How is Earnings News Transmitted to Stock Prices?

Job Market Paper

Charles Martineau*

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ABSTRACT

I analyze 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. I find no evidence of slow price reaction at the daily horizon. 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. Additional evidence regarding volatilities, spreads, and trade volumes suggests that markets anticipate the magnitude of surprises. Hidden orders constitute a larger share of executed limit orders following earnings announcements than at other times. I relate these findings to recent theoretical work on hidden liquidity and price discovery.

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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, 2003, Hu, Pan, and Wang, 2015).[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, occur 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]

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]

[1] Other related work on price formation following macroeconomic news includes Jones, Lamont, and Lumsdaine (1998), Fleming and Remolona (1999), Balduzzi, Elton, and Green (2001), Green (2004), Andersen, Bollerslev, Diebold, and Vega (2007), 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 (2003) and focus on when the impact of earnings surprises on the conditional mean changes in stock returns dissipates.

[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

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 (e.g., Andersen, Bollerslev, Diebold, and Vega, 2003, 2007), 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, 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

(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 of the Appendix, I show how the post-earnings announcements drift has changed since 1984.

[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).

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]

My results on price discovery at high frequency 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, 2003, 2007). Moreover, the details of my results on the speed of price formation confirm considerable market efficiency with respect to earnings news. For large stocks in recent data price formation is complete by the open when after-hours trading is present, and by 10 a.m. otherwise. Evidence is accumulating that the post-earnings announcement drift that has been central to prior literature is less relevant in current data – at least for large stocks.

An additional objective of this paper is to document whether prices adjust more to earnings surprises or to order flow at the time of the announcement. Theory associates the arrival of public information with instantaneous price adjustment (e.g., Milgrom and Stokey,

[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.

1982, French and Roll, 1986). On the other hand, classical microstructure models suggest 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 following 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). 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).

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

[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.

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, 1998, 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 price volatility and also reflect the arrival of information. I focus the analysis during regular market hours prior to and after earnings announcements. Documenting the dynamics in volatilities, trade volumes, and bid-ask spreads prior to announcements provide an indication of whether markets anticipate the magnitude of earnings surprises similarly to the "calm-before-storm" effect documented in Jones, Lamont, and Lumsdaine (1998) and Akbas (2016).[10]

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. It also 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. Higher information asymmetry increases trading opportunities for informed traders, which may influence liquidity providers to increase bid-ask spreads.[11] 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

[10]Previous papers document at the daily-horizon wider bid-ask spreads, lower trade volumes, and higher price sensitivities (i.e., Kyle's lambda) on days prior to earnings announcements (see e.g., Lee, Mucklow, and Ready, 1993, Krinsky and Lee, 1996, Chae, 2005). Affleck-Graves, Callahan, and Chipalkatti (2002) find wider bid-ask spreads at the daily-horizon before eanrings announcements with large surprises. More recently, Akbas (2016) provides evidence that stocks experiencing unusually low trading volumes prior to earnings announcements have large negative earnings surprises.

[11]Hendershott, Livdan, and Schürhoff (2015) show that institutional traders trade ahead of earnings announcements and in the same direction as the earnings surprise.

earnings surprises following earnings announcements. Kim and Verrecchia (1991) predicts a positive relationship between both trade volume and price volatility and the magnitude of the surprise.[12] Additionally, Kim and Verrecchia (1994) predict that even though an earnings announcement is public information, liquidity providers may widen bid-ask spreads following an earnings announcement to protect themselves from traders with superior judgments on the actual implication of the news on the stock's fundamentals. Banerjee and Kremer (2010) further argues that that trade volume and volatility increases in the level of disagreement among investors on the interpretation of a public signal followed by a gradual decay. 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 impact on returns.

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 orders in the after-hours market following earnings announcements versus 12 percent in regular market hours.[13] 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

[12] Atiase and Bamber (1994) provide empirical evidence that trade volume is positively related to the price response on earnings announcement day. Numerous empirical studies document at the daily-horizon that trade volume increases following earnings announcements at the daily horizon (see e.g, Beaver, 1968, Morse, 1981, Kandel and Pearson, 1995, Bamber, Barron, and Stober, 1997).

[13] 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.

order book for a long period and, in turn, mitigate the risk of adverse selection (Harris, 1996).[14] 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, Section VI concludes.

[14]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).

I. Data

A. 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.[15] 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 day on which the reaction of investors to the earnings announcements trading on a U.S. exchange gets to impact the

[15] 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.

announcing firm's stock price.

