0.215	0.266	0.231	0.112
N	28	28	140	39

At least two channels might be responsible. First, markets might falsely interpret the Fed's intention and assign a small probability that the Fed wants to time important decisions to be made on days with PCs. Investors consequently lower their expectations of monetary policy action on days without PCs, and shift their attention accordingly. The decreased expectations in turn imply that any action from the Fed would be a surprise to markets, which the Fed does not like. It effectively limits the range of actions the Fed can take on non-PC days. This constraint of the Fed naturally feeds back to market expectations and investor attention.

Second, with information acquisition costs, a small difference in the perceived importance of FOMC meetings due to the introduction of PCs can be sufficient to shift attention away from announcements without PCs. This attention shift in turn can influence the Fed because investor attention is critical to the transmission of monetary policy (Stein, 1989; Blinder, Goodhart, Hildebrand, Lipton, and Wyplosz, 2001), and "monetary policy is more effective if it is more effective in coordinating market expectations" (Amato, Morris, and Shin, 2002, p.496). In this scenario, small initial changes in investor attention lead the Fed to slightly shift their policy decisions, which feeds back to market expectations and investor attention.

The data can help us understand whether the Fed intended to focus monetary policy to days with PCs, or whether this shift in focus was dictated by markets. In the first case, we should observe an immediate drop in the importance of monetary policy decisions on days without PCs. Depending on whether investors understand this or learn from past policy announcements, we expect to see changes in expectations and attention either instantly or developing over time. In the second case, while we cannot distinguish between the exact mechanism of how unintended consequences might arise, we would expect to see the magnitude of all of our findings to increase over time rather than observing an immediate impact. Of course, the two interpretations are not mutually exclusive.

To answer this question, we test whether press conferences had an immediate impact, or if their effects appeared gradually. Table 3.9 revisits our main regressions, but also interacts our variables of interest, PC or ΔPC, with a time trend variable T, which is set to 0 for the first meeting and increases by $1/8$ for each subsequent meeting. Since there are 8 meetings per year, T increases by one for every year.

The first three columns show results for our proxies of market expectations. Focusing on the interaction term, we see that it is not significantly different from zero for E-MINI announcement returns, but positive for the two ex-ante measures of Fed Fund Futures implied probabilities of interest

Table 3.9: Regressions with Time Trends

This table reports coefficients from regressions of log returns in E-MINI and VIX around FOMC announcements on a press conference indicator PC, equal to one if a meeting is followed by a press conference and zero otherwise, and from regressions of meeting-to-meeting changes in the probability of interest rate changes and log attention measures, in %, on changes ΔPC in PC, on interaction with a time trend T and control variables. T is 0 for the first meeting and increases by 1/8 for each meeting (by one for every year). ΔCPI, ΔUE, and ΔGDP are log changes in, respectively, the consumer price index, the unemployment rate, and the gross domestic product. $R_{\text{S\&P}}$ is the S&P 500 log return, over the 21-day interval ending 3 days before the announcement. Asymptotic heteroscedasticity robust and bootstrapped standard errors are presented in parenthesis and square brackets, respectively, and bootstrapped p-values in italics. Adjusted R^2 and the number of observations N are also reported. The sample period is April 2011 to October 2015. Detailed information on the construction of dependent variables is provided in the text.

	Ret (1)	$\Delta P(\updownarrow)$ (2)	$\Delta P(\uparrow)$ (3)	ΔVIX (4)	ΔBB (5)	ΔINW (6)	ΔWSJ (7)	ΔNYT (8)	ΔSVI (9)
Intercept	-0.750	-1.140	-2.694	1.157	13.328	31.170	-3.223	6.981	-30.052
	(0.32)	(2.31)	(2.34)	(1.74)	(14.87)	(21.70)	(17.56)	(21.85)	(19.67)
	[0.25]	[2.51]	[2.35]	[1.79]	[15.11]	[26.08]	[17.93]	[23.41]	[19.71]
	0.00	*0.66*	*0.25*	*0.52*	*0.38*	*0.23*	*0.85*	*0.76*	*0.12*
T	0.140	0.333	0.551	0.276	-0.534	-3.888	1.408	-3.065	3.040
	(0.09)	(0.67)	(0.73)	(0.73)	(4.18)	(6.47)	(4.54)	(6.26)	(6.11)
	[0.09]	[0.69]	[0.64]	[0.65]	[4.12]	[7.12]	[4.89]	[6.38]	[5.38]
	0.12	*0.63*	*0.39*	*0.67*	*0.90*	*0.58*	*0.77*	*0.63*	*0.57*
PC (ΔPC)	0.570	-6.258	-5.991	0.117	-9.689	52.850	-44.150	-6.816	-20.489
	(0.27)	(2.67)	(2.26)	(2.03)	(20.38)	(31.29)	(18.57)	(21.84)	(21.09)
	[0.34]	[2.50]	[2.34]	[2.45]	[15.07]	[26.01]	[17.88]	[23.33]	[19.66]
	0.09	*0.01*	*0.01*	*0.96*	*0.52*	*0.04*	*0.01*	*0.77*	*0.30*
PC (ΔPC) $\times T$	0.022	3.690	3.730	-2.284	14.933	-0.587	26.819	10.790	17.154
	(0.11)	(1.01)	(0.98)	(1.01)	(6.76)	(10.57)	(6.36)	(8.01)	(8.70)
	[0.13]	[0.94]	[0.88]	[0.97]	[5.68]	[9.80]	[6.73]	[8.79]	[7.40]
	0.88	*0.00*	*0.00*	*0.02*	*0.01*	*0.95*	*0.00*	*0.22*	*0.02*
ΔCPI	0.058	2.202	4.124	0.333	-41.747	-72.745	-2.235	-5.083	24.144
	(0.37)	(3.43)	(2.62)	(2.57)	(24.71)	(36.90)	(24.57)	(26.63)	(26.28)
	[0.34]	[3.90]	[3.65]	[2.52]	[23.49]	[40.49]	[27.84]	[36.28]	[30.60]
	0.88	*0.58*	*0.26*	*0.89*	*0.07*	*0.07*	*0.95*	*0.89*	*0.43*
ΔUE	-1.509	2.031	1.048	15.707	-1.938	17.543	-60.963	-68.453	-142.403
	(0.76)	(6.97)	(6.77)	(6.26)	(40.23)	(84.55)	(48.54)	(78.20)	(51.43)
	[0.74]	[8.59]	[8.04]	[5.43]	[51.69]	[89.28]	[61.31]	[80.04]	[67.33]
	0.05	*0.81*	*0.90*	*0.00*	*0.97*	*0.84*	*0.32*	*0.39*	*0.04*
ΔGDP	-0.027	0.276	0.495	0.112	-2.643	-2.678	-1.712	-0.175	2.421
	(0.05)	(0.57)	(0.61)	(0.40)	(3.79)	(6.68)	(4.36)	(5.58)	(4.64)
	[0.06]	[0.63]	[0.59]	[0.41]	[3.78]	[6.52]	[4.48]	[5.84]	[4.93]
	0.63	*0.66*	*0.40*	*0.78*	*0.48*	*0.68*	*0.71*	*0.97*	*0.62*
$R_{\text{S\&P}}$	0.060	-0.247	0.072	-0.391	-2.344	-4.985	-1.825	-2.812	1.854
	(0.04)	(0.30)	(0.24)	(0.19)	(1.78)	(2.80)	(2.10)	(2.12)	(2.47)
	[0.02]	[0.29]	[0.27]	[0.17]	[1.74]	[3.01]	[2.07]	[2.70]	[2.28]
	0.01	*0.40*	*0.80*	*0.02*	*0.18*	*0.10*	*0.38*	*0.30*	*0.42*
Adjusted R^2	0.317	0.437	0.435	0.358	0.503	0.400	0.466	0.106	0.185
N	37	36	36	37	36	36	36	36	36

rate changes. This suggests that the effect of PCs on announcement returns is approximately constant throughout our sample period, but expectations measured from Fed Funds Futures increased over time.

Column (4) shows the results for the changes in the VIX at announcements. The coefficient on the PC indicator of 0.117 is insignificant, suggesting that resolution of macroeconomic uncertainty was unrelated to press conferences early in the sample. The interaction term, in contrast, is significantly negative at -2.284. This implies that, with each passing year in our sample, the difference in resolution of monetary policy uncertainty between days with and without PCs increases by over two percentage points of the VIX index.

Lastly, columns (5)-(9) show that the effect of PCs on investor attention also becomes more pronounced over time. In particular, the interaction term is significantly positive for three of our five proxies, including articles published on the Bloomberg terminal and in the Wall Street Journal and the Google search volume index. This is consistent with PCs acting as a device for coordinating attention.

Overall, our results for market expectations and investor attention clearly support the hypothesis that markets are slowly adjusting to the new communication policy. The increasing importance of press conferences on the amount of information released at FOMC announcements, as measured by changes to monetary policy uncertainty, is especially interesting. It suggests that the Fed did not initially choose to designate FOMC meetings with PCs as more important than those without, but is adjusting to their new policy and reacting to changes in market expectations and investor attention.

3.6 Conclusion to Chapter 3

In an effort to increase transparency, the Chair of the Board of Governors now holds a press conference following half of the scheduled FOMC announcements. While press conferences do not add significant information relative to the preceding announcement, we document that this information practice has unintended consequences: it curtails the range of actions the Fed can take and counteracts the declared transparency goal.

Holding press conferences after some, but not all, FOMC meetings skews expectations of important monetary policy decisions towards announcement days with press conferences. This is turn coordinates media and investor attention towards those meetings. Since managing market expectations is central to monetary policy, it is optimal for the Fed to focus their policy efforts on times when markets pay close attention.

As a result, the Fed, generally believed to be averse to surprising markets, now faces two obstacles to make important monetary policy decisions at meetings without press conferences: markets do not expect big decisions, and investors pay less attention. This constrains the possible monetary policy decisions. Naturally, these constraints diminish information flow and reduce transparency.

Taken to the extreme, our evidence raises the question why the FOMC meets and makes policy announcements when there are no press conferences. Resolving the constraints on actions and the associated reduced transparency requires that markets perceive all FOMC announcements equal. While this could be achieved by removing press conferences completely, in order to maintain their goal of increased transparency, the Fed should instead consider holding press conferences after every meeting, as many other central banks do.

Chapter 4

Media Attention, Macroeconomic Fundamentals, and the Stock Market

4.1 Introduction

Classical theories of asset pricing, based on exogenous information flows and efficient market pricing (e.g., Merton, 1973), provide no explicit role for investor attention. A growing literature establishes however that investor attention, to both firm-level and aggregate news, plays an important role in financial markets. For example, Da, Engelberg, and Gao (2011b) show that investor attention to individual stocks positively predicts subsequent short-run returns for those stocks.[61] Andrei and Hasler (2014) develop theoretical and empirical links between attention to the aggregate stock market and conditional moments of the aggregate stock market. Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) study interactions between firm-level and aggregate attention.

If attention in general is important to understanding financial markets, then what other types of attention, beyond firm-level and aggregate attention, might be worth studying? In this paper we propose new measures of attention, derived from news media coverage, to separate categories of macroeconomic fundamentals such as unemployment, output growth, inflation, and oil prices.

We focus on macroeconomic fundamentals for several reasons. First, the finance literature has long sought to connect asset prices to underlying macroeconomic factors (Chen, Roll, and Ross, 1986). Second, current evidence establishes that scheduled macroeconomic announcements have

[61] For further evidence regarding attention to individual stocks, see Huberman and Regev (2001); Barber and Odean (2008); DellaVigna and Pollet (2009).

strong impacts on asset prices (Andersen, Bollerslev, Diebold, and Vega, 2003a, 2007a; Savor and Wilson, 2013b), and we anticipate that such announcements should also impact attention. Third, while the asset pricing literature often tends towards stock-market based factors in describing the cross-section of returns (e.g., Fama and French, 1993), casual observation of news media coverage suggests that attention to systematic risks is more frequently framed in terms of macroeconomic factors such as unemployment and inflation as opposed to stock-market based factors like size and value. Finally, an interesting aspect of attention to macroeconomic fundamentals is that we can relate the dynamics of attention to the dynamics of the underlying macroeconomic fundamentals. This allows us to answer questions such as what types of changes in unemployment or output growth or inflation result in increases or decreases in attention to these fundamentals.

Our measures of attention are based on media coverage of different types of fundamental news. The categories of macroeconomic fundamentals are: unemployment, output growth, inflation, credit ratings, the housing market, interest rates, monetary policy, oil, and the U.S. dollar. We create lists of search words that capture attention to each of these fundamentals. For example, to capture attention to U.S. output growth, we use the following set of words: gross domestic product, GDP, gross national product, and GNP. We count the number of articles in the Wall Street Journal (WSJ) and New York Times (NYT) starting in 1980 for NYT and 1984 for WSJ until 2015 that include any of these search terms. Scaling by the total number of articles published gives us a measure of relative attention to each category of macroeconomic fundamental.

Our indices most directly measure media attention, but the media clearly has strong incentives to cover issues of interest to their readers, and prior literature often uses media attention as a proxy for investor attention (e.g., Barber and Odean, 2008; Yuan, 2015). A separate line of research, which we do not contribute to, investigates the causal role of media attention (e.g., Tetlock, 2007, 2010; Peress, 2014). We view media coverage as a useful proxy for investor attention because of the long time series it permits. Our indices permit daily estimates of attention beginning in 1980. More direct measures of investor attention, such as Google search (e.g., Da, Engelberg, and Gao, 2011b) have other advantages but provide shorter time series. Henceforth, we do not distinguish between media and investor attention, although this could be an interesting topic for future research. Although not the focus of our research, we do provide separate measures of attention for the NYT and WSJ, which suggests heterogeneity in attention across the different readerships of these outlets.

Our macroeconomic attention indices ("MAI") show interesting empirical properties. We first address comovement in attention, and show that the indices are not driven by a single factor. They are imperfectly correlated, and over time attention shifts across inflation, employment, monetary policy, and the other fundamentals. If these shifts in attention reflect changes in investor concerns, then only in very special cases could efforts to price assets reduce to a single factor representation of risk.

We next address the duration of cycles in attention. For the macroeconomic fundamentals we consider, the attention indices are stationary, but persistent. The conservative Bayesian Information Criterion suggests at most four lags in a monthly autoregression framework. However, when we aggregate the attention indices over different window lengths, similar to the MIDAS framework of Ghysels, Santa-Clara, and Valkanov (2006), we find that most of the series show evidence of cycles at multiple frequencies, ranging from one day to as long as one year. These aspects of attention are consistent with fractal behavior over a range of frequencies, producing a slow decay in autocorrelations over a range of lags that is often associated with long-memory. These patterns in attention are properties also observed in aggregate stock market volume and volatility in prior literature (see Andersen, Bollerslev, Diebold, and Ebens, 2001; Bollerslev and Mikkelsen, 1996).

We next seek to relate attention to movements in economic fundamentals. We associate each of the attention indices with a related macroeconomic variable, and, where possible, at least one scheduled announcement. As expected, high frequency variations in attention do relate to scheduled news announcements, and we document which announcements have the most impact on attention. Lower frequency movements in attention relate to movements in economic fundamentals. We decompose each of the economic series (e.g., unemployment, inflation) into simple moving averages over different window sizes. Attention relates to variations and squared variations in shorter-horizon simple moving averages of fundamentals relative to longer-horizon moving averages. All significant squared terms on variations are positive, consistent with the idea that changes in fundamentals lead to increased attention. The directional effect of signed changes in fundamentals on attention is generally also consistent with intuition. For example, increases in unemployment increase attention, and decreases in house prices increase attention. These findings are consistent with Andrei and Hasler (2016) where the authors investigate whether asymmetry in attention is rational and find that investors pay more attention to news the further away the predictive variable is from its long-term average.

In some cases the relation between attention and fundamentals is very strong. For example, over 50% of the variation in our unemployment attention index is explained by unemployment fundamentals, and the comovement is strong enough to be apparent in a simple plot (see Figure 4.1). We also document differences between the WSJ and NYT in the strength of the relation between their attention indices and fundamentals.

We further show that news media attention to macroeconomic fundamentals relates to measures of daily stock market activity. Controlling for macroeconomic announcements, increases in attention correlate with higher aggregate volume and higher aggregate volatility.

We then investigate how media attention to unemployment might act as a leading indicator to predict the surprise in the announced unemployment rate, -i.e. the difference between the actual and expected unemployment rate. Increasing media attention to unemployment leading to up to the employment announcement predicts the surprise in the unemployment rate and the S&P 500 stock return on announcement day.

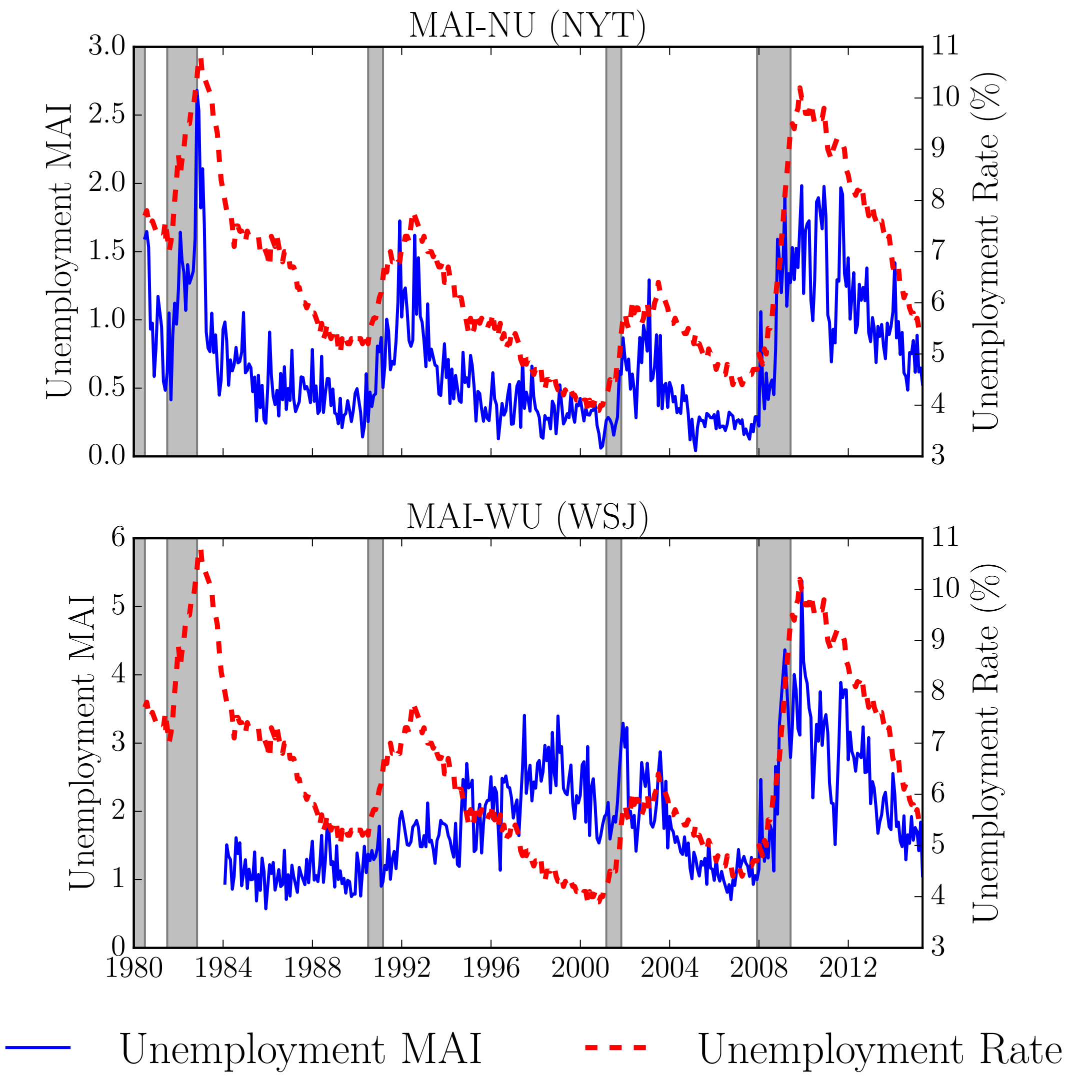
Finally, we examine how media attention to monetary policy can predict stock returns, changes in VIX, and changes in Fed fund rates on FOMC announcement days. We find that an increase in attention to monetary on days preceding FOMC announcements predicts positive stock returns, a decrease in VIX, and a decrease in Fed fun rates on FOMC announcement days.