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

$$S_{i,t} = \frac{\text{EPS}_{i,t} - E_{t-1}[\text{EPS}_{i,t}]}{P_{i,t-5}}, \tag{1}$$

where $\text{EPS}_{i,t}$ is the earnings per share of company i announced on day t, and $E_{t-1}[\text{EPS}_{i,t}]$ is the expectation of earnings per share, measured by the consensus analyst forecast. I scale the surprise using the stock price measured 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.[16] 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.

B. 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.[17] NASDAQ ITCH contains a series of messages that describe orders

[16] 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.

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

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.[18] 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 granularity. 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.[19] Trades are not signed in TAQ; the researcher must infer if a trade is a buy or a sell using trade classification algorithms.[20] 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.[21]

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

[18]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.

[19]See Section B in the Appendix for more institutional details surrounding hidden orders in NASDAQ ITCH.

[20]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.

[21]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.

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.[22]

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.

C. 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. Harris (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 V, I document the implication of hidden orders to price discovery following earnings announcements.

D. Summary statistics

Table I 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. 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

[22]See Figure A1 for a graphical presentation of the trading hours on NASDAQ.

following earnings announcements indicates, in part, poor information quality surrounding these stocks, which results in slower price discovery.

Panel C of Table I 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 16. Note that the median number of initiated trades and trade volume against hidden orders is higher when there is an earnings announcement.[23] 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.

II. 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.

A. 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

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

benchmark portfolios obtained from Ken French's website.[24] 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 1 the average cumulative abnormal returns (CAR) within each earnings surprises quintile and their corresponding 95 percent confidence intervals around earnings announcements. The first striking result is how "flat" the CAR are following earnings announcements at day 0. Earnings surprises appear to be incorporated into the first trading day. I report in Table II Panel A the tabulated format of the abnormal returns (AR) and the CAR 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 II shows the difference in AR and CAR between each quintile and quintile 3. Panel C shows the average AR and CAR for the top and bottom earnings surprises decile and the difference between both deciles. Table II shows no evidence of slow price formation at the daily horizon.

I report in Table III the estimated coefficients of a cross-sectional regression of AR and CAR on stock i's respective earnings surprise $S_{i,t}$. 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 of the Appendix, I show how the post-earnings announcements drift has

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

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.

B. Are there intraday post-earnings announcement drifts?

I now investigate at high frequency the stock return response to earnings announcements. In Figure 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). From Figure 2, we see a similar picture to Figure 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.

C. 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.[25] 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.[26] 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 IV 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 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 number 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

[25] 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.

[26] 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).

prior to earnings announcements.[27] As expected, Table IV 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:

$$r_{i,t}^{ah} = \alpha + \beta S_{i,t} + S_{i,t} \cdot ProbNoTrade_{i,t} + ProbNoTrade_{i,t} + \epsilon_{i,t}, \tag{2}$$

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. $r_{i,t}^{ah}$ 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.[28] 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.[29]

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

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

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

[29] $ProbNoTrade_{i,t}$ is a generated regressor. The error terms from the logit regression and the regression specified in 2 are essentially uncorrelated (0.01); thus, adjustment for the generated regressors is minimal.

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 $S_{i,t} \cdot BMO_{i,t}$, 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.[30] But, the interaction term $S_{i,t} \cdot BMO_{i,t}$ 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-

[30]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.

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.

D. 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 (2003, 2007).

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:

$$r_{i,\tau} = \alpha + \beta_\tau S_{i,t} + \gamma_\tau r_{i,t}^{ah} + \delta r_\tau^m + \epsilon_{i,\tau}. \tag{3}$$

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 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.

In Figure 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 (0.002·0.88) 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 VI 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 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. 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 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.

III. Price Discovery following Earnings Surprises in the After-Hours Market

A. 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 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.[31] 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 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. 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.[32]

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

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

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 I 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.[33]

B. 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 of total trades) and a trade bin k contains a fraction of the total trades.[34] 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

[33] In Section C 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.

[34] 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.

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 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. 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.[35] 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:

$$r_{i,k} = \alpha + \beta_k S_{i,t} + \epsilon_{i,k}, \tag{4}$$

where k defines a trade bin. Similar to Figure 6, I show in Figure 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. Panel A shows that price discovery occurs over the first three

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

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.

C. 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 trade. 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 (1999) 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

$$\Delta P_t = S_t + OI_t, \tag{5}$$

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:

$$OI_k = \frac{B_k - S_k}{B_k + S_k}, \tag{6}$$

where B_k and S_k respectively correspond to trade buys and sells in shares units in trade bin k.[36] I show in Figure 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.

In Figure 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.[37] 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. 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, net order flow is required to explain the price drift following earnings announcements.