This paper relates to at least three literatures. The first is research on the links between attention and financial markets. Theoretical studies built on rational inattention framework highlights the importance of attention allocation to asset prices (e.g., Sims, 2003; Peng and Xiong, 2006; Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2016). Andrei and Hasler (2014) establish the links between attention to aggregate stock market volatility and risk premium and Andrei and Hasler (2016) show that attention is time-varying. Also, recent studies create direct measures of stock-specific investor attention using search frequency in Google and find that investor attention predicts stock prices (Da, Engelberg, and Gao, 2011b; Da, Gurun, and Warachka, 2014). We extend this literature by creating measures of attention to macroeconomic fundamentals and examining their links to fundamentals as well as the stock market.

Second, we contribute to the literature relating macroeconomic news to asset prices. Andersen, Bollerslev, Diebold, and Vega (2003a, 2007a) show that macroeconomic announcements have an impact on financial assets at high-frequency. Boyd, Hu, and Jagannathan (2005) find that unemployment announcements impact stock prices condition on business cycle. Gilbert (2011) documents that macro announcements revisions have strong relation with the stock market index. Recent studies find that Federal Open Market

Figure 4.1: Attention to Unemployment

This figure shows the monthly unemployment attention indices for the Wall Street Journal (MAI-WU) and the New York Times (MAI-NU) and the monthly unemployment rate. The blue line is the attention index (MAI) and the red dotted line is the unemployment rate. The units are in percentage. The gray vertical bars are NBER recessions.



Committee (FOMC) announcements have significant impact on market risk premium (Savor and Wilson, 2013b; Cieslak, Morse, and Vissing-Jorgensen, 2015b). Media coverage of macroeconomic risks can also be used as a conditioning variable in testing asset pricing models (Matthies and Liu, 2015). We show that high-frequency movements in media attention to macro fundamentals are linked to macroeconomic announcements, while lower-frequency fluctuations are linked to the fundamentals itself. Further, we show that changes in media attention predict both surprises and stock returns on unemployment announcement days.

Finally, our paper relates to the literature on text search methods. Examples include Antweiler and Frank (2004), Tetlock (2007), Fang and Peress (2009b). In particular, Baker, Bloom, and Davis (2015) measure economic policy uncertainty using, in part, newspaper articles mentioning policy uncertainty. The authors show that economic policy uncertainty (EPU) index affects both aggregate and firm-level activities. Our research differs by focusing on attention to macroeconomic risks.

4.2 Macroeconomic Attention Indices

We create indices of news-media attention to the following macroeconomic risks: output growth, inflation, employment, interest rates, monetary policy, housing, credit conditions, oil, and the U.S. dollar. For each fundamental, we create a list of related words and phrases, shown in Table 4.1. We aim for the lists to be objectively reasonable.

Table 4.1: Newspapers Search Words

This table presents the search words used to select the articles related to nine specific macroeconomic fundamentals in the Wall Street Journal (WSJ) and New York Times (NYT). The nine macroeconomic fundamentals are credit ratings, Gross Domestic Product (GDP), housing market, inflation, interest rate, monetary, oil, U.S. dollar, and unemployment.

Category	Newspapers search words
Credit Rating	(credit rating) OR (bond rating)
GDP	gross domestic product OR GDP OR GNP or gross national product
Housing Market	(housing market) OR (house sale) OR (new home start) OR (home construction) OR (residential construction) OR (housing sale) OR (home price)
Inflation	inflation AND (economy OR economic OR Federal Reserve)
Interest Rate	interest rate AND (economic or economy OR federal reserve)
Monetary	(federal reserve OR federal open market committee OR fomc) AND (interest rate OR monetary OR inflation OR economy OR economic OR unemployment)
Oil	oil
U.S. Dollar	U.S. dollar OR U.S. exchange rate OR U.S. currency
Unemployment	(unemployment OR population out of work) AND (economy OR economic)

We search articles in the Wall Street Journal (WSJ) and New York Times (NYT). These publications cover general news, economic news, and financial news, and have been used in numerous prior studies. We use two different publications to provide a sense of the robustness, and also to illuminate differences in attention across outlets with different audiences. WSJ is generally regarded as having a tighter focus on the economy and financial markets as well as a more conservative editorial slant, while NYT provides broader coverage of general news and has a more politically liberal reputation.[62] For the NYT, the sample period is from June 1, 1980 to April 30, 2015. For the WSJ, the sample period is from January 1, 1984 to April 30, 2015. During these sample periods broad digital coverage of the publications is available. We consider only the newspaper print editions. Table 4.2 presents MAI and reports the data sources for associated fundamentals to each MAI.

[62]The differences in media slant and its economic impact are well-documented in the literature (see e.g., DellaVigna and Kaplan (2007); Gentzkow and Shapiro (2010)).

Table 4.2: Macroeconomic Attention and Macroeconomic Fundamentals

This table presents the macroeconomic attention indices (MAI) for credit ratings, gross domestic product (GDP), housing market, inflation, interest rate, monetary, oil, US dollar, and unemployment and its related macroeconomic fundamentals and announcements. The table also reports the data sources for the fundamentals. The announcement dates are from Bloomberg except for the historical GDP announcements (pre-1997) that are from the U.S. Bureau of Economic Analysis.

MAI	Fundamental		Macroeconomic Announcement	
	Fundamental	Source of Fundamental	Name of Announcement	Frequency
Credit Rating	Corp. Relative Spread[*]	Moody's Corporate Bond Yield		
GDP	QtQ real GDP log growth rate	Federal Reserve of St-Louis	Gross Domestic Product (GDP)	Quarterly
Housing	Nominal Home Price Index	Robert Shiller's website[**]	Case-Shiller Home Price	Monthly
Inflation	log growth in CPI	Bureau of Labor Statistics	Consumer Price Index (CPI)	Monthly
Interest	Federal Fund Rate	Federal Reserve of St-Louis	Federal Open Market Committee	8 per year
Monetary	Federal Fund Rate	Federal Reserve of St-Louis	Federal Open Market Committee	8 per year
Oil	Crude Oil Spot Price	Energy Information Admin.		
Unemployment[†]	Unemployment rate	Bureau of Labor Statistics	Employment Situation	Monthly
USD	Trade Weighted USD Index	Federal Reserve of St-Louis		

[*] The relative spread is the difference between BAA and AAA in corporate bond yields divided by AAA.

[**] US home prices 1890 to present, http://www.econ.yale.edu/ shiller/data.htm.

[†] Unemployment rates are from the initial release.

4.2.1 Construction of the Attention Indices

Each day in the sample period, we count the number of articles in each publication that satisfy the search criteria for each macro fundamental. This provides a daily count $N_{p,f,t}$, where p indexes the publication (WSJ or NYT) of articles showing some form of attention to each fundamental f. We normalize these counts by dividing by the average number of articles per day $\hat{N}_{p,t}$ for publication p during the calendar month including observation t.

The "unadjusted" macroeconomic attention index for each individual publication p is:

$$\text{MAI-}p\text{U}_{f,t} = \frac{N_{p,f,t}}{\hat{N}_{p,t}}. \tag{4.1}$$

The unadjusted attention indices measure the percentage of articles on a given day that have content related to the macroeconomic fundamental of interest.

We define related measures that are demeaned, or alternatively demeaned and standardized. Let $\mu_{p,f}$ and $\sigma_{p,f}$ denote respectively the time-series means and standard deviations of the daily unadjusted attention indices MAI-p$U_{f,t}$. The demeaned measures are denoted

$$\text{MAI-}p\text{D}_{f,t} = \text{MAI-}p\text{U}_{f,t} - \mu_{p,f},$$

and the standardized measures are denoted

$$\text{MAI-}p_{f,t} = \text{MAI-}p\text{D}_{f,t}/\sigma_{p,f}.$$

We also define two composite indexes of attention. The first composite index, denoted MAI-C1, is an average of the demeaned NYT and WSJ indices in time periods when both are available, and the NYT index only in the 1980-1983 period:

$$\text{MAI-C1}_{ft} = \begin{cases} (\text{MAI-WD}_{ft} + \text{MAI-ND}_{ft})/2 & \text{from Jan. 1, 1984 to Apr. 30, 2015,} \\ \text{MAI-ND}_{ft} & \text{from June 1, 1980 to Dec. 31, 1983.} \end{cases} \tag{4.2}$$

Demeaning the individual publication indices before averaging ensures that we will not induce a level effect driven simply by the change in composition that occurs in 1984 when the WSJ data becomes available.

The second composite index, denoted MAI-C2, is an average of the standardized NYT and WSJ indices when both are available:

$$\text{MAI-C2}_{ft} = \begin{cases} (\text{MAI-W}_{ft} + \text{MAI-N}_{ft})/2 & \text{from Jan. 1, 1984 to Apr. 30, 2015,} \\ \text{MAI-N}_{ft} & \text{from June 1, 1980 to Dec. 31, 1983.} \end{cases} \tag{4.3}$$

Standardizing ensures that both publications contribute equally to the variation of MAI-C2. While the weighting of the two composite indices is different, neither is superior in any sense. The publication with more variation in its own attention index will be weighted more heavily in MAI-C1 relative to MAI-C2. If one believes that greater variation in attention over time reflects more information, then the weighting of MAI-C1 may be preferred to MAI-C2.

All of the indices build on simple counts of the number of articles related to a macroeconomic fundamental, as a proportion of all articles. Many elaborations of this approach are possible, for example weighting articles by their number of words, or attempting to measure the intensity of relevance rather than a simple binary coding. We take a basic approach for simplicity, and expect other measurement methods to be explored in future research. We emphasize that the indices measure attention only, and do not attempt to distinguish other possible article attributes such as positive versus negative sentiment.

4.2.2 Empirical Properties of the Attention Indices

Table 4.3, Panel A provides summary statistics for the unadjusted daily attention indices for both NYT and WSJ. For the WSJ, the index averages range from a low of about 0.5% of articles for credit to a high of over 2% for inflation and oil. NYT coverage of macroeconomic fundamentals is uniformly lower as a proportion of all coverage. The NYT index means have a lowest value of 0.08% for U.S. dollar coverage, and the highest index means are inflation (0.90%), unemployment (0.81%), and oil (0.76%). Consistent with the higher mean attention levels in the WSJ, the standard deviation of attention is also uniformly higher for the WSJ than the NYT. This implies that the weight of the WSJ in the composite indices MAI-C1 will be higher than in the composite indices MAI-C2.

Table 4.3: Descriptive Statistics

This table presents the descriptive statistics for the macroeconomic attention indices (MAI). Panel A shows the daily unadjusted media attention indices (MAI) for the Wall Street Journal (MAI-WU $_{f,t}$) and New York Times (MAI-NU $_{f,t}$), the Economic Policy Uncertainty (EPU) index, the implied volatility (VXO), and the three-month detrended log S&P 500 trade volume. Columns Mon to Sun are the daily averages for each MAI. Panels B shows the correlation between the demeaned macroeconomic attention composite indices (MAI-C1), EPU, VXO, and the 60-day detrended S&P 500 trade volume at the daily frequency. Obs. stands for the number of observations, and St. dev. stands for the standard deviation.

Panel A: Daily unadjusted MAI descriptive statistics (1980-2015)

	Obs.	Mean	St. Dev.	Min	Max	Mon	Tues	Wed	Thur	Frid	Sat	Sun
Wall Street Journal												
Credit Rating	11443	0.46	0.89	0.00	9.67	0.50	0.58	0.73	0.57	0.62	0.22	0.00
GDP	11443	1.41	1.54	0.00	12.91	2.09	1.65	1.82	1.77	1.94	0.62	0.00
Housing	11443	0.71	1.46	0.00	17.18	0.62	0.68	1.40	0.84	0.99	0.42	0.00
Inflation	11443	2.24	2.06	0.00	15.71	3.28	2.47	3.01	2.86	3.15	0.87	0.00
Interest	11443	0.95	1.23	0.00	13.54	1.21	1.02	1.40	1.31	1.30	0.40	0.00
Monetary	11443	1.91	1.95	0.00	18.62	2.60	2.11	2.61	2.63	2.50	0.90	0.00
Oil	11443	2.34	2.57	0.00	19.47	2.82	2.98	3.37	3.05	3.16	0.97	0.00
Unemp.	11443	1.44	1.64	0.00	14.07	2.00	1.48	2.09	1.59	2.18	0.73	0.00
USD	11443	0.78	1.08	0.00	9.60	0.97	1.07	1.07	1.03	1.08	0.24	0.00
New York Times												
Credit Rating	12752	0.20	0.43	0.00	10.06	0.11	0.21	0.24	0.23	0.20	0.17	0.23
GDP	12752	0.51	0.58	0.00	5.65	0.37	0.43	0.46	0.49	0.53	0.43	0.88
Housing	12752	0.29	0.57	0.00	7.23	0.11	0.18	0.28	0.28	0.28	0.20	0.68
Inflation	12752	0.90	0.91	0.00	12.26	0.66	0.70	0.93	0.89	0.94	0.82	1.37
Interest	12752	0.26	0.38	0.00	3.12	0.19	0.21	0.27	0.28	0.26	0.24	0.34
Monetary	12752	0.92	0.77	0.00	8.68	0.60	0.78	0.98	1.04	1.06	0.95	1.05
Oil	12752	0.76	0.84	0.00	8.94	0.50	0.73	0.80	0.84	0.81	0.70	0.91
Unemp.	12752	0.81	0.90	0.00	10.53	0.58	0.55	0.70	0.67	0.92	0.78	1.48
USD	12752	0.08	0.20	0.00	3.34	0.01	0.08	0.07	0.08	0.08	0.07	0.18
Other Variables												
EPU	11077	102.61	70.29	3.38	719.07	111.25	102.56	96.44	90.01	93.26	90.70	134.02
VXO	7386	20.73	9.06	8.51	150.19	20.80	20.67	20.68	20.79	20.74		
Volume	8798	20.17	1.48	16.52	23.16	20.09	20.19	20.20	20.19	20.17	20.20	20.16

Panel B: Daily MAI-C1 correlation (1980-2015)

	Credit Rating	GDP	Housing	Inflation	Interest	Monetary	Oil	Unemp.	USD	EPU	VXO	Volume
Credit Rating	1.00	0.16	0.16	-0.02	0.13	0.17	0.14	0.15	0.15	0.13	0.20	0.29
GDP	0.16	1.00	0.15	0.21	0.16	0.23	0.12	0.33	0.10	0.10	0.08	0.25
Housing	0.16	0.15	1.00	0.08	0.24	0.26	0.13	0.16	0.06	0.04	0.02	0.38
Inflation	-0.02	0.21	0.08	1.00	0.34	0.45	0.31	0.22	0.18	0.02	0.02	-0.24
Interest	0.13	0.16	0.24	0.34	1.00	0.57	0.33	0.14	0.29	0.08	0.16	0.14
Monetary	0.17	0.23	0.26	0.45	0.57	1.00	0.29	0.27	0.24	0.16	0.17	0.20
Oil	0.14	0.12	0.13	0.31	0.33	0.29	1.00	0.02	0.37	0.03	0.08	0.02
Unemp.	0.15	0.33	0.16	0.22	0.14	0.27	0.02	1.00	-0.02	0.21	0.17	0.16
USD	0.15	0.10	0.06	0.18	0.29	0.24	0.37	-0.02	1.00	0.02	0.23	0.03
EPU	0.13	0.10	0.04	0.02	0.08	0.16	0.03	0.21	0.02	1.00	0.28	0.07
VXO	0.20	0.08	0.02	0.02	0.16	0.17	0.08	0.17	0.23	0.28	1.00	0.10
Volume	0.29	0.25	0.38	-0.24	0.14	0.20	0.02	0.16	0.03	0.07	0.10	1.00

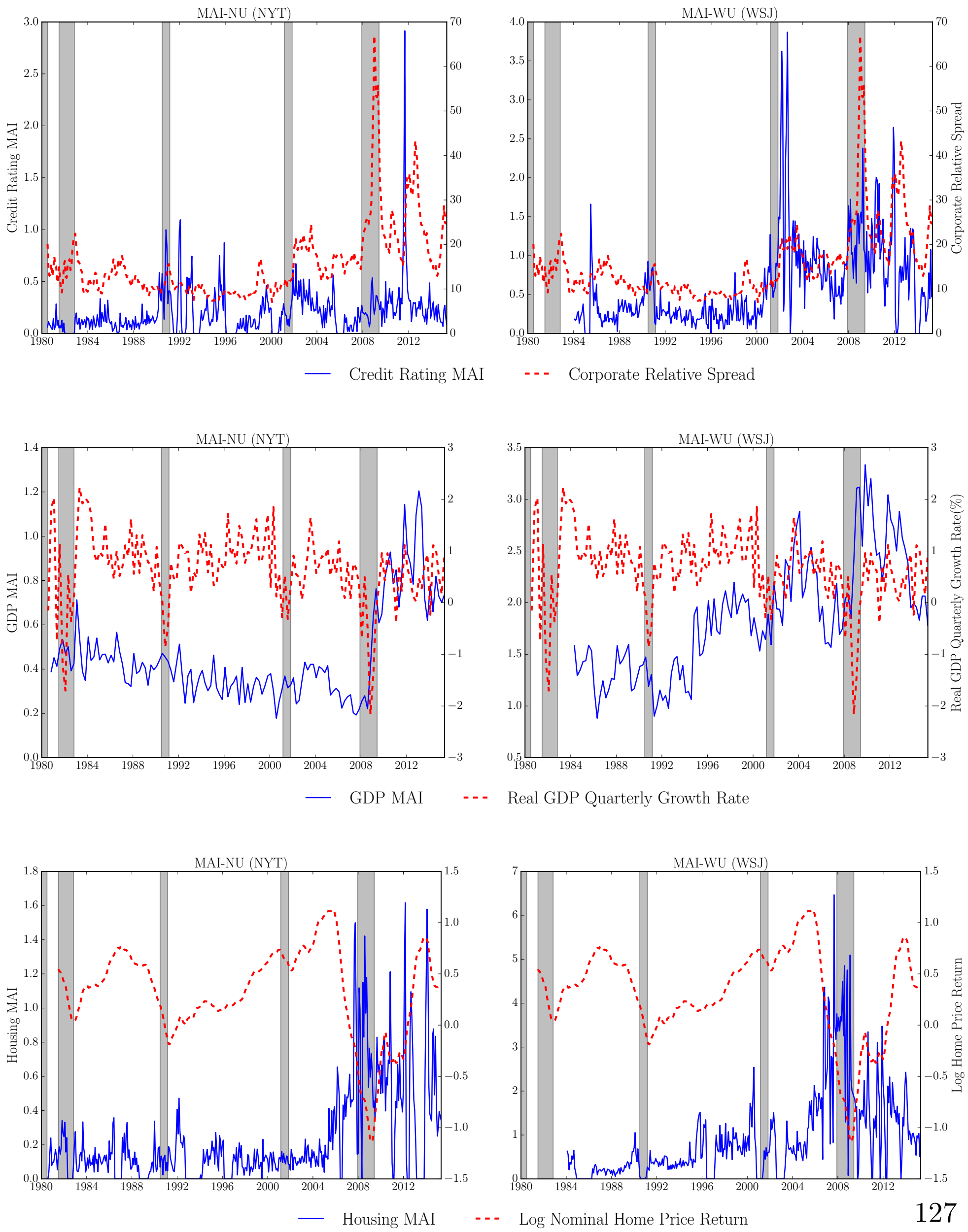
Table 4.3, Panel A also provides index means by day of the week. The Saturday edition of WSJ generally has less coverage of macro fundamentals than other days of the week. For NYT, the Saturday edition appears to have roughly similar content to other days, while the large Sunday edition offers more coverage than other days. While the effects of weekend news coverage are interesting and potentially important, for simplicity in the remainder of our analysis we discard all non-trading days (weekends and holidays). To account for potential day-of-the weak seasonalities in news coverage, all of our empirical results use day-of-the-week dummy variables.

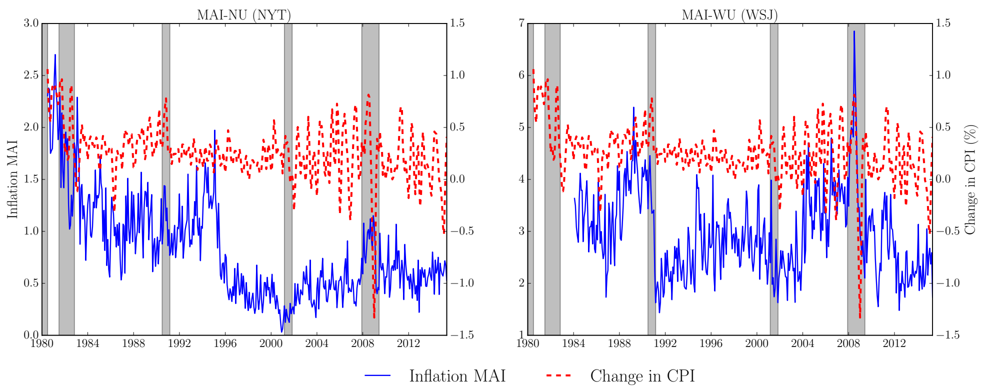
Figure 4.2 plots the attention indices. For reference, each attention index is associated with a series of macroeconomic fundamentals that seems relevant.[63] For example, the output growth attention index is plotted on the same axes with the log quarter-to-quarter growth in real GDP. The full list of attention indices versus the associated macroeconomic fundamentals plotted in Figure 4.2 is given in Table 4.2.

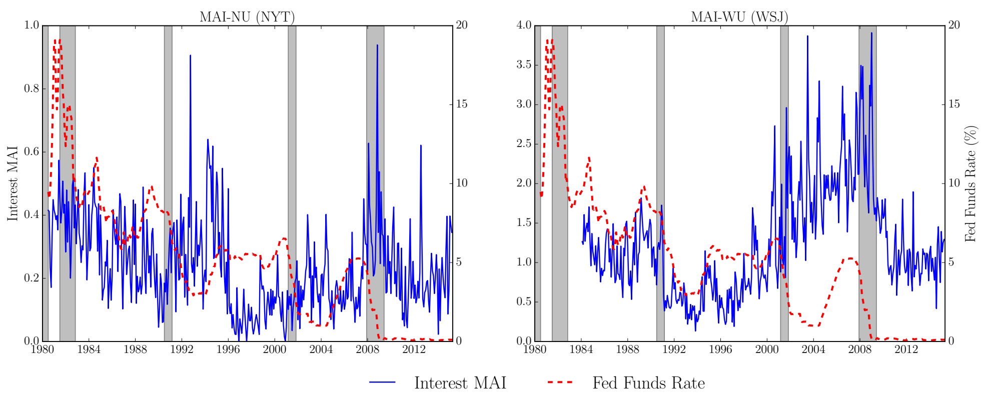
[63] This approach follows Carroll (2003), who plots a monthly news count index of inflation from the New York Times and the Washington Post against CPI, from 1981 to 2001.

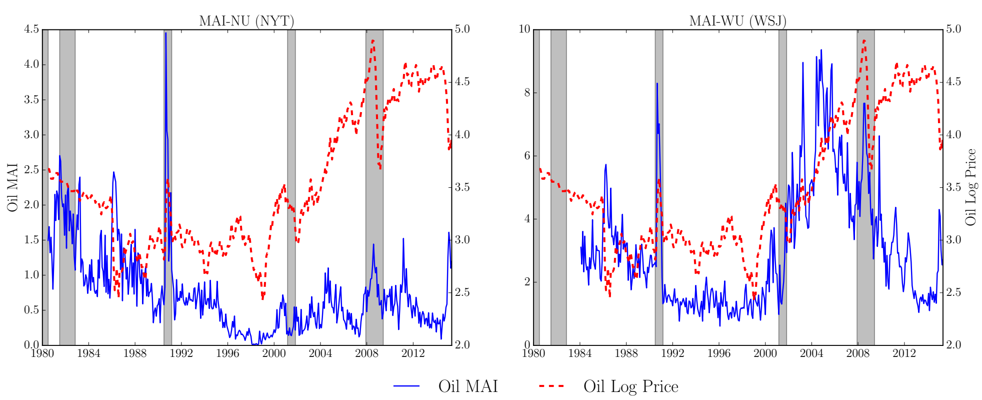
Figure 4.2: Macro Attention and Macroeconomic Fundamentals

This figure shows the monthly macroeconomic attention indices (MAI) for the Wall Street Journal (MAI-WU) and the New York Times (MAI-NU) against related monthly macroeconomic fundamentals described in Table 4.2. The blue line represents a macroeconomic attention index (left y-axis) and the red dotted line (right y-axis) the MAI related macroeconomic fundamental (see Table 4.2). The units are in percentage. The gray vertical bars are NBER recessions.




MAI-NU (NYT)
MAI-WU (WSJ)
Inflation MAI
Change in CPI (%)
Inflation MAI
Change in CPI


MAI-NU (NYT)
MAI-WU (WSJ)
Interest MAI
Fed Funds Rate (%)
Interest MAI
Fed Funds Rate


MAI-NU (NYT)
MAI-WU (WSJ)
Oil MAI
Oil Log Price
Oil MAI
Oil Log Price

We emphasize several properties of the attention indices. First, the indices do not appear to be driven by a single factor. They are imperfectly correlated, and over time attention shifts across different fundamentals. Second, attention is highly persistent. All series show fluctuations that last over periods at least as long as several years, including both gradual trends and sharp changes. Third, the indices also show cycles at a range of higher frequencies, including short bursts of attention. Finally, attention seems to be at least loosely related to underlying fundamentals. This is seen most clearly in the plot for employment, where broad patterns in attention seem to match closely with the level of the unemployment rate. We now investigate each of these aspects of the plots using statistical analyses.

Table 4.3 shows daily (Panel B) and monthly (Panel C) correlations among the composite attention indices MAI-C1, as well as correlations with other series of interest: implied volatility (VXO) from the Chicago Board Options Exchange (CBOE)[64], economic policy uncertainty (EPU) from Baker, Bloom, and Davis (2015)[65], detrended S&P 500 trade volume (Volume) from the Center for Research in Security Prices (CRSP), and lagged values of the VXO and Volume. The results confirm the imperfect correlation of the attention indices. In daily data, the highest inter-MAI correlations MAI are between monetary and inflation (0.45), monetary and interest rates (0.57), oil and inflation (0.31), US dollar and oil (0.37), and inflation and interest rates (0.34). Not all correlations are positive. For example, in monthly data the MAI for GDP and inflation are negatively correlated (-0.14) and credit rating and inflation (-0.18). We also are interested in correlations between the attention indices and other variables. In the monthly data, the highest correlations with EPU are unemployment (0.35), credit rating (0.28), and monetary (0.15). The highest correlations with VXO are US dollar (0.33), credit rating (0.32), and unemployment (0.32).

To address stationarity, we estimate AR (p) models for each attention index from monthly data. Following Campbell and Yogo (2006), we use the lag length that minimized the Bayesian information criteria (BIC). The minimum BIC for all of our MAI occurs at four lags or less. Table 4.4 shows these AR estimates, controlling for monthly fixed-effects. The table also reports Dickey-Fuller p-values for the null hypothesis that each series has a unit root. The DF statistics reject the presence of unit roots except for the US dollar MAI.[66]

[64]Data source: https://www.cboe.com/micro/vix/historical.aspx.
[65]The data is available at http://www.policyuncertainty.com/.
[66]The US dollar MAI-C2 rejects the unit root with a p-value of 0.09.

Table 4.4: Persistence of Macroeconomic Attention

Panel A of this table presents AR (p) models of the monthly demeaned macroeconomic attention composite indices (MAI-C1), controlling for monthly time-fixed effects. DF (p-value) are the p-values for the Dickey-Fuller (DF) statistics that test the null of a unit root in each time series. Panel B reports the estimates from an OLS regression of the daily demeaned macroeconomic attention composite indices (MAI-C1) on various moving average lags of itself. L1 corresponds to the lag of itself and L5, L21, L62, L250, and L1000 are the moving average for 5, 21, 62, 250, and 1000 days preceding the observed values at time t. We control for day-of-week fixed effects. The standard errors are reported in parenthesis and are calculated using Newey-West standard errors (10 lags). Obs. stands for the number of observations. *, **, and *** denote the statistical significance at the 10%, 5%, 1% levels, respectively.

Panel A: Monthly MAI-C1 AR(4) coefficients and DF statistics

	Credit Rating	GDP	Housing	Inflation	Interest	Monetary	Oil	Unemp.	USD
const	0.01	0.03	-0.02	0.09**	0.02	0.07	0.14*	0.01	-0.02
	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.05)	(0.08)	(0.04)	(0.03)
AR(1)	0.70***	0.25***	0.47***	0.51***	0.58***	0.50***	0.71***	0.62***	0.69***
	(0.08)	(0.04)	(0.10)	(0.05)	(0.05)	(0.04)	(0.05)	(0.06)	(0.06)
AR(2)	-0.02	0.29***	0.10	0.21***	0.17**	0.13**	0.17***	0.17***	0.06
	(0.10)	(0.04)	(0.08)	(0.04)	(0.07)	(0.05)	(0.04)	(0.05)	(0.06)
AR(3)	-0.01	0.30***	0.29***	0.05	-0.00	0.15**	0.02	0.11**	0.01
	(0.07)	(0.05)	(0.10)	(0.05)	(0.06)	(0.07)	(0.08)	(0.05)	(0.05)
AR(4)	0.15**	0.08	0.01	0.10**	0.10**	0.04	0.01	0.01	0.18***
	(0.07)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)
DF (p-value)	0.00	0.02	0.04	0.00	0.01	0.00	0.00	0.00	0.13
Adj-R2	0.58	0.70	0.63	0.67	0.62	0.54	0.79	0.78	0.82
Obs.	415	415	415	415	415	415	415	415	415

Panel B: Daily MAI-C1 regressions on lagged attention

	Credit Rating	GDP	Housing	Inflation	Interest	Monetary	Oil	Unemployment	U.S. Dollar
const	-0.09***	0.08**	-0.21***	0.09**	-0.04	-0.11**	-0.21***	0.04	-0.08***
	(0.02)	(0.04)	(0.03)	(0.05)	(0.03)	(0.04)	(0.05)	(0.04)	(0.02)
L1	0.07***	0.05***	0.06**	0.03**	0.12***	0.17***	0.06***	0.00	-0.01
	(0.02)	(0.01)	(0.03)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
L5	0.28***	0.11***	0.56***	0.13***	0.16***	0.19***	0.38***	0.23***	0.18***
	(0.05)	(0.03)	(0.06)	(0.03)	(0.03)	(0.03)	(0.05)	(0.04)	(0.04)
L21	0.44***	-0.01	0.05	0.30***	0.24***	0.23***	0.36***	0.22***	0.51***
	(0.07)	(0.07)	(0.09)	(0.06)	(0.07)	(0.05)	(0.05)	(0.07)	(0.07)
L62	0.02	0.41***	0.12**	0.34***	0.18**	0.12*	0.13***	0.30***	0.13*
	(0.07)	(0.10)	(0.06)	(0.07)	(0.09)	(0.07)	(0.05)	(0.08)	(0.08)
L250	0.12*	0.43***	0.20**	0.09	0.25***	0.23***	0.03	0.26***	0.19***
	(0.06)	(0.10)	(0.08)	(0.06)	(0.07)	(0.08)	(0.03)	(0.07)	(0.06)
L1000	0.02	-0.04	-0.01	0.03	-0.01	0.01	0.02	-0.09***	-0.04
	(0.06)	(0.06)	(0.05)	(0.05)	(0.04)	(0.05)	(0.02)	(0.03)	(0.03)
Obs.	8109	8109	8109	8109	8109	8109	8109	8109	8109
Adj-R2	0.29	0.15	0.43	0.17	0.23	0.26	0.54	0.32	0.41

To further explore time-series dependence, Figure 4.3 shows autocorrelation plots of each composite series MAI-C1 for lag lengths from 1 to 250 trading days. We plot the autocorrelations for residuals after controlling for day-of-the-week dummies and month-of-the-year dummies. The plots show very slow decay in this range of frequencies, and the autocorrelations are significantly larger than zero at 250 lags for all series. Several of the autocorrelation plots show apparent cycles in dependence. For example, GDP shows strong increases in correlations at each monthly interval. Other series (housing, US dollar) have increases in autocorrelations at weekly intervals. These cycles are consistent with the importance of periodic news announcements.

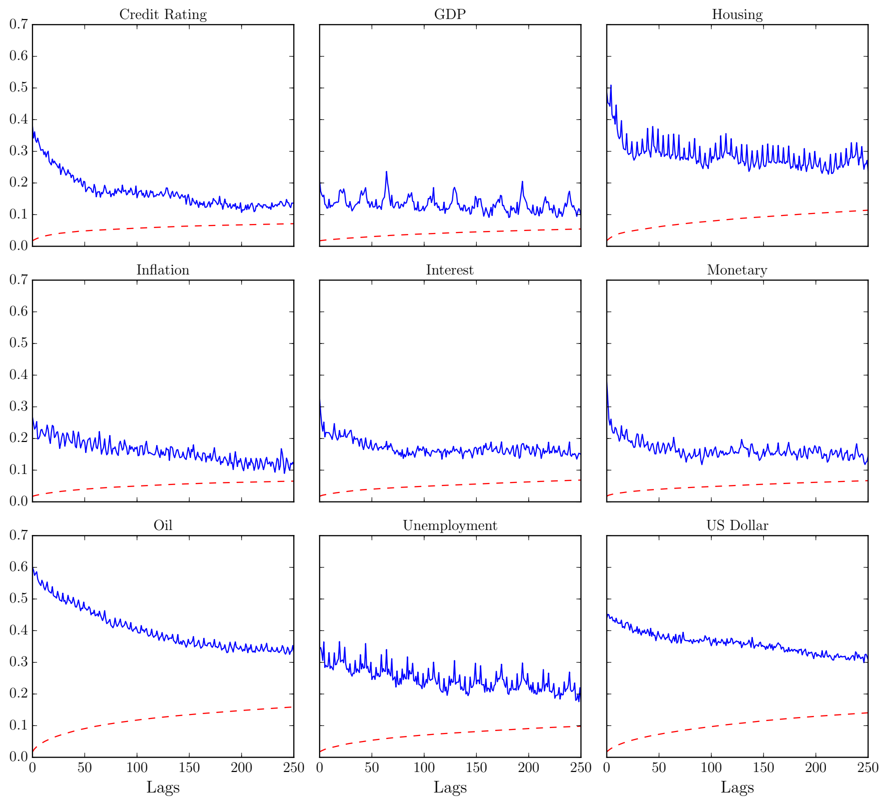
To account for potential long-memory dependence as well as multiple cycles in news variation, we use regressions that aggregate the attention indices over different horizons similarly to MIDAS regression (see Ghysels, Santa-Clara, and Valkanov, 2006). Specifically, we construct simple moving averages of the attention indices over window sizes of 1 day, 5 days, 21 days (monthly), 62 days (quarterly), and 250 days (annual), and 1000 days (business cycle).

Panel B of Table 4.4 shows results of regressing each attention index on lagged simple moving averages of its own history, for the full set of different window sizes. All of the series show persistence at multiple frequencies, with the majority having significant positive persistence in daily, weekly, monthly, quarterly, and annual-length moving averages in the multiple regression framework.

One exception is credit rating attention, which does not show significant persistence beyond monthly horizons. A separate monthly cycle is not present in GDP attention, although it does show significant persistence at all other cycle lengths between daily and annual. This result seems intuitive given the quarterly reporting cycle for GDP growth. These results are consistent with slow, approximately hyperbolic decay in the persistence of attention to each of the fundamental factors. The presence of multiple frequencies in attention to financial news are also broadly consistent with the motivation and theoretical framework in Calvet and Fisher (2007), who hypothesize fractal patterns in news about the fundamentals impacting asset prices. We next determine whether the fluctuations of the individual attention indices can be related to macroeconomic fundamentals.

Figure 4.3: Autocorrelation in Macroeconomic Attention

This figure shows the autocorrelations (ρ_k) for residuals after controlling for day-of-the-week dummies and month-of-the-year dummies for each of the composite macroeconomic attention index MAI-C1 for k lags ranging from 1 to 250 trading days. The dashed line represents the 95% critical value for the test $\rho_k \leq 0$, where we use the "large-lag" standard errors of Anderson (1976). These standard errors account for the observed autocorrelations for lags less than k.



4.3 Attention and Macroeconomic Fundamentals

Intuition suggests that high frequency fluctuations in attention could be driven by economic announcements, while lower frequency variations might be related to movements in economic fundamentals. We test these ideas.

4.3.1 Macroeconomic Announcements

Prior literature has established links between economic announcements and returns and volatility for the foreign exchange and stock market (Andersen, Bollerslev, Diebold, and Vega, 2003a, 2007a). We now investigate the relationship between macroeconomic announcements and attention to macroeconomic fundamentals. Attention could be limited to simply reporting on announcements. Alternatively, attention might be high in advance of announcements as news media strive to anticipate the content of announcements, or to put the potential outcomes of an announcement into a broader context for the benefit of their readers.

Cross-sectionally, our analysis can tell us which types of announcements have the largest impacts on macroeconomic attention. If the media play an important role in the transmission of economic news, then understanding the allocation of media resources to covering different types of announcements should be informative about which announcement matters most to readers.

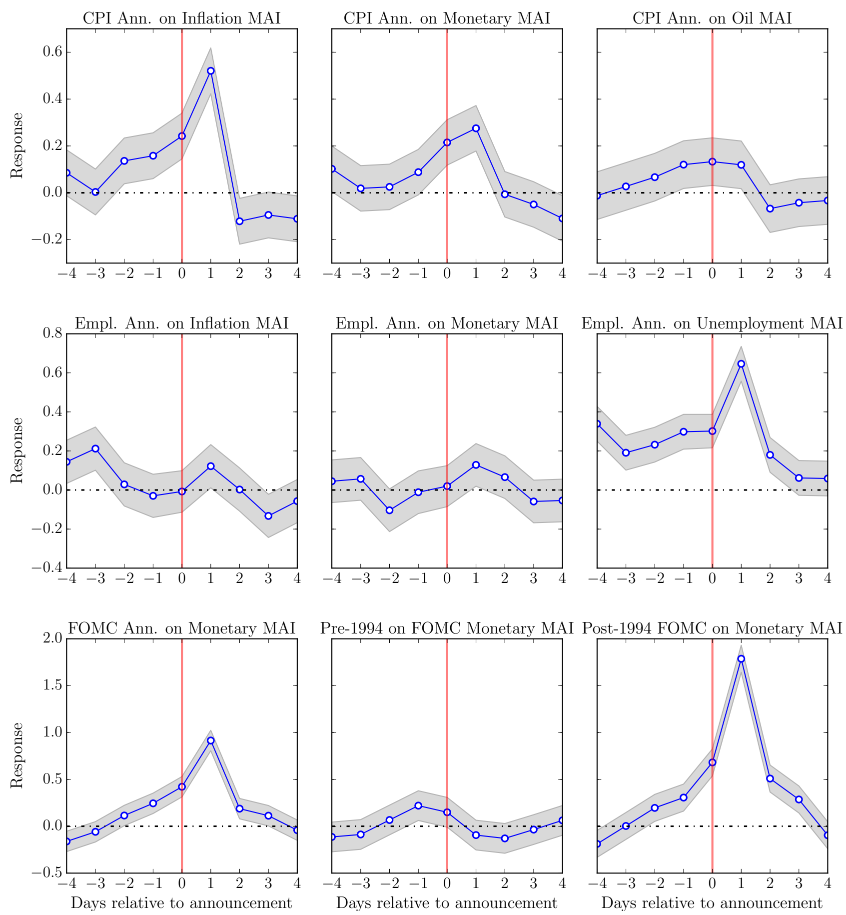
The economic announcements we consider are: consumer price index (CPI), employment situation, and Federal Open Market Committee (FOMC) announcements. The announcement dates span the entire sample length of our indices. The CPI, and employment situation announcement dates are from the Bureau of Labor Statistics and FOMC announcement dates are from the Federal Reserve Board. Macroeconomic attention can be influenced by multiple announcements, hence we study the most intuitive links between the macroeconomic attention indices and macroeconomic announcements as shown in Table 4.2. The specification we use is:

$$\text{MAI-C1d}_{f,t} = \alpha + \sum_{\delta=-4}^{\delta=4} \beta_\delta Ann_{j,t+\delta} + \epsilon_t \tag{4.4}$$

where $\text{MAI-C1d}_{f,t}$ is the composite index MAI-C1 detrended by its own 60-day simple moving average. The variables $Ann_{j,t+\delta}$ are equal to 1 if there is an announcement on day-$t+\delta$, 0 otherwise, and we let δ take integer values from -4 to 4. Since the model specification contains many variables we show the regression coefficients, β_δ and their 95 percent confidence intervals in Figure 4.4. In the first row, attention to inflation increases leading up to the CPI announcement, and the index is at its highest one day after the announcement. CPI announcements also raise attention more moderately in the monetary and oil attention indices.