Table VII Panel A 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. I also include as independent variables the log of the total number of trades ($Trd_{i,k}$) and interaction terms $S_{i,t} \times Trd_{i,k}$ and $OI_{i,k} \times Trd_{i,k}$. Order imbalance may play a larger role if there is more trade. The results of these regressions confirm the general findings of Figure 9: prices

[36] 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.

[37] 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.

adjust primarily to news and not order imbalance in the first trade bin. Even though the coefficients of the interaction term in Columns (3) and (6) are significant, there is no significant improvement in R^2. I repeat the same analysis in Panel B 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 remain similar to those for Panel A. 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 news. This indicates that liquidity providers are largely responsible for the initial price adjustment in response to news through limit order quote updates. This result contrasts with Evans and Lyons (2002, 2008) and 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.

IV. 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, 1998, Andersen, Bollerslev, Diebold, and Vega, 2003) study the response of abnormal volatility in bond and foreign exchange prices following macroeconomic news and associate the response to price discovery.[38] In this section, I examine how the mag-

[38]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 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

nitude 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 (1998) and Akbas (2016).

in trade volume and price volatility.

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

$$r_\tau = \alpha + \rho r_{\tau-1} + \gamma r_\tau^m + \beta_\tau S_t \cdot \mathbb{1}_{\{\tau \in t\}} + \epsilon_\tau, \tag{7}$$

where τ corresponds to a five-minute interval between 9:30 a.m. and 4 p.m., 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. 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 (7) for each stock i separately.

Following the estimation of Equation 7, 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

$$QS_{i,s,t} = \frac{Ask_{i,s,t} - Bid_{i,s,t}}{P_{i,s,t}}, \tag{8}$$

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

$$Turn_{i,\tilde{\tau},t} = \frac{V_{i,\tilde{\tau},t}}{Out_{i,t}}, \tag{9}$$

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 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. Early 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:

$$|\hat{\epsilon}_{i,\tilde{\tau}}| - |\bar{\epsilon}_{i,\tilde{\tau}}| = a + b_{\tilde{\tau}}|S_{i,t}| + c\frac{\sigma_{d(t)}}{\sqrt{13}} + e_{i,\tilde{\tau}}, \tag{10}$$

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 (10) on three trading days around the earnings announcement. In total, I estimate 39 $\hat{b}_{\tilde{\tau}}$ (13 per trading day).

In Figure 11, Panel A, I plot the estimated $\hat{b}_{\tilde{\tau}}$. 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 interquartile 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 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 (10) 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 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 A3 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 (10) 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 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.

V. Hidden Liquidity around Earnings Announcements

Despite earnings surprises largely incorporating prices instantly, actual trading does matter with respect to explaining the remaining price adjustment following earnings surprises. For a trade to occur, there has to be liquidity in the limit order book. 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. 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). Therefore, abolishing hidden orders may deter liquidity following earnings announcements and consequently deteriorate the speed of price discovery.

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

$$rs_{i,j} = \begin{cases} \frac{m_{i,j} - p_{i,t}}{m_{i,t-1}} * 100, & \text{if trade } j \text{ was a passive buy} \\ \frac{p_{i,t} - m_{i,j}}{m_{i,t-1}} * 100, & \text{if trade } j \text{ was a passive sell,} \end{cases} \tag{11}$$

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:

$$rs^o_{i,k,t} = Displayed_{i,k,t} + Hidden_{i,k,t} + \epsilon_{i,k,t}. \tag{12}$$

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

Table VIII 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. 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

[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.

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.

VI. Conclusion

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.

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Figure 1. 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 2011 and 2015.