Figure 4.4: Macroeconomic Attention around Macroeconomic Announcements

This figure shows the lag and forward estimated coefficients β_δ from an OLS regression of detrended macroeconomic attention indices MAI-C1 on announcement dummies as specified in Equation (4.4). The shaded area corresponds to the 95% confidence interval around the estimated coefficients. The x-axis is the number days since the announcement. The first row shows attention around the consumer price index (CPI) announcements, the second row the Employment situation announcements, and the third row the Federal Open Market Committee (FOMC) announcements for different MAI-C1. The vertical line represents the day of the announcement.



For unemployment announcements (second row), macroeconomic attention increases two days in advance of the announcement, spikes on the announcement day, and remains high for two days after the announcement. Unemployment announcements do not impact other MAI, such as inflation and monetary.

FOMC announcements (the third row) have moderate impacts on the attention index associated with monetary policy in the full sample. However, a subsample analysis shows that the effects are indistinguishable prior to 1994, when policy actions were not publicly announced. After 1994 when the FOMC started public announcements of the policy action, the pattern in attention becomes more pronounced. Boguth, Carlson, Fisher, and Simutin (2016) use our monetary policy attention index and show that times when investors expect important decisions from the Federal Open Market Committee, attention is high prior to committee meeting.

4.3.2 Macroeconomic Fundamentals

Beyond the link between economic announcements and daily spikes in attention, what accounts for the lower-frequency fluctuations in the attention indices? Figure 4.1 and 4.2 suggests attention dynamics could reflect changing economic conditions.

Prior literature has attempted to establish links between macroeconomic variables and financial market variables such as volatility (Schwert, 1989). We expect that macroeconomic attention connects economic news with financial markets, serving an intermediary function. A benefit of measuring macroeconomic attention is that we can measure not just aggregate interest in financial and economic news, we can also tell what writers are talking about. Hence the low frequency variations in our different MAI should pick up changing patterns in concerns for different macroeconomic fundamentals.

To study how variations in macroeconomic fundamentals impact macroeconomic attention, we decompose the macro variables into detrended moving averages over different window sizes. That is, given a particular macroeconomic fundamental F_t (e.g., unemployment rate, change in log CPI, change in log house price index), we can decompose the fundamental into a set of detrended moving averages:

$$F_t \equiv (F_t - \overline{F}_{t,t-2}) + (\overline{F}_{t,t-2} - \overline{F}_{t,t-11}) + (\overline{F}_{t,t-11} - \overline{F}_{t,t-47}) + \overline{F}_{t,t-47}, \quad (4.5)$$

where $\overline{F}_{t,t-k}$ is the simple moving average of the fundamental from $t-k$ to t. The components on the right hand side of the equation, each in parentheses, are detrended moving averages over window sizes that are expanding approximately geometrically. These could be capable of capturing the low-frequency patterns in autocorrelations documented for the attention indices in Table 4.4. We regress the monthly attention indices on these detrended moving averages and their squared values:

$$\begin{aligned} MAI_{f,t} = \alpha &+ \beta_1(F_t - F_{t,t-2}) + \beta_2(F_t - F_{t,t-2})^2 + \\ &\beta_3(F_{t,t-2} - F_{t,t-11}) + \beta_4(F_{t,t-2} - F_{t,t-11})^2 + \\ &\beta_5(F_{t,t-11} - F_{t,t-47}) + \beta_6(F_{t,t-11} - F_{t,t-47})^2 + \epsilon_t. \end{aligned} \tag{4.6}$$

Table 4.5 reports results for regression (4.6) for the NYT (Panel A) and WSJ (Panel B) indices. The results show generally that attention responds to changes in macro fundamentals. Adjusted R^2 range from 0 to over 50%, with most of the regressions having at least one significant coefficient on fundamentals.

Table 4.5: Macroeconomic Attention and Macroeconomic Fundamentals

This table presents the results of an OLS regression of monthly macroeconomic attention indices (MAI) on different macroeconomic fundamentals. Panel A and Panel B report the results for the New York Times macroeconomic attention indices (MAI-NU) and the Wall Street Journal (MAI-WU) respectively. The general regression is specified in equation 4.6. F corresponds to the associated fundamental to each MAI as described in Table 4.2 and F_t is the moving average over t days of the respective macroeconomic fundamental. We control for monthly fixed effects. The standard errors are reported in parenthesis and are calculated using Newey-West standard errors (10 lags). Obs. stands for the number of observations. *, **, *** denote the statistic significance at the 10%, 5%, 1% levels, respectively.

Panel A: MAI-NU (New York Times)

MAI:	Credit Rating	GDP	Housing	Inflation	Interest	Monetary	Oil	Unemployment	US Dollar
F:	Credit Rating Spreads	GDP Growth	Home Price Ret	Δ CPI	Fed Fund	Fed Fund	Oil Price Ret	Unemp. Rate	USD Index Ret
$F_t - F_{t,t-2}$	0.022		-0.221*	-0.171**	-0.020	-0.022	-0.003	0.034	0.000
	(0.014)		(0.122)	(0.068)	(0.018)	(0.035)	(0.004)	(0.155)	(0.001)
$F_{t,t-2} - F_{t,t-11}$	-0.001	0.059*	-0.317***	-0.533***	0.004	-0.010	0.005	0.063	-0.001
	(0.004)	(0.031)	(0.110)	(0.163)	(0.013)	(0.034)	(0.009)	(0.091)	(0.004)
$F_{t,t-11} - F_{t,t-47}$	-0.011	0.154	-0.013	0.641	-0.019***	-0.041*	0.044*	0.140***	-0.020
	(0.012)	(0.100)	(0.107)	(0.758)	(0.006)	(0.021)	(0.024)	(0.048)	(0.012)
$(F_t - F_{t,t-2})^2$	0.000		0.538***	-0.476***	0.030***	0.059***	0.002***	0.632	0.000
	(0.001)		(0.117)	(0.170)	(0.007)	(0.017)	(0.001)	(0.737)	(0.001)
$(F_{t,t-2} - F_{t,t-11})^2$	-0.000	0.055	0.242***	-0.260	0.014**	0.048***	0.003***	0.229**	-0.004*
	(0.000)	(0.039)	(0.086)	(0.177)	(0.006)	(0.014)	(0.001)	(0.104)	(0.002)
$(F_{t,t-11} - F_{t,t-47})^2$	0.001	0.190	0.413**	6.503***	0.007***	-0.005	-0.007	0.066***	-0.016
	(0.001)	(0.150)	(0.202)	(2.207)	(0.002)	(0.008)	(0.006)	(0.025)	(0.012)
const	0.189***	0.416***	0.004	0.644***	0.187***	0.819***	0.488***	0.559***	0.068***
	(0.038)	(0.057)	(0.043)	(0.078)	(0.026)	(0.067)	(0.083)	(0.065)	(0.018)
Obs.	419	125	419	419	419	419	376	419	419
Adj-R2	0.05	0.06	0.35	0.15	0.16	0.09	0.28	0.51	-0.00

Panel B: MAI-WU (Wall Street Journal)

MAI:	Credit Rating	GDP	Housing	Inflation	Interest	Monetary	Oil	Unemployment	US Dollar
F:	Credit Rating Spreads	GDP Growth	Home Price Ret	Δ CPI	Fed Fund	Fed Fund	Oil Price Ret	Unemp. Rate	USD Index Ret
$F_t - F_{t,t-2}$	0.053**		-0.272	-0.259	-0.280	-0.488	-0.016	-0.193	0.007
	(0.023)		(0.302)	(0.185)	(0.242)	(0.361)	(0.011)	(0.268)	(0.013)
$F_{t,t-2} - F_{t,t-11}$	0.024**	0.176	-0.680***	0.704	0.161	0.198	0.016	0.141	-0.022
	(0.012)	(0.120)	(0.256)	(0.444)	(0.163)	(0.241)	(0.020)	(0.247)	(0.042)
$F_{t,t-11} - F_{t,t-47}$	0.022	0.294	-0.268	4.609***	0.132	0.129	0.172*	0.241**	-0.362***
	(0.023)	(0.293)	(0.318)	(1.321)	(0.090)	(0.117)	(0.099)	(0.103)	(0.136)
$(F_t - F_{t,t-2})^2$	-0.002		0.486	-0.274	0.571	0.162	0.006***	3.176**	0.016**
	(0.003)		(0.479)	(0.358)	(0.640)	(0.826)	(0.001)	(1.413)	(0.008)
$(F_{t,t-2} - F_{t,t-11})^2$	0.001	0.315**	0.672***	1.139**	0.362***	0.343*	0.007***	0.202	0.055**
	(0.001)	(0.147)	(0.236)	(0.455)	(0.123)	(0.177)	(0.001)	(0.183)	(0.022)
$(F_{t,t-11} - F_{t,t-47})^2$	0.001	0.399	2.393***	12.976**	0.075**	0.070	-0.003	0.082*	0.295**
	(0.001)	(0.454)	(0.458)	(6.190)	(0.038)	(0.065)	(0.019)	(0.043)	(0.148)
const	0.558***	1.740***	0.142	3.015***	1.032***	2.364***	2.728***	1.866***	0.829***
	(0.084)	(0.121)	(0.106)	(0.105)	(0.110)	(0.183)	(0.359)	(0.133)	(0.159)
Obs.	376	125	376	376	376	376	376	376	376
Adj-R2	0.11	0.06	0.47	0.19	0.13	0.03	0.08	0.33	0.14

To help synthesize the results, we first focus on aspects that are similar across Panels A and B, or across attention in both the NYT and WSJ. Confirming the idea that change raises attention, many of the coefficients on *squared* changes in fundamentals are significant and positive in both panels. For the NYT, of the fifteen significant coefficients on squared changes in fundamentals, thirteen are positive. For the WSJ, all fifteen of the fifteen squared changes on fundamentals are positive. These results are consistent with theories where changes in fundamentals raise attention, such as in Andrei and Hasler (2014, 2016).

A second intuitive idea is that for a given magnitude of the absolute change, attention will be higher when the change is in a direction that is associated with "bad" versus "good" times. Focusing on the significant coefficients on *signed* changes in fundamentals, many of the series show consistent results across the NYT and WSJ in the intuitive direction suggesting that bad news raises attention: Attention to credit rises when relative credit spreads rise; attention to housing rises when house prices fall; attention to unemployment rises when unemployment increases.

We also see interesting differences across the WSJ and NYT attention indices. In general, the R^2 for the WSJ attention index regressions on fundamentals are higher than for the NYT. One notable exception is unemployment. More than 50% of the variation of the NYT attention index is explained by movements in the unemployment rate, consistent with the very strong comovement apparent in Figure 1, compared to the lower R^2 of 33% for explaining WSJ attention to unemployment. Why do unemployment fundamentals have less explanatory power for WSJ attention than for NYT attention? Examining the plots in Figure 1, the NYT has shown a consistently positive relation between unemployment and attention to unemployment. For the WSJ, in the 1980's and 1990's attention moved almost inversely with the unemployment level. Starting in the 2000's and certainly by the financial crisis, WSJ coverage of unemployment began to comove positively with changes in unemployment, similar to the NYT. This is consistent with the idea that the readership and editorial policy of the NYT have been more consistently focused on unemployment than the WSJ over time; however, following the financial crisis, the WSJ became more attentive to unemployment in a manner similar to NYT.[67]

Consistent with this idea of different focuses and audiences between the NYT and WSJ, we also see a difference in how inflation impacts attention.

[67] Another contributing factor could be the retirement of conservative editor Robert Bartley, who retired from the WSJ in 2000 after serving for thirty years.

An increase in inflation tends to raise attention to inflation at the WSJ, but reduces attention at the NYT. This is again consistent with the idea that the WSJ tends to be more politically conservative and associated with monetarist views on inflation than the NYT, which tends towards more Keynesian views on the economy.

4.4 Attention and Stock Market Activity

Beber, Brandt, and Kavajecz (2011) conjecture that market participants are continually digesting news about the macroeconomy, which impacts their preferences, expectations, and risk tolerances. As a result, macroeconomic news induce them to trade. The authors show that market trade volume segmented by economic sectors contain important macroeconomic information and in turn predict important macroeconomic announcements.

We study the link between daily macroeconomic attention and stock market activity. Let $Vlmd_t$ be the logarithm of the daily aggregate trade volume of S&P 500 firms, detrended by its own 60-day moving average, following Tetlock (2007). We run the regression:

$$Vlmd_t = \alpha_f + \beta_f MAI_{5-20,f,t} + \gamma_f Ann_t + \delta_f Ann_t \cdot MAI_{5-20,f,t} + \epsilon_{f,t}, \quad (4.7)$$

where $MAI_{5-20,tt}$ is the difference between the five-day and twenty-day moving average of MAI-C1 to macro fundamental f. $Ann_{j,t}$ is equal to 1 if there is an announcement on day-t, zero otherwise.[68]

Table 4.6 shows that for all MAI, rising attention is associated with an increase in market volume. When we include macro announcements in the regressions, many of the announcements have significant impacts on volume, but the inclusion of these variables does not alter inferences about the importance of attention. Interaction terms do not have a consistent sign, and do not alter inference about the effects of attention or announcements on trading volume.

[68] To simplify the analysis, we do not differentiate between all GDP announcements (advance, preliminary, and final).

Table 4.6: Media Attention and Aggregate Trade Volume

This table presents the results of an OLS regression of the daily detrended S&P 500 trade volume on the difference between the 5-day and 20-day moving average MAI-C1 and a dummy (Ann) equal to one if there is a related announcement specified in Table 4.2, zero otherwise. We detrend the log trade volume using the moving average of the log trade volume of the past 60 trading days. For all model specifications, we control for day-of-week fixed effects. The standard errors are reported in parenthesis and are calculated using Newey-West standard errors (250 lags). Obs. stands for the number of observations. *, **, *** denote the statistical significance at the 10%, 5%, 1% levels, respectively.

MAI:	Inflation			Monetary			Interest		
Ann:	CPI			FOMC			FOMC		
MAI_{5-20}	0.052***	0.051***	0.056***	0.066***	0.065***	0.066***	0.058***	0.057***	0.058***
	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.013)	(0.013)	(0.013)
Ann		0.034***	0.043***		0.026***	0.027***		0.030***	0.031***
		(0.007)	(0.007)		(0.009)	(0.010)		(0.009)	(0.009)
$MAI_{5-20}\times$Ann			-0.104***			-0.011			-0.043
			(0.024)			(0.035)			(0.039)
const	0.002	0.000	0.001	0.002	0.002	0.002	0.002	0.002	0.002
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Obs.	8787	8787	8787	8787	8787	8787	8787	8787	8787
Adj-R2	0.06	0.06	0.06	0.07	0.07	0.07	0.05	0.05	0.05

MAI:	GDP			Unemployment			Credit Rating	Oil	USD
Ann:	GDP Report			Employment					
MAI_{5-20}	0.027***	0.027***	0.026***	0.030***	0.029***	0.030***	0.068***	0.026***	0.075***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.018)	(0.010)	(0.019)
Ann		0.005	0.003		0.013	0.018			
		(0.008)	(0.008)		(0.011)	(0.013)			
$MAI_{5-20}\times$Ann			0.035			-0.031			
			(0.036)			(0.034)			
const	0.002	0.002	0.002	0.002	-0.000	-0.000	0.002	0.013**	0.028***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.007)	(0.006)
Obs.	8787	8787	8787	8787	8787	8787	8787	7368	8321
Adj-R2	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.06

Another way to look at the impact of macroeconomic attention on stock market activity is to investigate the relationship between macroeconomic attention and implied volatility, measured by the VXO index, which is available beginning in 1986. We implement the following regression for each attention index:

$$VXO_t = \alpha_f + \beta_f MAI_{20-250,f,t} + \gamma_f Ann_t + \delta_f Ann_t \cdot MAI_{f,20-250,t} + \epsilon_{f,t} \tag{4.8}$$

Table 4.7 shows that increases in macroeconomic attention on interest rates, GDP, unemployment, credit ratings and USD positively relate to increases in implied volatility. The R^2 are highest for unemployment (13%) and GDP (7%). Results are similar if we detrend VXO using a 250-day moving average. Thus, controlling for macroeconomic announcements, increases in attention is associated with an increase in both aggregate volume and volatility.

Overall the results of this section provide strong evidence that increases in attention to macro fundamentals is positively correlated with the aggregate stock market activities.

4.5 Using Attention for Forecasting

Given the links between media attention and macroeconomic fundamentals, it is natural to consider whether media attention might help to predict fundamentals on macroeconomic announcements. We are particularly interested to understand the link between the MAI to unemployment and the employment situation announcements and the MAI to monetary policy and FOMC announcements. Our decision to focus on unemployment is partly motivated by the plots in Figure 4.1 which suggest that the unemployment attention indices might act as a leading indicator, and partly motivated by findings in prior literature that the unemployment report is important for stock market returns (Boyd et al., 2005). We also ask whether attention to monetary policy can forecast the stock returns, change in implied volatility, and the Fed fund rate on FOMC announcements. Lucca and Moench (2015b) show that a significant fraction of the risk premium is earned on FOMC announcements. Savor and Wilson (2013b) further show that implied volatility significantly decrease on FOMC announcements.

4.5.1 Unemployment Announcements

We construct measures of "surprises" in the monthly employment report in two ways. First, we consider a simple random walk model of unemploy-

Table 4.7: Media Attention and Implied Volatility

This table presents the results of an OLS regression of the daily implied volatility proxied by VXO regressed on the difference between the 20-day and 250-day moving average MAI-C1 and a dummy (Ann) equal to one if there is a related announcement specified in Table 4.2, zero otherwise. For all model specifications, we control for day-of-week fixed effects. The standard errors are reported in parenthesis and are calculated using Newey-West standard errors (250 lags). Obs. stands for the number of observations. *, **, *** denote the statistical significance at the 10%, 5%, 1% levels, respectively.

MAI:	Inflation			Monetary			Interest		
Ann:	CPI			FOMC			FOMC		
MAI_{20-250}	-2.730	-2.729	-2.750	3.443**	3.442**	3.448**	4.709*	4.708*	4.727*
	(3.362)	(3.362)	(3.335)	(1.600)	(1.599)	(1.601)	(2.606)	(2.606)	(2.606)
Ann		0.259	0.266		-0.205	-0.207		-0.244	-0.246
		(0.182)	(0.184)		(0.224)	(0.225)		(0.237)	(0.240)
$MAI_{20-250}\times$Ann			0.438			-0.213			-0.591
			(0.764)			(0.569)			(1.112)
const	20.720***	20.703***	20.703***	20.722***	20.722***	20.722***	20.732***	20.733***	20.733***
	(1.231)	(1.227)	(1.226)	(1.249)	(1.249)	(1.249)	(1.257)	(1.257)	(1.258)
Obs.	7386	7386	7386	7386	7386	7386	7386	7386	7386
Adj-R2	0.01	0.01	0.01	0.02	0.02	0.02	0.01	0.01	0.01

MAI:	GDP			Unemployment			Credit Rating	Oil	USD
Ann:	GDP Report			Employment					
MAI_{20-250}	11.370**	11.377**	11.398**	11.079***	11.080***	11.103***	7.603***	0.511	6.786**
	(4.613)	(4.614)	(4.600)	(4.075)	(4.074)	(4.079)	(2.898)	(1.148)	(2.654)
Ann		0.286	0.279		0.207	0.206			
		(0.200)	(0.199)		(0.153)	(0.156)			
$MAI_{20-250}\times$Ann			-0.420			-0.475			
			(1.168)			(0.761)			
const	20.650***	20.628***	20.628***	20.645***	20.598***	20.598***	20.765***	20.762***	20.805***
	(1.139)	(1.135)	(1.135)	(1.087)	(1.088)	(1.088)	(1.218)	(1.252)	(1.245)
Obs.	7386	7386	7386	7386	7386	7386	7361	7361	7005
Adj-R2	0.07	0.07	0.07	0.13	0.13	0.13	0.05	0.00	0.02

ment, under which the prediction for the following month's unemployment rate is the prior month's unemployment rate, and the surprise is defined as the change in unemployment. Second, we use the regression model of Boyd, Hu, and Jagannathan (2005) to generate the unemployment forecasts, which we call the Boyd, Hu, and Jagannathan (2005) surprise. The authors' forecasting model uses information from related macroeconomic variables, including industrial production, T-bill rate, corporate bond yield spreads, and past unemployment rate. The surprise is defined as the difference between the announced unemployment rate and the unemployment forecast.

The date of reference for the actual unemployment rate is the release date of the employment situation announcement made by the U.S. Bureau of Labor Statistics.