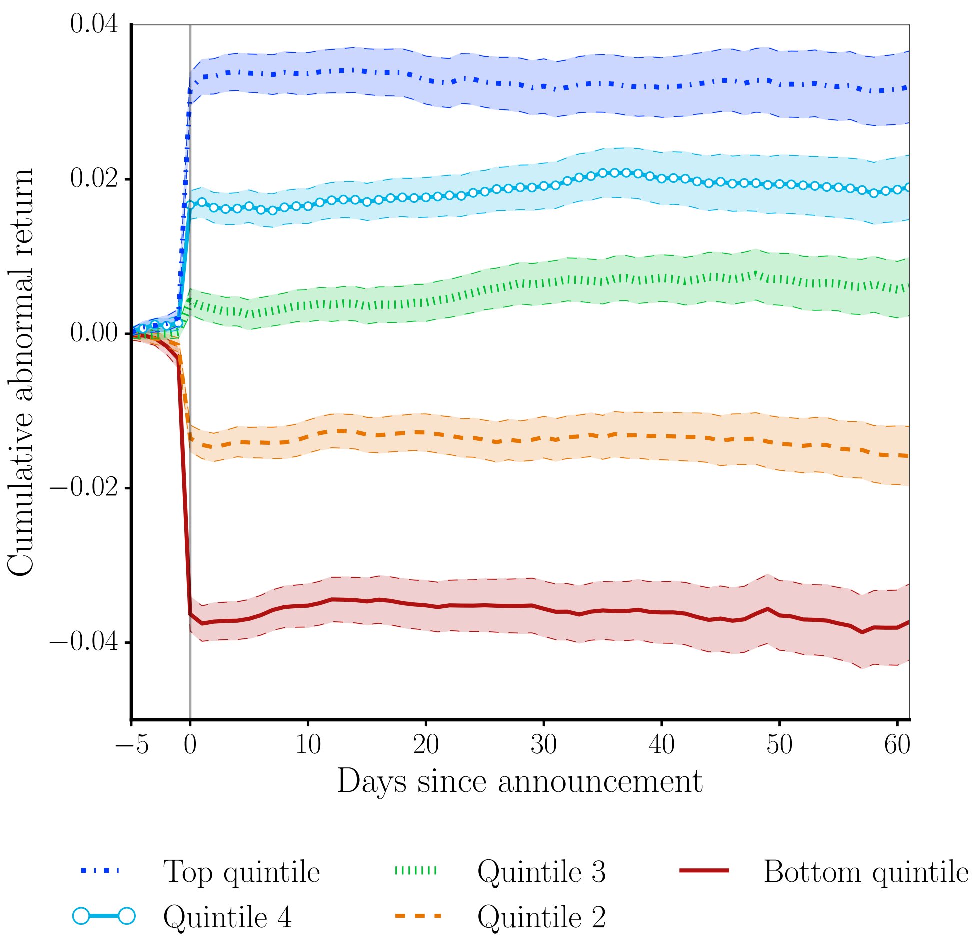


Figure 2. Cumulative Abnormal Intraday Returns around Earnings Announcements

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.

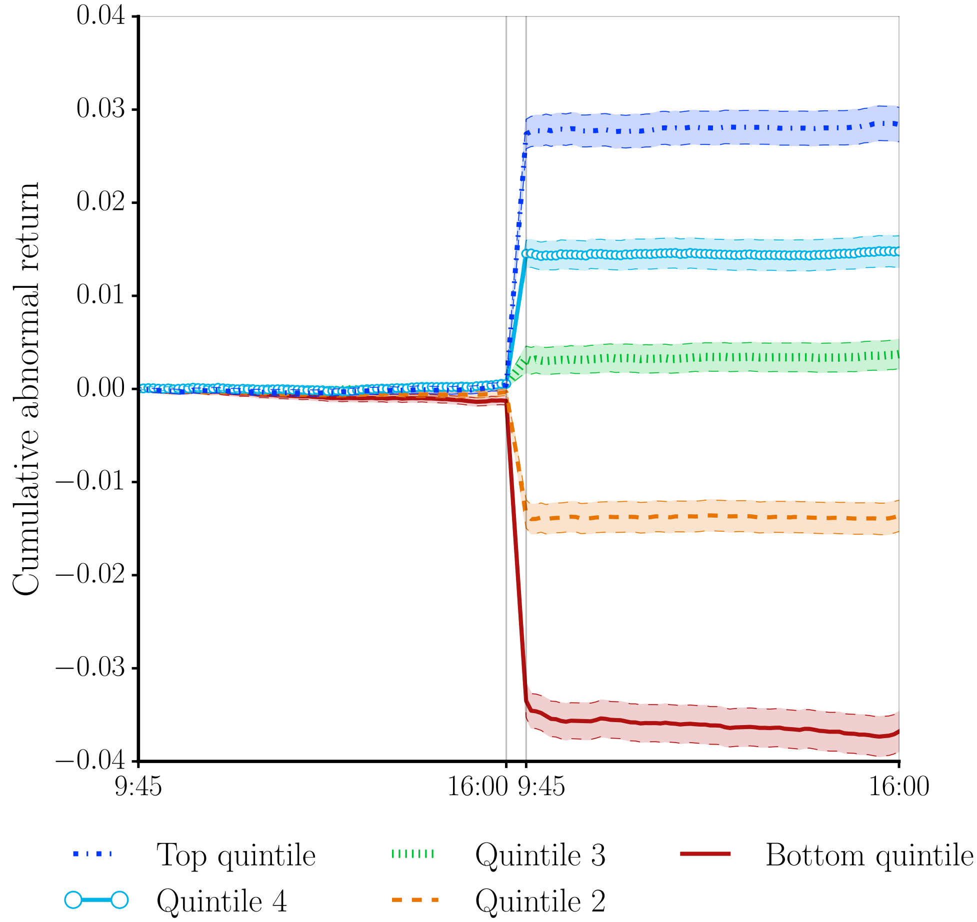


Figure 3. The Response of Stock Returns to Earnings Surprises at the Opening of Markets

This figure shows the estimated response coefficients $\hat{\beta}_\tau$ from the stock return conditional mean regression (3):

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

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.

Figure 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.

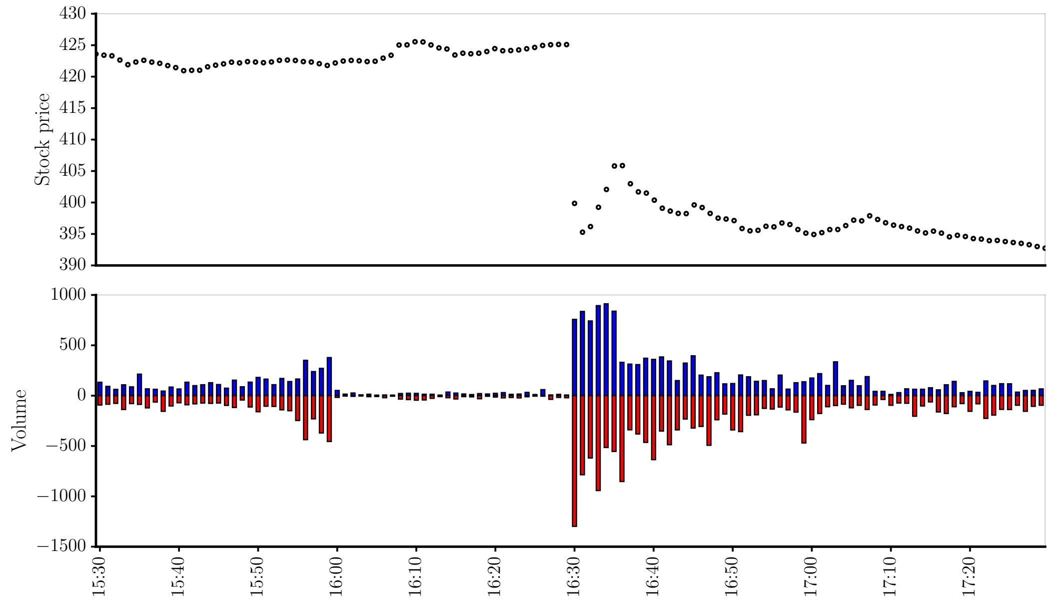
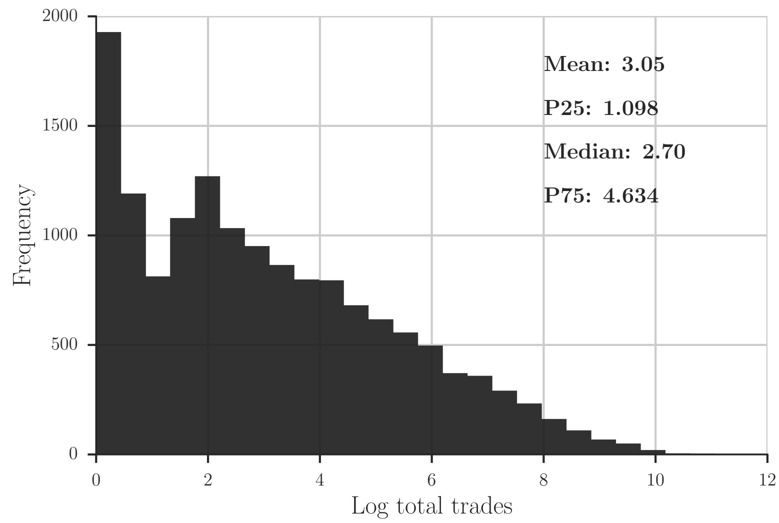