For predictor variables, we carry out separate analyses using detrended levels of the composite indices MAI-C1. Specifically, to capture very short run movements, we use the difference between the 5-day simple moving average and the 20-day simple moving average of the attention indices (MAI $_{5-20}$). To capture a range of other movements, we similarly calculate 5-, 20-, and 60-day moving averages detrended by the 252-day moving average (i.e., MAI $_{5-252}$, MAI $_{20-252}$, MAI $_{60-252}$). Following Boyd et al. (2005), we also interact each of the predictor variables with NBER recession dummies. Since the NBER dummies are not known in advance, regressions using these interactions are not predictive. Boyd et al. (2005) hypothesize that "bad news" for unemployment means different things in expansions and contractions, and the interaction variables allow us to see whether the predictive ability of attention, if it exists, concentrates in contractions.

To investigate the link between unemployment surprises and our attention index to unemployment, we estimate the following regression:

$$Surp_t = c + MAI_{t-1} + MAI_{t-1} \cdot NBER + +e_t, \tag{4.9}$$

where Ret_t is the daily return of S&P 500 index, MAI_{t-1} is the detrended MAI-C1 for unemployment, $NBER$ is an indicator variable for NBER recession, and $Surp_t$ is unemployment announcement surprise.[69]

Table 4.8 shows that the detrended unemployment attention variables are significantly related to surprises in the unemployment report, and that the interaction variables are often important. Under the random walk model, attention indices positively predict future surprises in unemployment, and variables are significant when interacted with the NBER recession dummies. Hence, increases in macroeconomic attention to unemployment positively predict future changes in unemployment, and this relationship is strong during recessions. Changes in macroeconomic attention retain the ability to explain future changes in employment relative to the Boyd et al. (2005) regression model.

[69]When the Employment Situation announcement occurs on Good Friday (U.S. holiday) we use the stock return on the following trading if the market is close.

Table 4.8: Unemployment Surprise Forecasts on Employment Situation Announcement Days

This table presents the results of an OLS regression of the unemployment surprise regressed on the one-day lag detrended demeaned daily composite MAI-C1 for unemployment at different frequencies and an interaction term between MAI-C1 and an NBER dummy. For example, MAI_{5-20} is the difference between the five-day and twenty-day moving average of MAI-C1 for unemployment. The NBER dummy equals one if the unemployment surprise occurs during a NBER recession, zero otherwise. The surprise is calculated as the difference between the actual unemployment for month t reported in month $t+1$ and the random-walk (i.e. the previous month unemployment rate) in Panel A and the forecasted unemployment rate as in Boyd, Hu, and Jagannathan (2005) in Panel B. The standard errors are reported in parenthesis and are calculated using the White's heteroskedasticity robust standard errors. Obs. stands for the number of observations. *, **, *** denote the statistical significance at the 10%, 5%, 1% levels, respectively.

Panel A: Random-Walk

MAI:	MAI_{5-20}		MAI_{5-250}		MAI_{20-250}		MAI_{60-250}	
MAI	0.040	0.020	0.074***	0.042**	0.142***	0.090**	0.216***	0.110**
	(0.027)	(0.026)	(0.019)	(0.019)	(0.033)	(0.035)	(0.045)	(0.052)
MAI×NBER		0.298**		0.194***		0.183**		0.375***
		(0.138)		(0.051)		(0.080)		(0.083)
const	-0.010	-0.010	-0.012	-0.017*	-0.002	-0.009	-0.001	-0.012
	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)
Obs.	418	418	407	407	407	407	407	407
Adj-R2	0.00	0.02	0.04	0.08	0.06	0.07	0.07	0.11

Panel B: Boyd et al. (2005) Surprise

MAI:	MAI_{5-20}		MAI_{5-250}		MAI_{20-250}		MAI_{60-250}	
MAI	0.024	0.017	0.046***	0.036**	0.089***	0.078***	0.129***	0.092**
	(0.023)	(0.023)	(0.016)	(0.017)	(0.024)	(0.029)	(0.034)	(0.043)
MAI×NBER		0.106		0.065		0.040		0.134**
		(0.095)		(0.043)		(0.054)		(0.064)
const	-0.018**	-0.018**	-0.020***	-0.021***	-0.013*	-0.015*	-0.013*	-0.017**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)
Obs.	418	418	407	407	407	407	407	407
Adj-R2	0.00	0.00	0.02	0.03	0.03	0.03	0.04	0.05

Figure 4.5 shows graphically how attention changes before and after unemployment surprises. There are four panels, corresponding to all combinations of the main two unemployment surprises, and the two unemployment attention indices. For each unemployment surprise, we separate the data into three equal-sized bins of small, medium, and large surprises. We then plot in event time the average attention over a period one year prior to the surprise, out to one year subsequent to the surprise.

The results show similar patterns. When the unemployment surprise is particularly low, on average attention to unemployment in the media has been declining over the past year, and continues to decline over the following year. Conversely, when the unemployment surprise is large and positive, on average attention has been increasing over the prior year, and continues to increase over the following year. When the unemployment surprise is in the middle tercile, on average attention is approximately flat over the prior and following years, and at a lower level than for large positive or negative surprises. These findings are consistent with the regression results, and confirm that attention moves both before and after changes in reported fundamentals.

It is natural to think that if changing attention to unemployment predicts unemployment announcement surprises, then it may also predict market returns on the day of the employment announcement. This topic relates to prior research by Boyd et al. (2005), who show that unemployment surprises generally relate positively to market returns on the announcement date, but the relationship turns negative during NBER recessions. In Table 4.9, we revisit their results using the two different measures of unemployment surprise defined previously, and adding measures of macroeconomic attention as explanatory variables. We specify:

$$Ret_t = c + MAI_{t-1} + MAI_{t-1} \cdot NBER + Surp_t + Surp_t \cdot NBER + e_t. \quad (4.10)$$

where Ret_t is the daily return of S&P 500 index.

The first column of Table 4.9 shows results with only the variables used by Boyd et al. (2005). The coefficient estimates are consistent with their results: unemployment surprises positively relate to market returns, but the relationship turns negative in recessions. Both the surprise and the interaction term are significant at the 5% and 10% level.

The remaining columns of Table 4.9 consider as explanatory variables, separately and with the Boyd et al. (2005) surprise as controls, measures of changes in attention to unemployment. The short-horizon trend in attention

Figure 4.5: Attention to Unemployment around Employment Situation Announcements

This figure shows the daily 60-day moving average of the unemployment attention index for the Wall Street Journal (MAI-WU) and the New York Times (MAI-NU) around the employment situation announcements. The window is 250 trading days before and after each announcement. We separate the random-walk and the Boyd, Hu, and Jagannathan (2005) surprises into terciles. The MAI around low surprises is in blue (solid line), medium surprises is in red (dotted line), and high surprises is in black (dashed line).

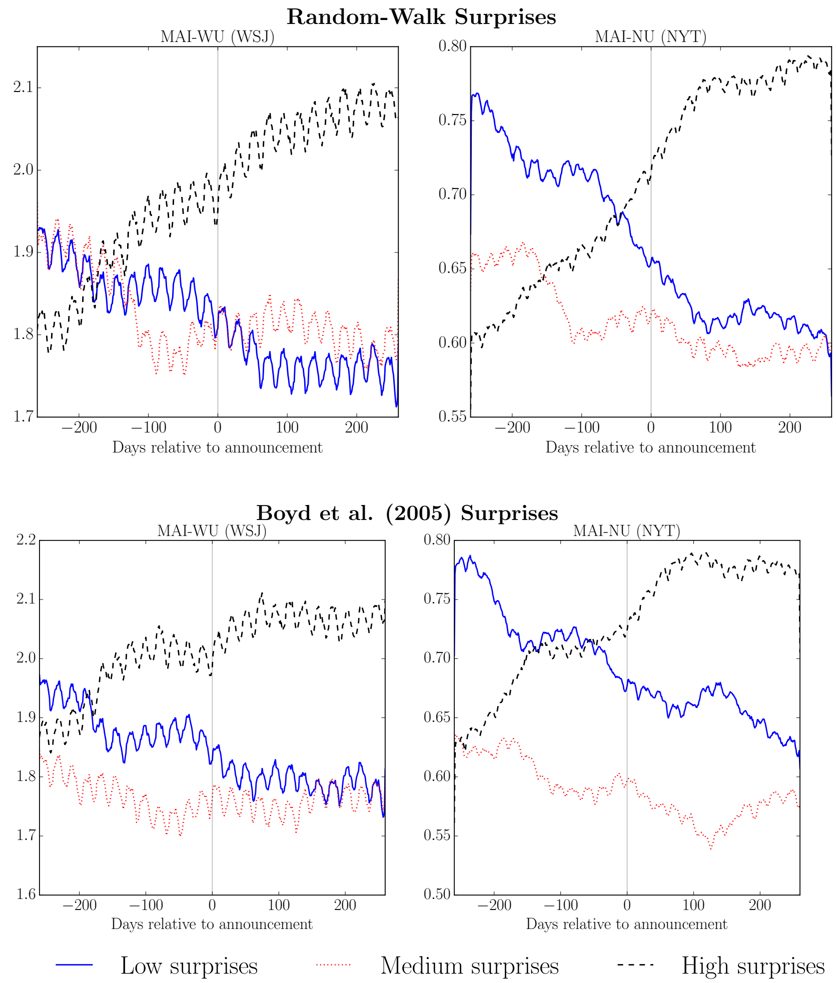


Table 4.9: S&P Return Forecast on Employment Situation Announcement Days

This table presents the results of an OLS regression of the daily S&P 500 log return on the employment situation announcement date regressed on the Boyd, Hu, and Jagannathan (2005) surprise (Surp_{Boyd}) of the unemployment announcement, the surprise interacted with an NBER dummy, the one-day lag detrended unemployment attention index composite index MAI-C1, and the detrended unemployment attention index interacted with an NBER dummy. For example, $\text{MAI}_{5-20,t}$ is the difference between the five-day and twenty-day moving average of MAI-C1 for unemployment. The NBER dummy equal one if the unemployment surprise occurs during a NBER recession, zero otherwise. We show the results for two different detrended frequencies for the unemployment attention index. The standard errors are reported in parenthesis and are calculated using the White's heteroskedasticity robust standard errors. Obs. stands for the number of observations. *, **, *** denote the statistical significance at the 10%, 5%, 1% levels, respectively.

MAI:		MAI_{5-20}			MAI_{20-250}		
MAI		0.361**	0.319**	0.295*	0.278	-0.059	-0.106
		(0.159)	(0.160)	(0.161)	(0.212)	(0.223)	(0.221)
MAI×NBER			0.617	0.800		1.177**	1.442***
			(0.787)	(0.721)		(0.514)	(0.511)
Surp_{Boyd}	0.620*			0.572			0.725**
	(0.354)			(0.352)			(0.366)
Surp_{Boyd}×NBER	-2.022*			-2.282*			-3.184**
	(1.229)			(1.278)			(1.323)
const	0.052	-0.015	-0.015	0.011	0.032	-0.015	0.009
	(0.057)	(0.061)	(0.061)	(0.062)	(0.058)	(0.060)	(0.060)
Obs.	419	418	418	418	407	407	407
Adj-R2	0.01	0.01	0.01	0.02	0.00	0.02	0.04

(5-day minus 20-day moving average) is positive and significant at the 5% level in all specifications, and remains significant with the Boyd et al. (2005) variables as controls. The medium-horizon attention trend (20-day minus 250-day moving average), positively relates to the market return, but is not significant independently. However, interacted with the NBER recession dummy, the coefficients are uniformly positive and significant. The sign is opposite to the coefficient on the surprise itself interacted with the NBER recession dummy.

It is important to distinguish between the trend in attention, which reflects anticipation, and the surprise itself, which reflects a realization. Consistent with the results of Boyd et al. (2005), during a recession a higher realization of unemployment on the announcement date leads to lower market returns. We add to this that rising attention before the announcement date tends to be associated with higher market returns on the announcement date, as uncertainty is resolved.

4.5.2 FOMC Announcements

We now investigate whether our attention indices to monetary policy can predict stock returns, changes in implied volatility, and changes in Fed fund rates on FOMC announcements. We focus specifically on the period post 1994 when FOMC decisions are publicly announced. We use a similar OLS regression framework as in Equation (4.9) but using the S&P 500 returns, changes in implied volatility proxied by VXO, or changes in Fed fund rates as dependent variables. Changes in Fed fund rate consist of a random-walk surprise measure.

Table 4.10, Panel A shows that, controlling for the interaction between NBER dummies and MAI, our attention index to monetary policy predicts positive stock returns on FOMC announcements. The short-horizon trend in attention (5-day minus 20-day moving average) is positive and significant at the 5% level. Similar results hold for long-horizon trend in attention (60-day minus 250-day moving average). We next investigate whether attention to monetary can predict changes in VIX on FOMC announcement days.

Table 4.10: Forecasts on FOMC Announcements

This table presents the results of an OLS regression of the daily S&P 500 log returns (in percent) and changes in the implied volatility (ΔVXO) on a FOMC dummy, a detrended monetary macro attention composite index (MAI-C1), and the MAI-C1 interacted with the FOMC dummy. The FOMC dummy equal one on FOMC days. We show the results for two different detrended frequencies for the monetary attention index. For example, MAI_{5-20} is the difference between the five-day and 20-day moving average of MAI-C1. The standard errors are reported in parenthesis and are calculated using the Newey-West standard errors (six lags). *, **, *** denote the statistical significance at the 10%, 5%, 1% levels, respectively. The sample period is June 1, 1980 to April 30, 2015.

Panel A: S&P 500 returns (1994-2015)

MAI:	MAI_{5-20}		MAI_{5-250}		MAI_{20-250}		MAI_{60-250}	
MAI	0.362	0.591**	0.115	0.287*	-0.096	0.062	0.432	0.546**
	(0.265)	(0.281)	(0.154)	(0.168)	(0.204)	(0.212)	(0.368)	(0.260)
MAI×NBER		-0.675		-0.489*		-0.666		-0.561
		(0.480)		(0.277)		(0.546)		(1.539)
const	0.329***	0.337***	0.330***	0.344***	0.323***	0.332***	0.323***	0.327***
	(0.089)	(0.090)	(0.091)	(0.092)	(0.091)	(0.091)	(0.089)	(0.086)
Obs.	171	171	171	171	171	171	171	171
Adj-R2	0.01	0.02	-0.00	0.01	-0.00	-0.00	0.01	0.00

Panel B: Changes in implied volatility (1994-2015)

MAI:	MAI_{5-20}		MAI_{5-250}		MAI_{20-250}		MAI_{60-250}	
MAI	-4.423**	-6.079***	-2.124*	-3.152**	-0.574	-1.043	-3.272*	-3.660*
	(1.849)	(2.236)	(1.104)	(1.369)	(1.431)	(1.747)	(1.922)	(1.899)
MAI×NBER		4.887*		2.926*		1.975		1.901
		(2.876)		(1.676)		(2.767)		(6.309)
const	-2.088***	-2.149***	-2.128***	-2.214***	-2.066***	-2.093***	-2.031***	-2.043***
	(0.579)	(0.581)	(0.599)	(0.611)	(0.608)	(0.614)	(0.585)	(0.584)
Obs.	171	171	171	171	171	171	171	171
Adj-R2	0.05	0.06	0.02	0.03	-0.01	-0.01	0.01	0.00

Panel C: Changes in Fed fund rates (1994-2008)

MAI:	MAI_{5-20}		MAI_{5-250}		MAI_{20-250}		MAI_{60-250}	
MAI	-0.105	0.007	-0.127*	-0.007	-0.218**	-0.017	-0.326***	-0.096
	(0.151)	(0.089)	(0.072)	(0.059)	(0.109)	(0.087)	(0.124)	(0.120)
MAI×NBER		-0.215		-0.251***		-0.615***		-0.731**
		(0.247)		(0.084)		(0.179)		(0.288)
const	-0.028	-0.026	-0.025	-0.020	-0.025	-0.017	-0.012	-0.012
	(0.032)	(0.032)	(0.030)	(0.030)	(0.030)	(0.029)	(0.028)	(0.028)
Obs.	104	104	104	104	104	104	104	104
Adj-R2	0.01	0.02	0.06	0.12	0.07	0.21	0.07	0.15

Panel B shows that an increase in the short-horizon trend in attention predicts a decrease in VIX, which suggests that an increase attention predicts a decrease in uncertainty on FOMC announcement days. The coefficient on the interaction term MAI×NBER is positive and significant, indicating that an increase in attention predicts greater resolution of uncertainty on FOMC announcements during expansion than during recessions. Finally, we examine the relationship between changes in the Fed fund rates and attention on FOMC announcements.

Panel C shows that our attention measure to monetary predicts negative changes in Fed fund rates, meaning that attention increases before the Fed announces a cut in Fed fund rates. This is consistent with the fact that during 1994-2008, most of the Fed's decision on interest rate was to lower rather than increase the Fed fund rate.[70] More importantly, the relationship is stronger during recessions. This is consistent with Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016), who show that investors pay more attention to macroeconomic risks during recessions.

4.6 Conclusion to Chapter 4

We build indices of investor attention to macroeconomic fundamentals using news articles from WSJ and NYT. Attention indices rises around macroeconomic announcements and following changes in fundamentals over quarterly, annual, and business cycle horizons. The effect of announcements and changes in fundamentals on indices is asymmetric, with bad news raising attention more than good news. Attention indices have important implications to financial markets, and we show that aggregate trade volume and volatility coincide with rising attention, controlling for announcements. We further show that attention predicts surprises as well as stock returns on unemployment and FOMC announcement days.

Our paper adds to the growing literature documenting the importance of investor attention in financial markets (e.g. Andrei and Hasler, 2014; Da, Engelberg, and Gao, 2011b). Future work could go in many directions. We find evidence of time-varying attention to different macroeconomic fundamentals in the news media. In the spirit of the Merton (1980) Intertemporal Capital Asset Pricing Model, such attention dynamics could be related to time-variation in the risks or risk premia associated with different types

[70] We focus on the 1994-2008 period because the Fed reached the so-called 'zero lower bound' and did not change the Fed fund rate after 2008. The most recent rate change was the increase in December 2015.

of macroeconomic fundamentals. Another possible extension is to combine both investors' sentiment and attention to macroeconomic fundamentals and relate to stock market returns.

Chapter 5

Conclusion

This thesis is a collection of three essays on Information Economics. I focus specfically on the impact of public news on financial markets and asset prices. The first essay, Chapter 2, examines the speed of price discovery following earnings announcements and the role of order flow to price discovery. Past research usually assumes that liquidity providers are not sophisticated enough to process public information and, in turn, rely on the incoming order flow from sophisticated traders to adjust prices. Contrary to past research, I find that earnings surprises are the main determinant that explains price changes following earnings announcements and not order flow. Yet, important questions remain to be answered. For example, despite fast price discovery following earnings surprises, why is the impact of earnings surprises on stock volatility and trade volume remains abnormally high for several hours or for even more than one trading day?

In Chapter 3, I analyze the impact of Federal Open Market Committee (FOMC) announcement press conferences on financial markets and investor attention to monetary policy. In an effort to increase transparency, the Chair of the Board of Governors now holds a press conference following half of the scheduled FOMC announcements. I find that holding press conferences after some, but not all, FOMC meetings skew expectations of important monetary policy decisions towards announcement days with press conferences. In turn, the introduction of press conferences coordinates media and investor attention towards those meetings. This may pose a problem for the Federal Reserve, which is generally believed to be averse to surprising markets. If the Federal Reserve must announce an important decision on days with no press conference, it risks surprising markets because investors did not expect any important news.

In Chapter 4, I build indices of investor attention to macroeconomic fundamentals using news articles from the Wall Street Journal and the New York Times. I document the dynamics in attention, its fluctuation over time, and its relationship to macroeconomic fundamentals. Investor attention indices have important implications for financial markets, and we show that aggregate trade volume and volatility coincide with rising attention, controlling for announcements. I further show that attention predicts surprises as well as stock returns on unemployment and FOMC announcement days. More importantly, understanding investor attention to macro risk through media attention to macroeconomic fundamentals provides useful information beyond the dates and contents of macroeconomic announcements.

5.1 Future Work

I plan extend each chapter to new research projects. In the first essay, I only explore the evolution of price discovery since the 1980s for the largest 1,500 U.S. stocks. I plan to extend the analysis to the complete cross-section of U.S. stocks and document the evolution of the post-earnings announcement drifts over time. Despite not being a simple task, I would like to pin down the main factor explaining the near disappearance of the post-earnings announcement drifts at the daily horizon. Also, I would like to understand how faster price discovery following earnings announcements influence asset pricing factors in the cross-section of stocks.