Figure 5. Statistics on After-Hours Trading following Earnings Announcements

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

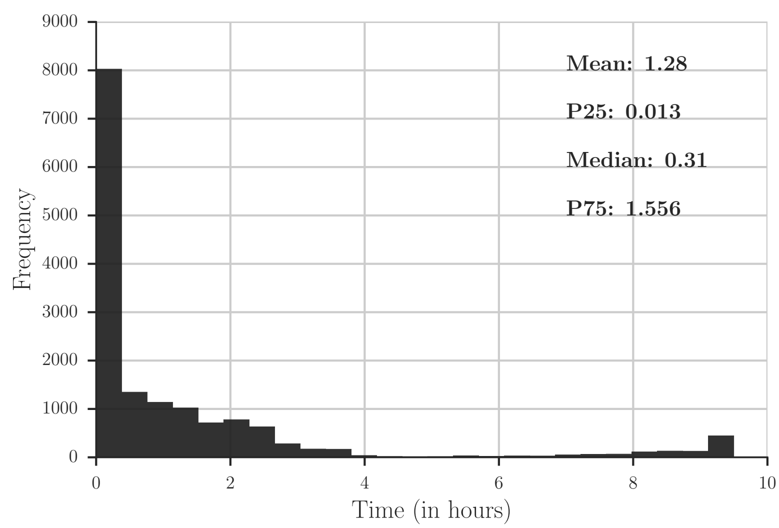


Figure 6. Cumulative Returns following Earnings Announcements in the After-Hours Market

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.

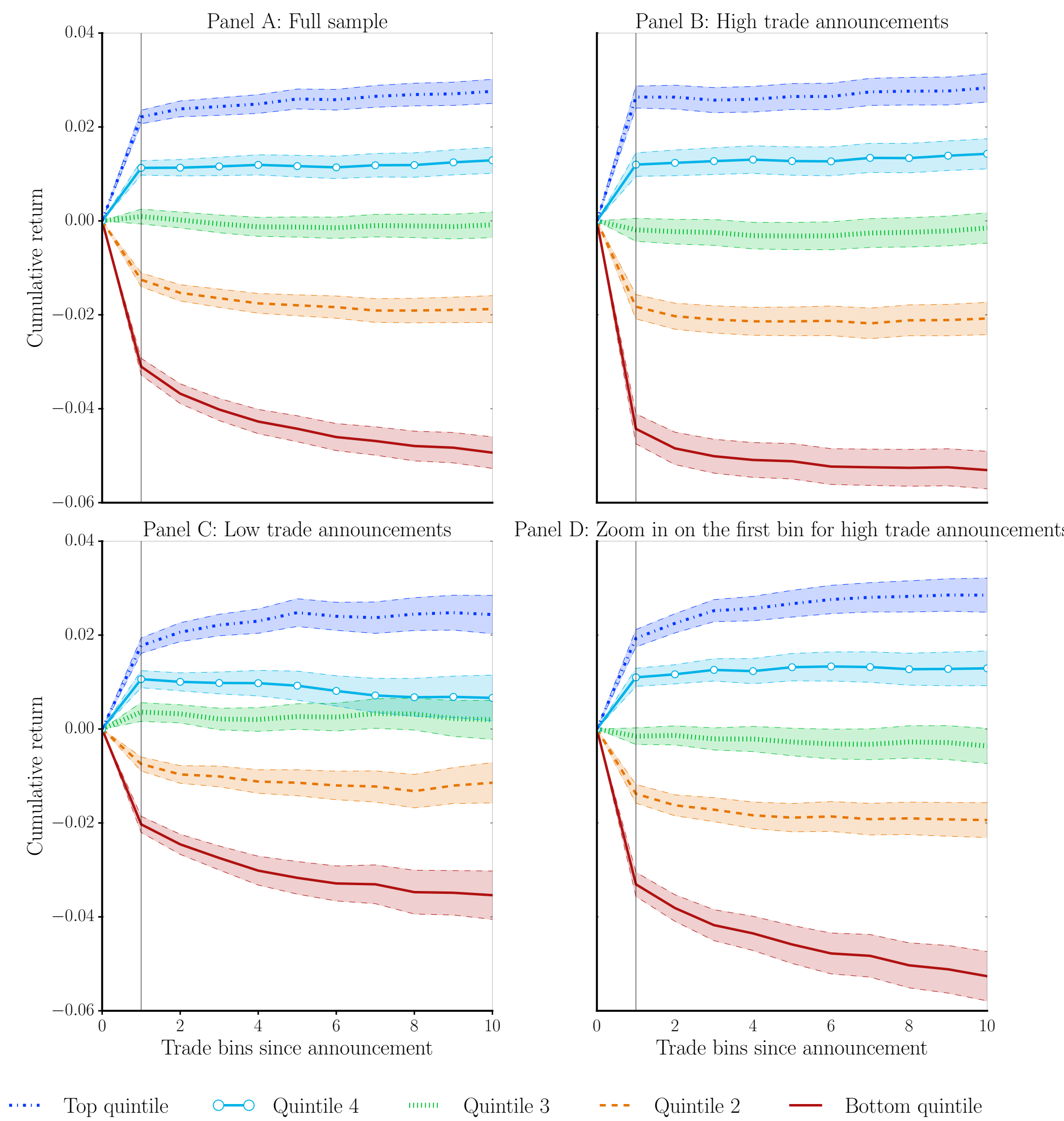


Figure 7. The Response of Stock Returns to Earnings Surprises in the After-Hours Market

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

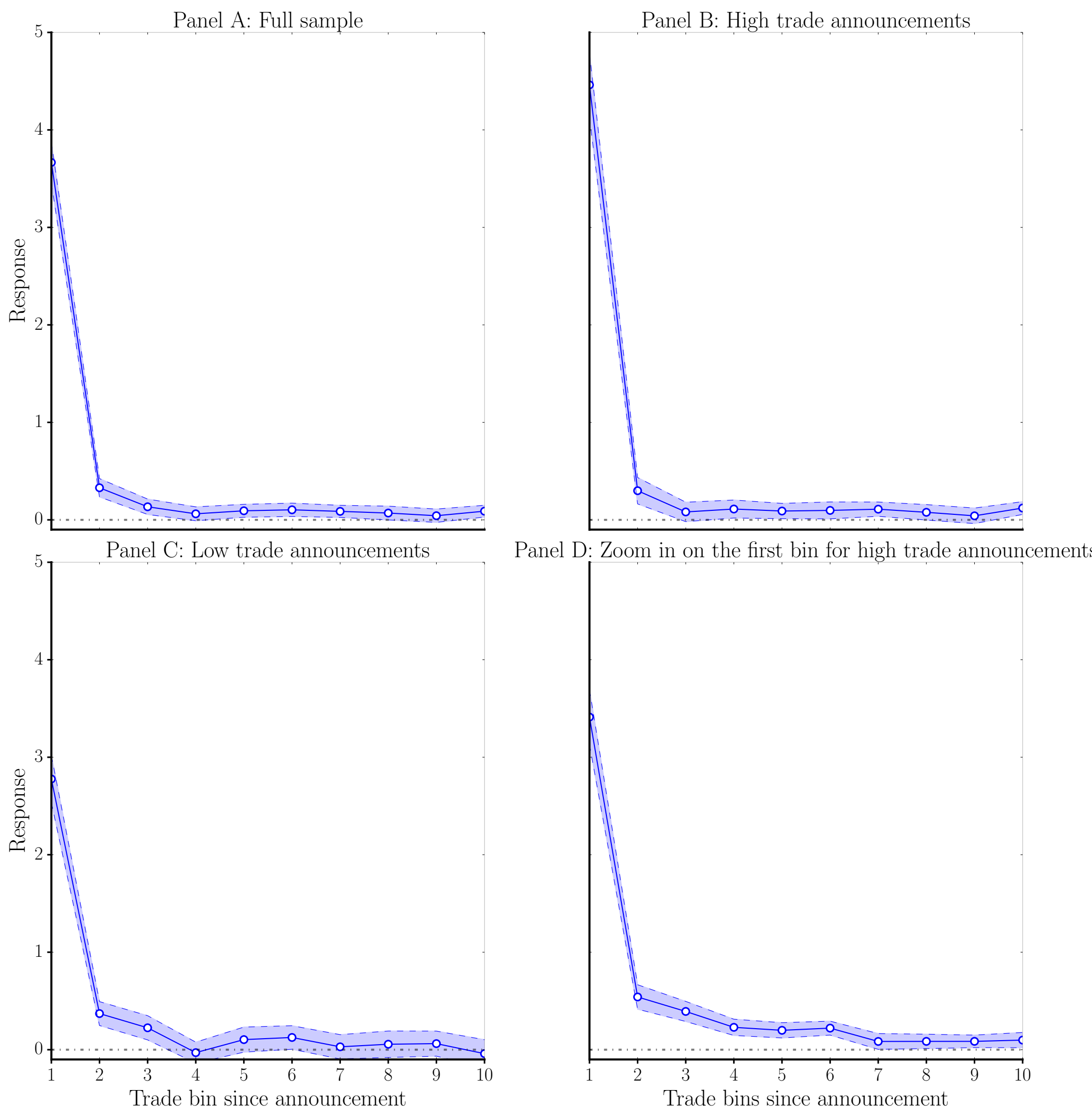


Figure 8. Order Imbalance following Earnings Announcements in the After-Hours Market

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 announcements. 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.