In the second chapter, I am currently extending the analysis to price discovery following FOMC announcements in the equity market using changes in eurodollar futures as a measure of FOMC surprises. I find that surprises are larger on FOMC announcement days when there is a press conference. Moreover, FOMC announcement surprises incorporate equity prices within minutes. But, using a non-parametric approach to examine price formation following FOMC announcements relative to future indicative prices, I find that prices following announcements remain noisy and that it takes several hours before price formation is complete. Despite large trade volume following FOMC announcements, prices are not efficient.

With the third chapter of my thesis, there is a lot of potential research avenue to explore with the newly constructed dataset on investor attention to macroeconomic risks. For example, is a macroeconomic risk factor priced in the cross-section of stocks conditioned only when investors pay attention to that particular risk?

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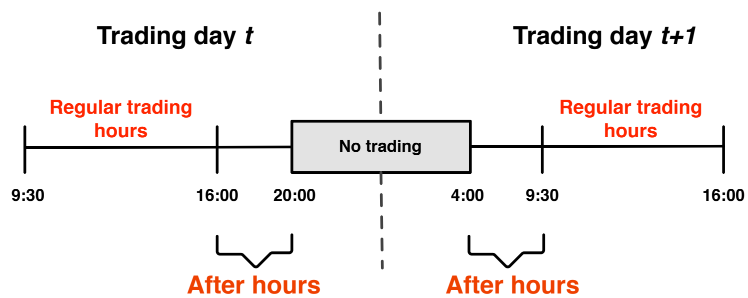
Appendix A

Appendix to Chapter 2

A.1 Trading Hours on NASDAQ

Figure A.1: Regular and After-Hours Trading for the NASDAQ Stock Exchange

This figure shows the regular trading hours (9:30 a.m. to 4 p.m) and the after-hours trading sessions (4 p.m. to 8 p.m. and from 4 a.m. to 9.30 a.m.) on the NASDAQ stock exchange.



A.2 Post-Earnings Announcement Drifts since 1984

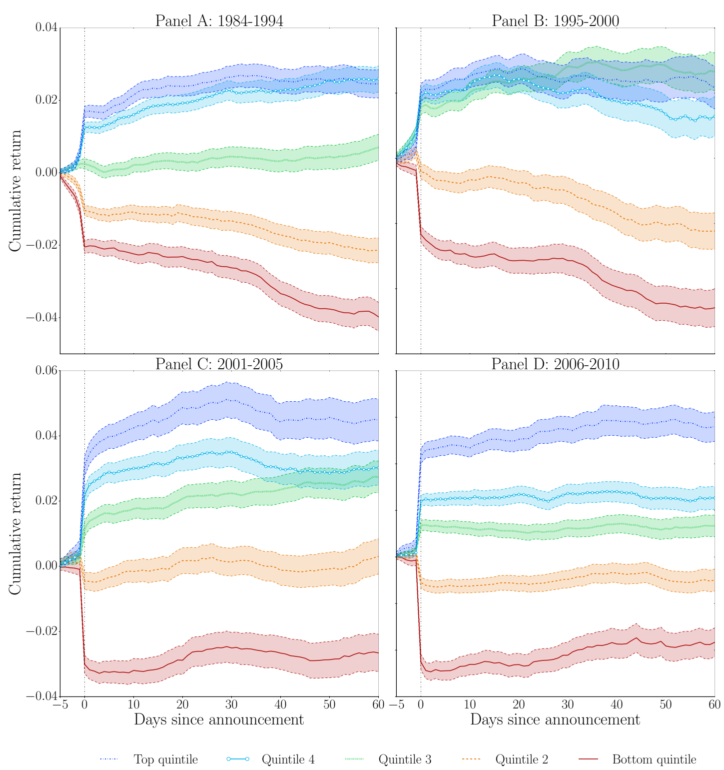
I plot in Figure A.2 the average cumulative abnormal returns (CAR) within each earnings surprises quintile and their corresponding 95 percent confidence intervals around earnings announcements for the largest 1,500 U.S. stocks for different time periods between 1984 to 2010. In total there are close to 114, 200 earnings announcements. Because I do not have the actual timestamp of each earnings announcement, the sample contains earnings announcements that were announced during both regular and after-market hours. Therefore, the day "0" contains both abnormal returns of the date of the announcement and the following trading day. I further exclude observations with returns in the top and bottom 5/1,000th of the distributions. But, I find that excluding outliers only have an impact on the bottom earnings quintile for the period of 2006 to 2010.

Figure A.2: Historical Cumulative Abnormal Daily Returns around Earnings Announcements

This figure shows the stocks' cumulative abnormal returns (CAR) from five trading days preceding to 61 trading days following earnings announcements for each earnings surprises quintile. The CAR are calculated as follows:

$$CAR[-5, 61]_{i,q} = \prod_{k=-5}^{61} (1 + R_{i,k}) - \prod_{k=-5}^{61} (1 + R_{p,k}),$$

where $R_{i,k}$ is the return of the stock i and $R_{p,k}$ is the return on the size and book-to-market matching Fama-French portfolio on day k for quarter q's earnings. Each line represents a different quintile sort for earnings surprises. The shaded areas are pointwise 95% confidence bands around the average abnormal returns. The vertical line corresponds to the earnings announcement day. The sample consists of earnings announcements from the largest 1,500 U.S. stocks between 1984 and 2010.



A.3 Institutional Details about Hidden Orders on NASDAQ ITCH

This note contains details about hidden order observations in NASDAQ TotalView-ITCH.

In NASDAQ TotalView-ITCH, we do not observe submitted hidden orders by liquidity providers. Prior to October 6, 2010, trades against a hidden order would display both the *Order Reference Number* associated with the hidden order and a *Buy/Sell Indicator*, which indicated whether the initiated trade was a buy or sell (see appendix in NASDAQ, 2016a). But, since October 6, 2010, all trades against hidden orders display a "0" as an *Order Reference Number* and, since July 14, 2014, all trades against hidden orders display "B" as a *Buy/Sell Indicator*.

These changes impose challenges to empiricists who wish to understand the drivers to the use of hidden orders versus displayed orders and the impact of hidden orders on stock prices, trade volume, etc. Just for example, in this paper when I study the impact of market-initiated trade imbalance (i.e., order flow imbalance) on stock returns, I must end my sample on July 13, 2014 because I do not have the *Buy/Sell Indicators* on trades against hidden orders from July 14, 2014 onward.

Why did NASDAQ do these changes? Some traders claim that providing the *Order Reference Number* and the *Buy/Sell Indicator* help high-frequency traders figure out market directions.[71] For example, *Order Reference Number* linked to a trade is cumulative. This means that every time a trade executes against a fraction of the total shares from the same hidden order, the same *Order Reference Number* is attached to that trade. This allows NASDAQ ITCH subscribers to determine how many shares the hidden buyer or seller is willing to trade.

The objective of using hidden orders is not to provide other traders the ability to infer their strategies and potentially private information. After some pressure from the investor community, NASDAQ decided not to display *Order Reference Number* and the *Buy/Sell Indicator* in NASDAQ ITCH. But, empiricists who want to understand the greater details of the functioning of financial markets now have less detailed data to work with. NASDAQ ITCH was the only data source on hidden order activities on the U.S. stock exchanges.

[71] See the 2010 white paper "Exchanges and Data Feeds: Data Theft on Wall Street" by Sal Arnuk and Joseph Saluzzi of Themis Trading at `http://blog.themistrading.com/wp-content/uploads/2010/05/THEMIS-Data-Theft-On-Wall-Street-05-11-10.pdf`

NASDAQ does provide at a monthly fee of $2,000 data on the market's full liquidity, including reserve and hidden interest. The data are called Model View and provide a minute-by-minute summary of total displayed and hidden interest at each price point. The data are not available "live" and are reported with a two-week lag. Also, the minute-by-minute data are available only from 8 a.m. to 4 p.m. As shown in this paper, hidden orders are heavily used in the after-hours market.

A.4 High-frequency Trading Activites in the After-Hours Market

High-frequency traders (HFT) now represent a large share of market trading but are they also present in the after-hours market? To provide some insights on this question, I use a dataset that contains a sample of 120 NASDAQ-listed stocks that identify the liquidity taker and maker (provider) for each trade as a high-frequency trader or non-high-frequency trader. The data identify 26 proprietary high-frequency trading firms. Though the time series of these data does not span the time series of the NASDAQ ITCH data used in this study, it provides interesting insights. This is the first dataset that contains high-frequency traders identification for US stocks (see Brogaard, Hendershott, and Riordan (2014) for more details on this dataset). Table A.1 in the Appendix shows the fractions of HFT that supply liquidity (makers) and take liquidity (takers), and the fraction of total trades for which the liquidity taker or maker is an HFT. The data show that HFT activities decrease in the after-hours with earnings announcements by more than half for large firms, from 67 to 22 percent of total shares traded and from 73 to 30 percent for the total number of trades. For small firms, the total activity remains around 30 percent. These numbers suggest the presence of more institutional traders in the after-hours market than HFT. But high-frequency trading can still play a role around earnings announcements. Weller (2016) shows that algorithmic trading deters information acquisition prior to earnings announcements.

Table A.1: High-Frequency Trading Activities during Regular and After-Market Hours

This table reports the average fraction of trades, both in shares and total trades, with high-frequency trading activities during regular market hours (9:30 a.m. to 4 p.m.) and in the after-hours market (4 p.m. to 9:30 a.m.) with and without earnings announcements (EA). *Makers* stands for liquidity making for trades executed against limit orders submitted by a high-frequency trader. *Takers* stands for liquidity taking for trades initiated by a high-frequency trader. *Total* stands for total high-frequency trading activities with either both or one side of the trade involving a high-frequency trader. The numbers are in percentages. The sample consists of 120 NASDAQ-listed stocks. Sample firms are separated into size-tercile groups. The sample period is from January 1, 2008 to December 31, 2009.

		Shares		Trades		Shares	Trades
Trading Period	Firm Size	Makers	Takers	Makers	Takers	Total	Total
Market hours	Small	20	12	21	12	30	31
	Medium	35	18	39	21	48	53
	Large	42	40	46	45	67	73
After hours	Small	13	12	13	13	23	23
	Medium	16	16	17	17	30	31
	Large	17	16	21	18	30	33
After hours (EA)	Small	17	20	17	23	34	36
	Medium	11	13	13	14	22	24
	Large	13	11	17	17	22	30

A.5 Additional Results on the Impact of Earnings Surprises on Trade Volume, Volatility, and Bid-Ask Spreads

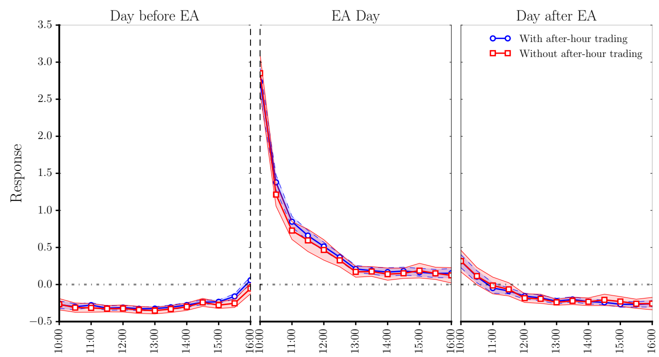
Figure A.3: The Response of Abnormal Volatility, Abnormal Quoted Spread, and Abnormal Turnover to Earnings Surprises around Earnings Announcements

This figure shows the estimated coefficient responses of abnormal volatility, abnormal quoted spread, and abnormal turnover to absolute earnings surprises around earnings announcements at each 30-minute interval during regular trading hours. The regression specifications are described in the main text. The left pane shows the day before the earnings announcement (EA), the middle pane is the EA day, and the right pane is the day after the EA. The EA occurs in the after-hours market (between 4 p.m. and 9:30 a.m.) indicated by the straight dashed vertical lines. The circle blue line represents stocks with after-hours trading and the square red line represents stocks with no after-hours trading activity following earnings announcements. Volatility is the sum of the five-minute absolute value of the residuals in Equation (2.8):

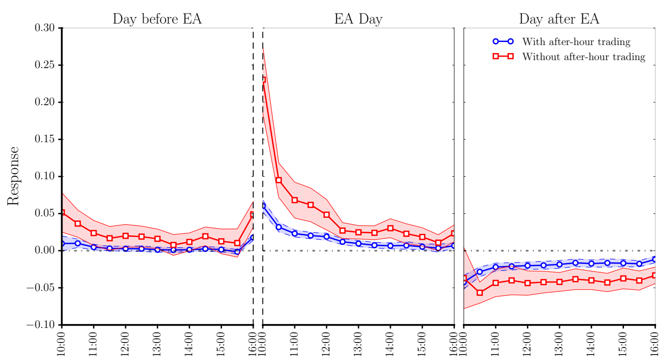
$$r_\tau = \alpha + \rho r_{\tau-1} + \gamma r_\tau^m + \beta_\tau S_t \cdot \mathbb{1}_{\{\tau \in t\}} + \epsilon_\tau,$$

over a 30-minute interval. Quoted spread is the average of the time-weighted one-second quoted spread defined as bid-ask spread divided by the midquote in a 30-minute interval. Turnover is the sum of total shares traded in a 30-minute interval divided by the number of shares outstanding and scaled by the standard deviation of that year. The shaded areas are pointwise 95% confidence bands around the estimated coefficients. The standard errors are calculated using the Driscoll and Kraay (1998) method.

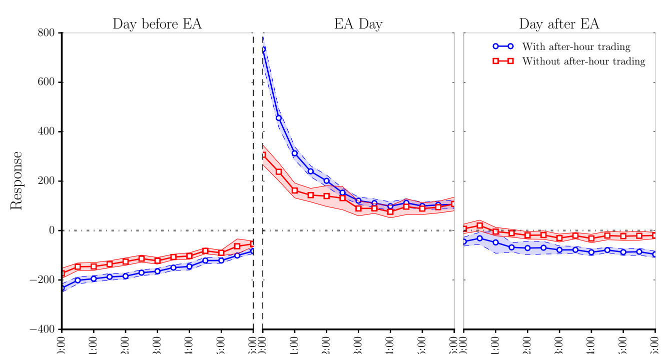
Panel A: Abnormal volatility response to earnings surprises



Panel B: Abnormal quoted spread response to earnings surprises



Panel C: Abnormal turnover response to earnings surprises



Appendix B

Appendix to Chapter 3

FOMC Transcripts Excerpts

While the FOMC minutes are typically released three weeks after each meeting, actual transcripts of meetings are made public only after 5 years. At the time of the writing of this paper, only the transcripts meetings up to and including 2011 are available. In this appendix, we summarize and present excerpts from relevant discussions pertaining to the creation of FOMC press conferences.[72]

The idea of holding regular PCs after FOMC announcements was first discussed in a conference call on October 15, 2010. The general opinion was favorable, with a notable word of caution from Ms. Yellen: *"A press conference does have some appeal, but it would probably become obligatory on a regular basis and would be quite a commitment for the Chairman to undertake."* Only Ms. Duke (member of the Board of Governors of the Federal Reserve System) strongly opposed the idea, but would later speak in favor of it at the March 2011 meeting.

PCs were further briefly discussed at the November 2010 meeting, with the idea to be investigated further by the communication subcommittee headed by Governor Yellen. Transcripts form the subcommittee meetings are non publicly available.

Ms. Yellen reported the recommendation of the subcommittee to introduce regular PCs by the chairman at the March 2011 meeting. The FOMC ultimately decided to announce PCs two weeks later, with the first one to be held following the April meeting. *"In light of those considerations, the subcommittee recommends that the Chairman conduct quarterly press conferences in the afternoon after the conclusion of each two-day FOMC meeting."* Note that prior to 2012, there were one-day and two-day meetings. Since 2012, all FOMC meetings take two-days. One of the motivation other than increased transparency was that the FOMC appeared to be lagging other countries on that aspect. In the words of Chairman Bernanke, *"I think the*

[72] All relevant transcripts can be found at
https://www.federalreserve.gov/monetarypolicy/fomchistorical2011.htm.

difference between the Fed and other central banks has become quite striking–every other central bank does have this method for communication."

Some members raised concerns regarding the possibility that quarterly PCs would differentiate meetings. For example, Mr. Kocherlakota felt that *"it's distinguishing the meetings in an unusual way. It's not like we only make important decisions at two-day meetings that require a lot of clarification. So if we are going to go down this path, I actually would suggest thinking about doing it every time."* Ms. Yellen's response was that *"The distinguishing feature of the two-day meetings is the economic projections and the ability that that would give the Chairman to explain our overall framework and put decisions into the context of them."* Mr. Lacker wondered what impact PCs would have on their decisions, *"whether there would be some hesitance to take actions in between press conference meetings, and I am not quite sure what the answer to that is, but I think it is worth considering."* In the end, Mr. Lacker sided in favor of PCs: *"I'd strongly support this press conference, and I think there are going to be some subtleties about it that are going to emerge in practice. I think we're going to have to resist the urge to wait to do things at just these quarterly meetings. I think when we want to do something, we're going to have to have the courage to go ahead and do it."* In the end, there was strong support for holding PCs.

There are at least three occasions at subsequent meeting were the timing of PCs explicitly entered discussions about some decision. First, at the April 2011 meeting which would be followed by the first PC, Mr. Lockart stated that *"I think it is possible with good communication to limit the announcement effect on the announcement of ceasing reinvestments, and I think we may be able to limit an announcement effect even with the initiation of small asset sales, but this will require skillful communication, and it seems to me that the timing would best coincide with the Chairman's press conferences so that he can explain that a rise in the fed funds rate is not necessarily imminent."*

Second, at the June 2011 meeting (PC), Mr. Lockart stated while discussing the idea of changing the wording of the press release that *"I think today's press conference affords the Chairman the opportunity, if you wish or if you get the question, to convey the Committee's sense of the risk context. "*

Finally, at the September 2011 meeting (non-PC), Ms. Pianalto suggested delaying action until the following meeting because of the associated PC: *"I prefer to continue to reinvest maturing agency debt and MBS into Treasuries. We told the public that we wanted to return our portfolio to a Treasury-only portfolio. If we decide that this is an appropriate way to go,* *I would rather wait to do this at our November meeting because that is a meeting where you will have a press conference. It will give you an opportunity to talk about the change in our reinvestment strategy."* Ultimately, the committee did not wait and adopted the measure at the September meeting, announcing Operation Twist.

Appendix C

Appendix to Chapter 4

C.1 Sample of news articles mentioning macroeconomic fundamentals

We present in this appendix samples of news articles from the Wall Street Journal (WSJ) and New York Time (NYT) that are selected to build our media attention indices to macroeconomic fundamentals.

Inflation

1) Jonathan Fuerbringer, "Do Deficit Impede Recovery? New Analysis", New York Times, January 21, 1983.

"These levels give rise to the persistent fear of renewed inflation with the Federal Reserve being forced, in an effort to keep the economy going, to ease its tight hold on the money supply and push down interest rates so that the deficit is easier to finance and the recovery will not be tripped up."

Unemployment

1) Ken Gilpin, "Jobs Data Push Bonds Up Sharply", New York Times, July 3, 1992.

"Stunning weakness in labor statistics for June and the Federal Reserve Board's equally striking response to the data caused an eruption in the credit markets yesterday. Prices of fixed-income securities rose sharply and interest rates fell."

2) Jonathan Fuerbringer, "Greenspan Speaks: Recession's Over," New York Times, March 10, 2002.

"The recovery, he told Congress, 'is already well under way.' His comments followed economic data showing a turnaround in manufacturing and a surge in the service sector. Then, on Friday, the Labor Department said the unemployment rate had slipped and that the number of lost jobs had shrunk to just 50,000. All this was uplifting for stocks and bad for bonds."

3) Kate Davidson, "Strong Jobs Report Clears Fed for Liftoff on Rates" Wall Street Journal, December 4, 2015.

"The U.S. economy delivered another month of sturdy job growth in November, clearing a path for the Federal Reserve to end later this month an extraordinary seven-year run of near-zero interest rates."

Monetary policy

1) Greg Ip, Nicholas Kulish and Jacob M. Schlesinger, "New Model: This Economic Slump Is Shaping Up to Be A Different Downturn," Wall Street Journal, January 5, 2001.

"One reason is that investors may respond quickly to a cut in Fed interest rates – as they did with Wednesday's huge rally in response to the surprise reduction of half a percentage point in short-term rates. That instantly eased some of the pain that had spread through the economy. The stock market has become the most important transmission mechanism of monetary policy,' says Jan Hatzius, senior economist at Goldman Sachs. And that's one reason, adds Brad DeLong, an economist at the University of California at Berkeley, that Fed moves have a bigger effect now."

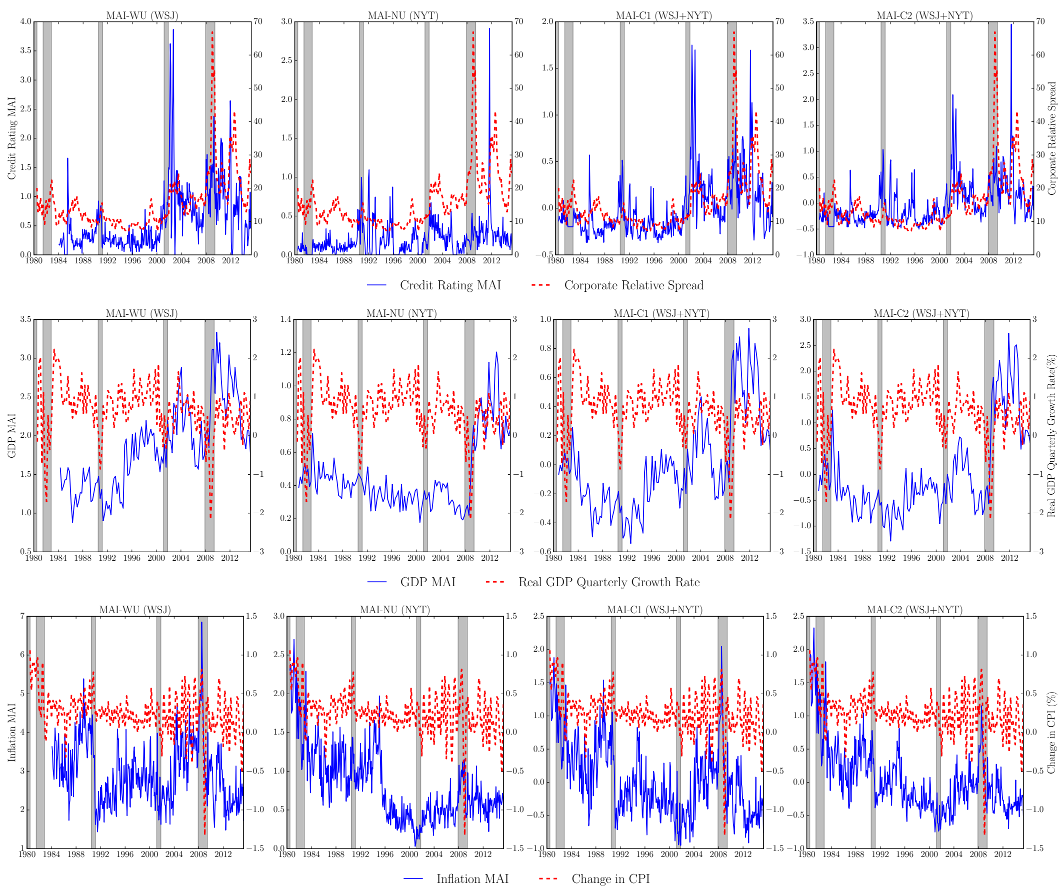
2) Michael Derby, "Yield Curve, Fresh Data Are Unsettling Factors—Back From Holiday Break, Investors Will Get a Look at FOMC's Dec. 12 Mintues," Wall Street Journal, January 3, 2006.

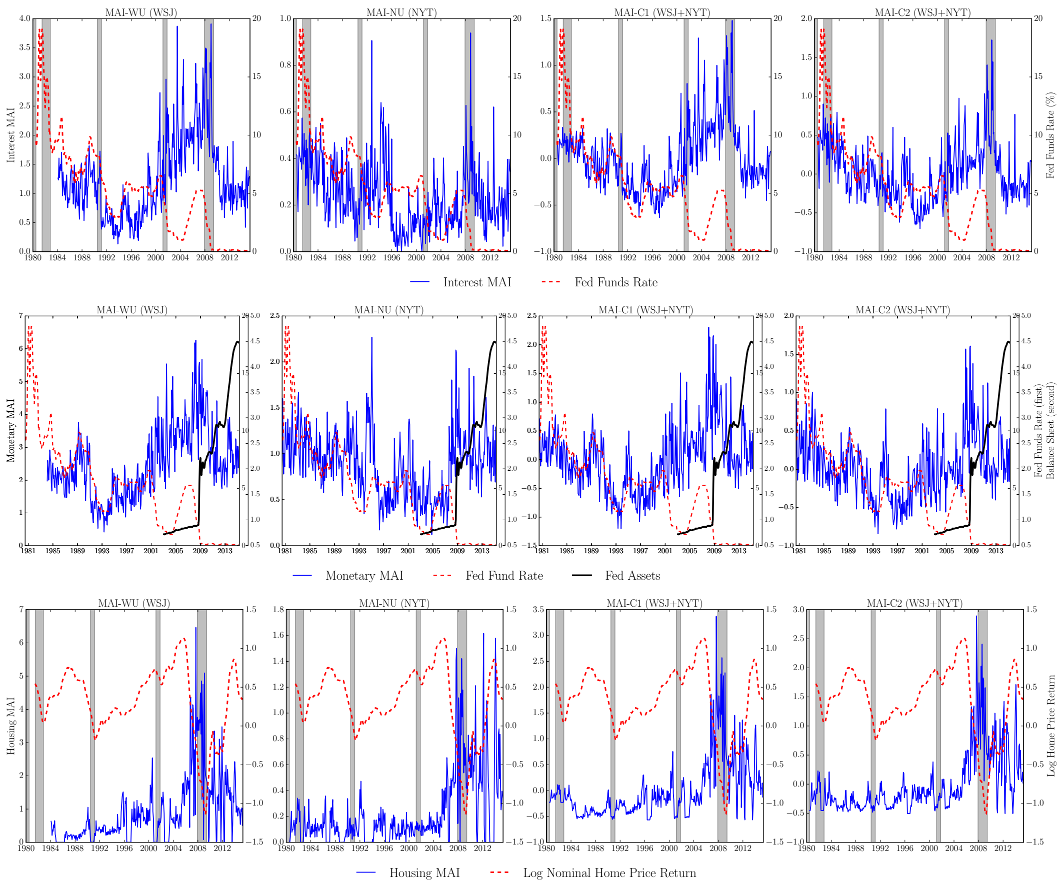
"Not only will the market digest reports on manufacturing and employment data, but the publication of the minutes from the Federal Open Market Committee's Dec. 13 meeting today also could help settle the debate over whether a yield-curve inversion makes sense... The Fed's role has become more important to the market after central bankers rejiggered their policy statement at their last gathering to suggest at least one more rise in the federal-funds rate, bringing it to 4.50% from 4.25%, is likely."

C.1.1 Additional Figures and Results

Figure C.1: Media Attention and Macroeconomic Fundamentals

This figure shows the monthly media attention indices for the Wall Street Journal (MAI-WU), the New York Times (MAI-NU), the demeaned composite index (MAI-C1), and the demeaned and standardized composite index (MAI-C2) against related macroeconomic fundamentals described in Table 4.2. The blue line represents a particular media attention index (MAI) (y-axis) and the red dotted line (secondary-y axis) is the related macroeconomic fundamental. The units are in percentage. The gray vertical bars are NBER recessions. See Table 4.2




MAI-WU (WSJ)
MAI-NU (NYT)
MAI-C1 (WSJ+NYT)
MAI-C2 (WSJ+NYT)
Interest MAI
Fed Funds Rate (%)
Interest MAI
Fed Funds Rate
Monetary MAI
Fed Funds Rate (first)
Balance Sheet (second)
Monetary MAI
Fed Fund Rate
Fed Assets
Housing MAI
Log Home Price Return
Housing MAI
Log Nominal Home Price Return

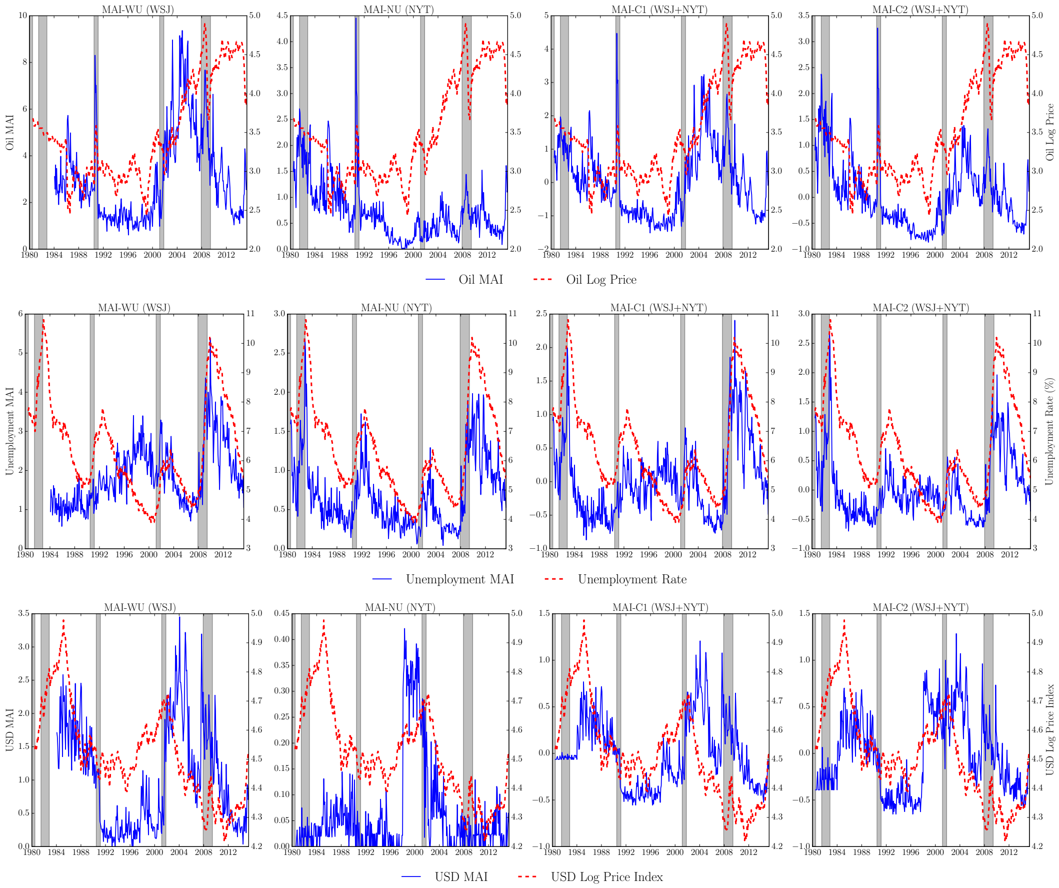

MAI-WU (WSJ)
MAI-NU (NYT)
MAI-C1 (WSJ+NYT)
MAI-C2 (WSJ+NYT)
Oil MAI
Oil Log Price
Unemployment MAI
Unemployment Rate (%)
USD MAI
USD Log Price Index

Table C.1: Descriptive Statistics and Correlation

This table presents the descriptive statistics for the monthly unadjusted media attention indices (MAI) for the Wall Street Journal (MAI-WU) and New York Times (MAI-NU), the Economic Policy Uncertainty (EPU) index, the implied volatility (VXO), and the three-month detrended log S&P 500 trade volume. Columns Jan to Dec are the monthly averages for each MAI. Panels B shows the correlation between the demeaned macroeconomic attention composite indices (MAI-C1), EPU, VXO, and the 60-day detrended S&P 500 trade volume at the monthly frequency.

Table C.2: Panel A: Descriptive Statistics for Monthly Unadjusted MAI

	Obs.	Mean	St. Dev.	Min	Max	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Wall Street Journal																	
Credit Rating	376	0.60	0.56	0.00	3.87	0.59	0.61	0.60	0.51	0.52	0.65	0.61	0.68	0.56	0.58	0.62	0.65
GDP	376	1.86	0.61	0.73	4.10	1.93	1.92	1.79	1.77	1.70	1.78	1.83	2.03	1.83	1.85	1.95	1.90
Housing	376	0.90	1.01	0.00	6.47	1.00	0.87	0.86	0.86	0.93	0.96	0.94	0.96	0.88	0.92	0.83	0.83
Inflation	376	2.96	0.82	1.43	6.85	3.15	3.08	2.93	2.81	3.00	3.05	2.79	3.00	2.98	2.81	2.87	3.01
Interest	376	1.24	0.69	0.13	3.91	1.34	1.12	1.25	1.13	1.18	1.31	1.20	1.39	1.22	1.24	1.26	1.31
Monetary	376	2.49	1.06	0.42	6.26	2.66	2.45	2.49	2.24	2.36	2.56	2.36	2.61	2.63	2.41	2.47	2.60
Oil	376	3.07	1.94	0.61	9.37	3.13	2.87	3.13	3.09	3.08	2.99	2.89	3.15	3.13	3.20	3.03	3.22
Unemp.	376	1.87	0.80	0.57	5.38	2.03	1.91	1.74	1.68	1.68	1.78	1.85	1.90	1.98	1.86	1.99	2.03
USD	376	1.04	0.79	0.00	3.45	1.21	0.99	1.01	0.99	0.97	0.89	1.08	1.05	1.08	1.07	1.12	1.05
New York Times																	
Credit Rating	419	0.20	0.23	0.00	2.91	0.23	0.19	0.17	0.17	0.17	0.18	0.20	0.21	0.19	0.21	0.23	0.22
GDP	419	0.46	0.23	0.11	1.55	0.51	0.45	0.42	0.46	0.40	0.43	0.45	0.43	0.46	0.46	0.48	0.50
Housing	419	0.23	0.28	0.00	1.62	0.28	0.27	0.21	0.18	0.18	0.17	0.23	0.28	0.25	0.26	0.20	0.22
Inflation	419	0.82	0.48	0.03	2.70	0.97	0.85	0.81	0.74	0.82	0.87	0.83	0.81	0.82	0.78	0.74	0.82
Interest	419	0.24	0.14	0.00	0.94	0.24	0.23	0.25	0.21	0.24	0.23	0.26	0.27	0.24	0.24	0.21	0.24
Monetary	419	0.89	0.36	0.12	2.27	1.02	0.96	0.91	0.77	0.81	0.88	0.90	0.94	0.94	0.85	0.82	0.89
Oil	419	0.74	0.58	0.00	4.46	0.82	0.75	0.78	0.72	0.68	0.71	0.72	0.78	0.73	0.75	0.63	0.77
Unemp.	419	0.68	0.45	0.04	2.68	0.81	0.71	0.61	0.55	0.61	0.61	0.70	0.66	0.72	0.76	0.76	0.71
USD	419	0.06	0.09	0.00	0.42	0.06	0.07	0.07	0.06	0.08	0.06	0.05	0.08	0.05	0.07	0.06	0.06
Other Variables																	
EPU	360	101.33	41.96	37.27	271.83	127.67	106.13	94.75	82.98	86.87	89.70	94.48	95.44	107.89	112.99	111.94	105.12
VXO	352	20.77	8.36	9.54	61.41	21.04	20.54	20.50	19.40	19.21	18.82	19.84	20.91	22.67	23.88	21.91	20.63
Volume	419	0.01	0.09	-0.35	0.31	0.12	-0.04	0.05	0.02	-0.03	0.02	0.05	-0.03	0.00	0.07	-0.08	-0.04

Panel B: Monthly MAI-C1 correlation (1980-2015)

	Credit Rating	GDP	Housing	Inflation	Interest	Monetary	Oil	Unemp.	USD	EPU	VXO	Volume
Credit Rating	1.00	0.48	0.30	-0.18	0.32	0.40	0.22	0.31	0.30	0.28	0.32	-0.01
GDP	0.48	1.00	0.36	-0.14	0.20	0.40	0.07	0.64	0.10	0.13	0.18	-0.08
Housing	0.30	0.36	1.00	0.03	0.45	0.48	0.16	0.20	0.06	-0.07	0.05	0.06
Inflation	-0.18	-0.14	0.03	1.00	0.35	0.36	0.43	-0.05	0.23	-0.01	0.03	0.06
Interest	0.32	0.20	0.45	0.35	1.00	0.77	0.59	0.04	0.56	0.04	0.23	0.03
Monetary	0.40	0.40	0.48	0.36	0.77	1.00	0.45	0.28	0.42	0.15	0.27	0.04
Oil	0.22	0.07	0.16	0.43	0.59	0.45	1.00	-0.11	0.59	0.07	0.08	0.05
Unemp.	0.31	0.64	0.20	-0.05	0.04	0.28	-0.11	1.00	-0.17	0.35	0.32	-0.05
USD	0.30	0.10	0.06	0.23	0.56	0.42	0.59	-0.17	1.00	0.07	0.33	0.03
EPU	0.28	0.13	-0.07	-0.01	0.04	0.15	0.07	0.35	0.07	1.00	0.44	0.05
VXO	0.32	0.18	0.05	0.03	0.23	0.27	0.08	0.32	0.33	0.44	1.00	0.06
Volume	-0.01	-0.08	0.06	0.06	0.03	0.04	0.05	-0.05	0.03	0.05	0.06	1.00

Table C.3: Persistence of Macroeconomic Attention

Panel A of this table presents AR (p) models of the monthly demeaned and standardized media attention composite indices (MAI-C2), controlling for monthly time-fixed effects. DF (p-value) are the p-values for the Dickey-Fuller (DF) statistics that test the null of a unit root in each time series. Panel B reports the estimates from an OLS regression of the daily demeaned and standardized media attention composite indices (MAI-C2) on various moving average lags of itself. L1 corresponds to the lag of itself and L5, L21, L62, L250, and L1000 are the moving average for 5, 21, 62, 250, and 1000 days preceding the observed values at time t. We control for day-of-week fixed effects. The standard errors are reported in parenthesis and are calculated using Newey-West standard errors (10 lags). Obs. stands for the number of observations. *, **, and *** denote the statistical significance at the 10%, 5%, 1% levels, respectively.

Panel A: Monthly MAI-C2 AR(4) Coefficients and DF statistics

	Credit Rating	GDP	Housing	Inflation	Interest	Monetary	Oil	Unemp.	USD
const	0.02	0.05	-0.01	0.08**	0.03	0.03	0.11**	-0.01	-0.04
	(0.05)	(0.04)	(0.05)	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)	(0.03)
AR(1)	0.66***	0.26***	0.60***	0.49***	0.53***	0.47***	0.66***	0.67***	0.54***
	(0.07)	(0.06)	(0.10)	(0.05)	(0.05)	(0.04)	(0.05)	(0.06)	(0.06)
AR(2)	0.01	0.28***	0.09	0.25***	0.15**	0.15***	0.18***	0.13**	0.19***
	(0.07)	(0.04)	(0.08)	(0.05)	(0.07)	(0.05)	(0.05)	(0.06)	(0.05)
AR(3)	0.05	0.31***	0.14	0.08	-0.03	0.08*	0.08	0.10*	0.13**
	(0.05)	(0.06)	(0.09)	(0.05)	(0.05)	(0.04)	(0.10)	(0.06)	(0.05)
AR(4)	0.09	0.06	0.03	0.09**	0.17***	0.06	-0.02	0.01	0.07
	(0.05)	(0.05)	(0.08)	(0.04)	(0.04)	(0.04)	(0.06)	(0.05)	(0.06)
DF (p-value)	0.00	0.05	0.02	0.00	0.00	0.00	0.00	0.00	0.09
Adj-R2	0.55	0.66	0.64	0.76	0.52	0.44	0.75	0.78	0.77
Obs.	415	415	415	415	415	415	415	415	415

Panel B: Daily MAI-C2 Frequency Regressions

	Credit Rating	GDP	Housing	Inflation	Interest	Monetary	Oil	Unemployment	U.S. Dollar
const	-0.15***	0.00	-0.21***	-0.02	-0.10***	-0.20***	-0.18***	-0.03	-0.22***
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
L1	0.08***	0.07***	0.04*	0.06***	0.13***	0.19***	0.11***	0.04**	0.01
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.01)
L5	0.28***	0.12***	0.46***	0.13***	0.15***	0.18***	0.39***	0.22***	0.16***
	(0.06)	(0.03)	(0.07)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
L21	0.40***	0.06	0.23***	0.26***	0.27***	0.23***	0.30***	0.25***	0.39***
	(0.09)	(0.07)	(0.08)	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)
L62	0.06	0.34***	0.06	0.36***	0.15*	0.13*	0.13**	0.26***	0.29***
	(0.06)	(0.10)	(0.07)	(0.07)	(0.08)	(0.07)	(0.05)	(0.08)	(0.07)
L250	0.08	0.41***	0.17**	0.08	0.25***	0.20***	0.01	0.23***	0.14**
	(0.06)	(0.11)	(0.08)	(0.06)	(0.07)	(0.07)	(0.03)	(0.06)	(0.05)
L1000	0.02	-0.05	0.01	0.05	-0.01	0.00	0.03	-0.08***	-0.03
	(0.05)	(0.06)	(0.06)	(0.04)	(0.04)	(0.05)	(0.02)	(0.03)	(0.03)
Obs.	8109	8109	8109	8109	8109	8109	8109	8109	8109
Adj-R2	0.28	0.18	0.42	0.20	0.18	0.25	0.52	0.36	0.34

Table C.4: Media Attention and Macroeconomic Fundamentals

This table presents the results of an OLS regression of monthly macroeconomic media attention indices (MAI) on different macroeconomic fundamentals. Panels A and Panel B report the results for the demeaned composite index (MAI-C1) and the demeaned and standardized composite index (MAI-C2), respectively. The general regression is specified in equation 4.6. F corresponds to the associated fundamental to each MAI as described in Table 4.2 and F_t is the moving average over t days of the respective fundamental. We control for monthly fixed effects. The standard errors are reported in parenthesis and are calculated using Newey-West standard errors (5 lags). Obs. stands for the number of observations. *, **, *** denote the statistic significance at the 10%, 5%, 1% levels, respectively.

Panel A: MAI-C1 (Demeaned)

MAI: **F:**	Credit Rating Credit Rating Spreads	GDP GDP Growth	Housing Home Price Ret	Inflation Δ CPI	Interest Fed Fund	Monetary Fed Fund	Oil Oil Price Ret	Unemployment Unemp. Rate	US Dollar USD Index Ret
$F_t - F_{t,t-3}$	0.034**		-0.250	-0.234**	-0.042	-0.031	-0.009	-0.013	0.004
	(0.015)		(0.176)	(0.104)	(0.040)	(0.057)	(0.006)	(0.175)	(0.006)
$F_{t,t-3} - F_{t,t-12}$	0.011	0.117	-0.462***	-0.085	-0.005	-0.015	0.010	0.164	-0.007
	(0.007)	(0.072)	(0.160)	(0.234)	(0.033)	(0.049)	(0.013)	(0.125)	(0.019)
$F_{t,t-12} - F_{t,t-48}$	0.003	0.224	-0.097	2.268***	0.010	-0.000	0.108**	0.171***	-0.186***
	(0.015)	(0.184)	(0.180)	(0.648)	(0.028)	(0.041)	(0.054)	(0.062)	(0.063)
$(F_t - F_{t,t-3})^2$	-0.001		0.517*	-0.407*	0.007	0.018	0.004***	1.022	0.007**
	(0.002)		(0.269)	(0.218)	(0.023)	(0.025)	(0.001)	(0.782)	(0.004)
$(F_{t,t-3} - F_{t,t-12})^2$	0.000	0.185**	0.451***	0.288	0.015	0.040**	0.005***	0.232**	0.023**
	(0.000)	(0.084)	(0.141)	(0.234)	(0.015)	(0.020)	(0.001)	(0.104)	(0.010)
$(F_{t,t-12} - F_{t,t-48})^2$	0.001	0.295	1.418***	9.858***	0.007	0.001	-0.005	0.075***	0.141**
	(0.001)	(0.296)	(0.329)	(1.605)	(0.007)	(0.013)	(0.011)	(0.026)	(0.067)
const	-0.031	-0.076	-0.472***	-0.062	-0.006	0.010	-0.300	-0.061	-0.099
	(0.041)	(0.076)	(0.054)	(0.077)	(0.068)	(0.093)	(0.183)	(0.078)	(0.070)
Obs.	419	125	419	419	419	419	376	419	419
Adj-R2	0.10	0.08	0.49	0.19	0.01	0.01	0.15	0.50	0.14

Panel B: MAI-C2 (Demeaned and Standardized)

MAI:	Credit Rating	GDP	Housing	Inflation	Interest	Monetary	Oil	Unemployment	US Dollar
F:	Credit Rating Spreads	GDP Growth	Home Price Ret	Δ CPI	Fed Fund	Fed Fund	Oil Price Ret	Unemp. Rate	USD Index Ret
$F_t - F_{t,t-3}$	0.049**		-0.312*	-0.216**	-0.054	-0.016	-0.005	-0.024	0.004
	(0.023)		(0.177)	(0.086)	(0.049)	(0.044)	(0.004)	(0.171)	(0.006)
$F_{t,t-3} - F_{t,t-12}$	0.010	0.300*	-0.501***	-0.378*	-0.001	-0.017	0.006	0.184	-0.007
	(0.009)	(0.171)	(0.164)	(0.203)	(0.032)	(0.032)	(0.008)	(0.113)	(0.018)
$F_{t,t-12} - F_{t,t-48}$	-0.006	0.636	-0.045	1.729**	-0.008	-0.017	0.060**	0.166***	-0.225***
	(0.023)	(0.463)	(0.180)	(0.704)	(0.024)	(0.025)	(0.027)	(0.053)	(0.069)
$(F_t - F_{t,t-3})^2$	-0.001		0.697***	-0.456**	0.053**	0.039**	0.003***	0.949	0.007*
	(0.003)		(0.225)	(0.189)	(0.022)	(0.015)	(0.000)	(0.801)	(0.004)
$(F_{t,t-3} - F_{t,t-12})^2$	0.000	0.414**	0.450***	-0.028	0.032*	0.050***	0.003***	0.236**	0.009
	(0.001)	(0.191)	(0.135)	(0.183)	(0.017)	(0.016)	(0.001)	(0.119)	(0.012)
$(F_{t,t-12} - F_{t,t-48})^2$	0.002	0.819	1.172***	9.650***	0.015**	-0.000	-0.005	0.070***	0.081
	(0.001)	(0.751)	(0.344)	(1.955)	(0.006)	(0.008)	(0.006)	(0.026)	(0.074)
const	-0.045	-0.194	-0.451***	-0.109	-0.064	-0.027	-0.219***	-0.067	-0.091
	(0.059)	(0.205)	(0.056)	(0.072)	(0.064)	(0.068)	(0.084)	(0.070)	(0.080)
Obs.	419	125	419	419	419	419	376	419	419
Adj-R2	0.08	0.08	0.47	0.22	0.12	0.07	0.25	0.54	0.09

Table C.5: Media Attention and Aggregate Trade Volume

This table presents the results of an OLS regression of the daily detrended S&P 500 trade volume on the difference between the 5-day and 20-day moving average MAI-C2 and a dummy (Ann) equal to one if there is a related announcement specified in Table 4.2, zero otherwise. We detrend the log trade volume using the moving average of the log trade volume of the past 60 trading days. For all model specifications, we control for day-of-week fixed effects. The standard errors are reported in parenthesis and are calculated using Newey-West standard errors (250 lags). Obs. stands for the number of observations. *, **, *** denote the statistical significance at the 10%, 5%, 1% levels, respectively.

MAI:	Inflation			Monetary			Interest		
Ann:	CPI			FOMC			FOMC		
MAI_{5-20}	0.059***	0.058***	0.063***	0.086***	0.085***	0.086***	0.049***	0.048***	0.049***
	(0.013)	(0.013)	(0.014)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Ann		0.035***	0.042***		0.027***	0.027***		0.030***	0.031***
		(0.007)	(0.007)		(0.009)	(0.010)		(0.009)	(0.009)
$MAI_{5-20}\times$Ann			-0.114***			-0.011			-0.033
			(0.032)			(0.038)			(0.032)
const	0.003	0.000	0.001	0.002	0.002	0.002	0.003	0.002	0.002
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Obs.	8787	8787	8787	8787	8787	8787	8787	8787	8787
Adj-R2	0.06	0.06	0.06	0.07	0.07	0.07	0.05	0.05	0.05

MAI:	GDP			Unemployment			Credit Rating	Oil	USD
Ann:	GDP Report			Employment					
MAI_{5-20}	0.019*	0.019*	0.017	0.034***	0.033***	0.034***	0.043***	0.043**	0.027*
	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)	(0.013)	(0.017)	(0.014)
Ann		0.005	0.003		0.014	0.017			
		(0.008)	(0.008)		(0.011)	(0.012)			
$MAI_{5-20}\times$Ann			0.058			-0.031			
			(0.041)			(0.039)			
const	0.002	0.002	0.002	0.003	-0.001	-0.000	0.002	0.013**	0.028***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.007)	(0.006)
Obs.	8787	8787	8787	8787	8787	8787	8787	7368	8321
Adj-R2	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.06

Table C.6: Media Attention and Implied Volatility

This table presents the results of an OLS regression of the daily implied volatility proxied by VXO regressed on the difference between the 20-day and 250-day moving average MAI-C2 and a dummy (Ann) equal to one if there is a related announcement specified in Table 4.2, zero otherwise. For all model specifications, we control for day-of-week fixed effects. The standard errors are reported in parenthesis and are calculated using Newey-West standard errors (250 lags). Obs. stands for the number of observations. *, **, *** denote the statistical significance at the 10%, 5%, 1% levels, respectively.

MAI:	Inflation			Monetary			Interest		
Ann:	CPI			FOMC			FOMC		
MAI_{20-250}	-2.427	-2.425	-2.466	5.647**	5.646**	5.668**	5.671**	5.670**	5.698**
	(4.705)	(4.706)	(4.667)	(2.415)	(2.415)	(2.416)	(2.558)	(2.558)	(2.562)
Ann		0.265	0.277		-0.178	-0.187		-0.196	-0.204
		(0.185)	(0.189)		(0.221)	(0.224)		(0.222)	(0.229)
$MAI_{20-250}\times$Ann			0.881			-0.750			-0.846
			(1.157)			(0.732)			(1.053)
const	20.728***	20.711***	20.711***	20.719***	20.720***	20.720***	20.724***	20.724***	20.724***
	(1.240)	(1.236)	(1.236)	(1.245)	(1.245)	(1.245)	(1.253)	(1.253)	(1.253)
Obs.	7386	7386	7386	7386	7386	7386	7386	7386	7386
Adj-R2	0.00	0.00	0.00	0.03	0.03	0.03	0.03	0.03	0.03

MAI:	GDP			Unemployment			Credit Rating	Oil	USD
Ann:	GDP Report			Employment					
MAI_{20-250}	12.939***	12.946***	12.995***	14.035***	14.037***	14.075***	5.462***	1.148	4.202**
	(5.008)	(5.009)	(4.994)	(4.866)	(4.866)	(4.879)	(1.719)	(1.781)	(1.921)
Ann		0.297	0.284		0.222	0.221			
		(0.199)	(0.202)		(0.155)	(0.159)			
$MAI_{20-250}\times$Ann			-0.973			-0.781			
			(1.097)			(0.996)			
const	20.632***	20.609***	20.609***	20.633***	20.583***	20.582***	20.766***	20.763***	20.777***
	(1.124)	(1.120)	(1.120)	(1.066)	(1.067)	(1.066)	(1.216)	(1.252)	(1.250)
Obs.	7386	7386	7386	7386	7386	7386	7361	7361	7005
Adj-R2	0.08	0.08	0.08	0.15	0.15	0.15	0.05	0.00	0.01

Table C.7: Unemployment Surprise Forecasts

This table presents the results of an OLS regression of the unemployment surprise regressed on various detrended daily media attention indices at different frequencies and an interaction term between the detrended media attention indices and an NBER dummy. The NBER dummy is equal to one if the unemployment surprise occurs during a NBER recession, zero otherwise. Panel A shows the result for MAI-WU, MAI-NU in Panel B, and MAI-C2 in Panel C. We use three different unemployment surprises. Each surprise is calculated as the difference between the actual unemployment for month t reported in month $t+1$ and (1) the random-walk (i.e. the previous month unemployment rate), (2) the forecasted unemployment rate as in Boyd, Hu, and Jagannathan (2005), or (3) the median of the forecasted unemployment rate by economists surveyed by Bloomberg. The standard errors are reported in parenthesis and are calculated using the White's heteroskedasticity robust standard errors. Obs. stands for the number of observations. *, **, *** denote the statistical significance at the 10%, 5%, 1% levels, respectively.

Panel A: MAI-WU (Wall Street Journal)

Random-Walk

MAI:	MAI_{5-20}		MAI_{5-250}		MAI_{20-250}		MAI_{60-250}	
MAI	0.030*	0.015	0.035***	0.013	0.054**	0.006	0.096**	0.002
	(0.016)	(0.016)	(0.013)	(0.012)	(0.026)	(0.025)	(0.037)	(0.037)
MAI×NBER		0.200***		0.128***		0.174***		0.319***
		(0.066)		(0.029)		(0.053)		(0.051)
const	-0.013	-0.013	-0.011	-0.014	-0.004	-0.011	-0.003	-0.014
	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Obs.	375	375	364	364	364	364	364	364
Adj-R2	0.01	0.04	0.02	0.07	0.02	0.05	0.03	0.09

Boyd et al. (2005) Surprise

MAI:	MAI_{5-20}		MAI_{5-250}		MAI_{20-250}		MAI_{60-250}	
MAI	0.019	0.014	0.024**	0.016	0.044**	0.025	0.068***	0.034
	(0.013)	(0.013)	(0.011)	(0.011)	(0.018)	(0.020)	(0.025)	(0.027)
MAI×NBER		0.057		0.047*		0.068*		0.117***
		(0.057)		(0.028)		(0.039)		(0.045)
const	-0.020***	-0.020***	-0.019**	-0.020***	-0.014*	-0.017**	-0.014*	-0.018**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)
Obs.	375	375	364	364	364	364	364	364
Adj-R2	0.00	0.00	0.02	0.02	0.02	0.02	0.02	0.03

Panel A: Continued.

	Bloomberg Surprise							
MAI:	MAI_{5-20}		MAI_{5-250}		MAI_{20-250}		MAI_{60-250}	
MAI	0.033**	0.021	0.019*	0.009	0.005	-0.014	0.013	-0.028
	(0.015)	(0.015)	(0.011)	(0.012)	(0.020)	(0.025)	(0.029)	(0.037)
MAI×NBER		0.138***		0.049**		0.059		0.118**
		(0.046)		(0.022)		(0.040)		(0.051)
const	-0.039***	-0.039***	-0.035***	-0.037***	-0.031***	-0.035***	-0.031***	-0.037***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)	(0.011)
Obs.	217	217	217	217	217	217	217	217
Adj-R2	0.02	0.05	0.01	0.02	-0.00	-0.00	-0.00	0.01

Panel B: MAI-NU (New York Times MAI)

Random-Walk

MAI:	MAI_{5-20}		MAI_{5-250}		MAI_{20-250}		MAI_{60-250}	
MAI	0.000	0.001	0.079***	0.051**	0.186***	0.131***	0.294***	0.178***
	(0.037)	(0.036)	(0.026)	(0.026)	(0.039)	(0.040)	(0.057)	(0.062)
MAI×NBER		-0.005		0.210**		0.224**		0.503***
		(0.181)		(0.104)		(0.112)		(0.141)
const	-0.006	-0.006	-0.008	-0.013	-0.002	-0.009	-0.003	-0.013
	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Obs.	418	418	407	407	407	407	407	407
Adj-R2	-0.00	-0.00	0.03	0.05	0.06	0.08	0.08	0.12

Boyd et al. (2005) Surprise

MAI:	MAI_{5-20}		MAI_{5-250}		MAI_{20-250}		MAI_{60-250}	
MAI	-0.001	-0.002	0.041*	0.034	0.095***	0.090**	0.164***	0.125**
	(0.032)	(0.034)	(0.021)	(0.023)	(0.031)	(0.035)	(0.048)	(0.058)
MAI×NBER		0.005		0.052		0.021		0.170*
		(0.111)		(0.057)		(0.077)		(0.101)
const	-0.015**	-0.015**	-0.017**	-0.018**	-0.014*	-0.015*	-0.014*	-0.018**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)
Obs.	418	418	407	407	407	407	407	407
Adj-R2	-0.00	-0.00	0.01	0.01	0.02	0.02	0.04	0.04

Bloomberg Surprise

MAI:	MAI_{5-20}		MAI_{5-250}		MAI_{20-250}		MAI_{60-250}	
MAI	-0.001	0.010	0.019	0.014	0.048	0.025	0.015	-0.069
	(0.038)	(0.040)	(0.029)	(0.032)	(0.045)	(0.058)	(0.065)	(0.080)
MAI×NBER		-0.150		0.032		0.069		0.270**
		(0.118)		(0.070)		(0.091)		(0.130)
const	-0.031***	-0.031***	-0.032***	-0.033***	-0.031***	-0.033***	-0.031***	-0.037***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)
Obs.	217	217	217	217	217	217	217	217
Adj-R2	-0.00	-0.00	-0.00	-0.01	0.00	-0.00	-0.00	0.01

Panel C: MAI-C2 (Demeaned and Standardized MAI)

Random-Walk

MAI:	MAI_{5-20}		MAI_{5-250}		MAI_{20-250}		MAI_{60-250}	
MAI	0.036	0.017	0.083***	0.051**	0.158***	0.110***	0.234***	0.136***
	(0.032)	(0.031)	(0.021)	(0.021)	(0.034)	(0.034)	(0.046)	(0.051)
MAI×NBER		0.228		0.211***		0.180*		0.382***
		(0.170)		(0.066)		(0.093)		(0.103)
const	-0.009	-0.008	-0.011	-0.017*	-0.002	-0.009	-0.002	-0.012
	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Obs.	418	418	407	407	407	407	407	407
Adj-R2	0.00	0.01	0.04	0.08	0.07	0.08	0.09	0.12

Boyd et al. (2005) Surprise

MAI:	MAI_{5-20}		MAI_{5-250}		MAI_{20-250}		MAI_{60-250}	
MAI	0.021	0.013	0.049***	0.038**	0.092***	0.084***	0.135***	0.099**
	(0.028)	(0.029)	(0.018)	(0.019)	(0.025)	(0.030)	(0.038)	(0.048)
MAI×NBER		0.096		0.070		0.031		0.142**
		(0.104)		(0.048)		(0.057)		(0.071)
const	-0.017**	-0.017**	-0.019**	-0.021***	-0.013*	-0.015*	-0.013*	-0.017**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)
Obs.	418	418	407	407	407	407	407	407
Adj-R2	-0.00	-0.00	0.02	0.03	0.03	0.03	0.04	0.05

Bloomberg Surprise

MAI:	MAI_{5-20}		MAI_{5-250}		MAI_{20-250}		MAI_{60-250}	
MAI	0.049	0.036	0.031	0.017	0.027	-0.002	0.018	-0.058
	(0.033)	(0.034)	(0.022)	(0.025)	(0.035)	(0.047)	(0.050)	(0.065)
MAI×NBER		0.335**		0.072		0.079		0.212**
		(0.168)		(0.047)		(0.072)		(0.093)
const	-0.036***	-0.038***	-0.034***	-0.036***	-0.031***	-0.034***	-0.031***	-0.038***
	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)	(0.011)
Obs.	217	217	217	217	217	217	217	217
Adj-R2	0.01	0.02	0.01	0.01	-0.00	-0.00	-0.00	0.01

Table C.8: S&P Return Forecast on Employment Situation Announcement Days

This table presents the results of an OLS regression of the daily S&P 500 log return on the employment situation announcement date regressed on the unemployment surprise as in Boyd, Hu, and Jagannathan (2005), the surprise interacted with an NBER dummy, the daily detrended unemployment media attention index composite index MAI-C2, and the detrended unemployment media attention index interacted with an NBER dummy. The NBER dummy is equal to one if the unemployment surprise occurs during a NBER recession, zero otherwise. We show the results for two different detrended frequencies for the unemployment media attention index. The standard errors are reported in parenthesis and are calculated using the White's heteroskedasticity robust standard errors. Obs. stands for the number of observations. *, **, *** denote the statistical significance at the 10%, 5%, 1% levels, respectively.

MAI:		MAI_{5-20}			MAI_{20-250}		
MAI		0.395**	0.372**	0.350**	0.282	-0.053	-0.105
		(0.172)	(0.174)	(0.175)	(0.194)	(0.193)	(0.192)
MAI·NBER			0.288	0.443		1.256**	1.502***
			(0.756)	(0.724)		(0.488)	(0.483)
$Surp_{Boyd}$	0.615*			0.585*			0.724**
	(0.354)			(0.351)			(0.368)
$Surp_{Boyd}\times$NBER	-1.938*			-2.174*			-3.070**
	(1.133)			(1.273)			(1.283)
const	0.047	-0.009	-0.009	0.017	0.031	-0.017	0.007
	(0.057)	(0.061)	(0.061)	(0.062)	(0.058)	(0.059)	(0.059)
Obs.	423	418	418	418	407	407	407
Adj-R2	0.01	0.01	0.01	0.01	0.00	0.02	0.04