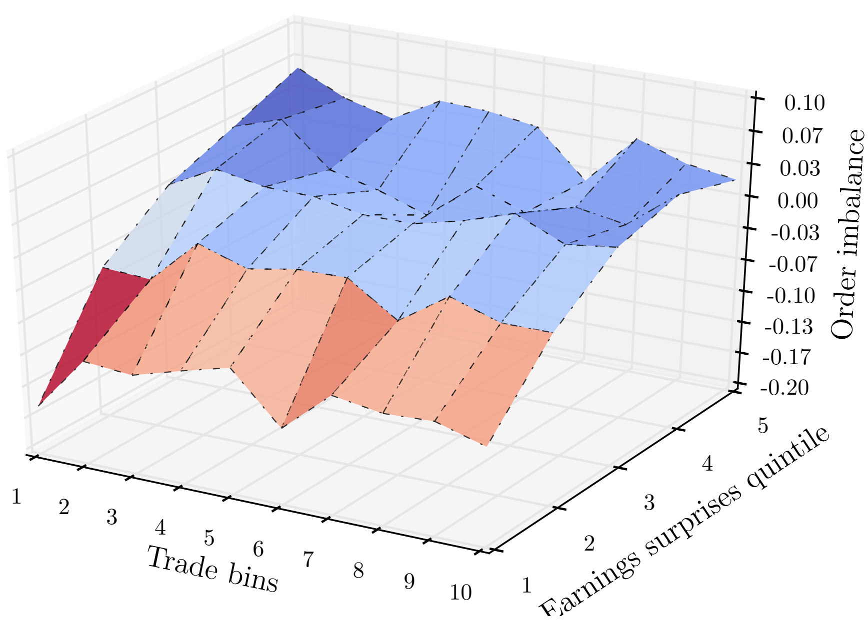


Figure 9. Explanatory Power of Earnings Surprises and Order Imbalance to Stock Returns in the After-Hours Market

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.

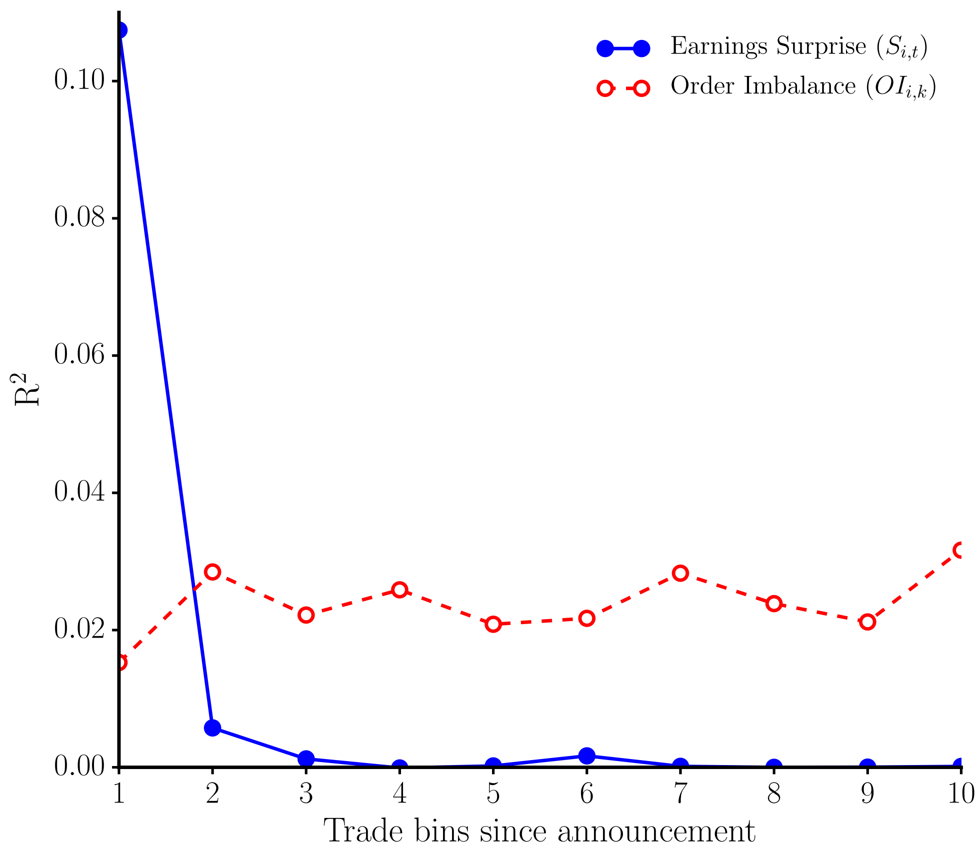


Figure 10. Average Volatility, Quoted Spread, and Turnover prior to Earnings Announcements

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 (7):

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

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 sample period is January 1, 2011 to December 31, 2015.

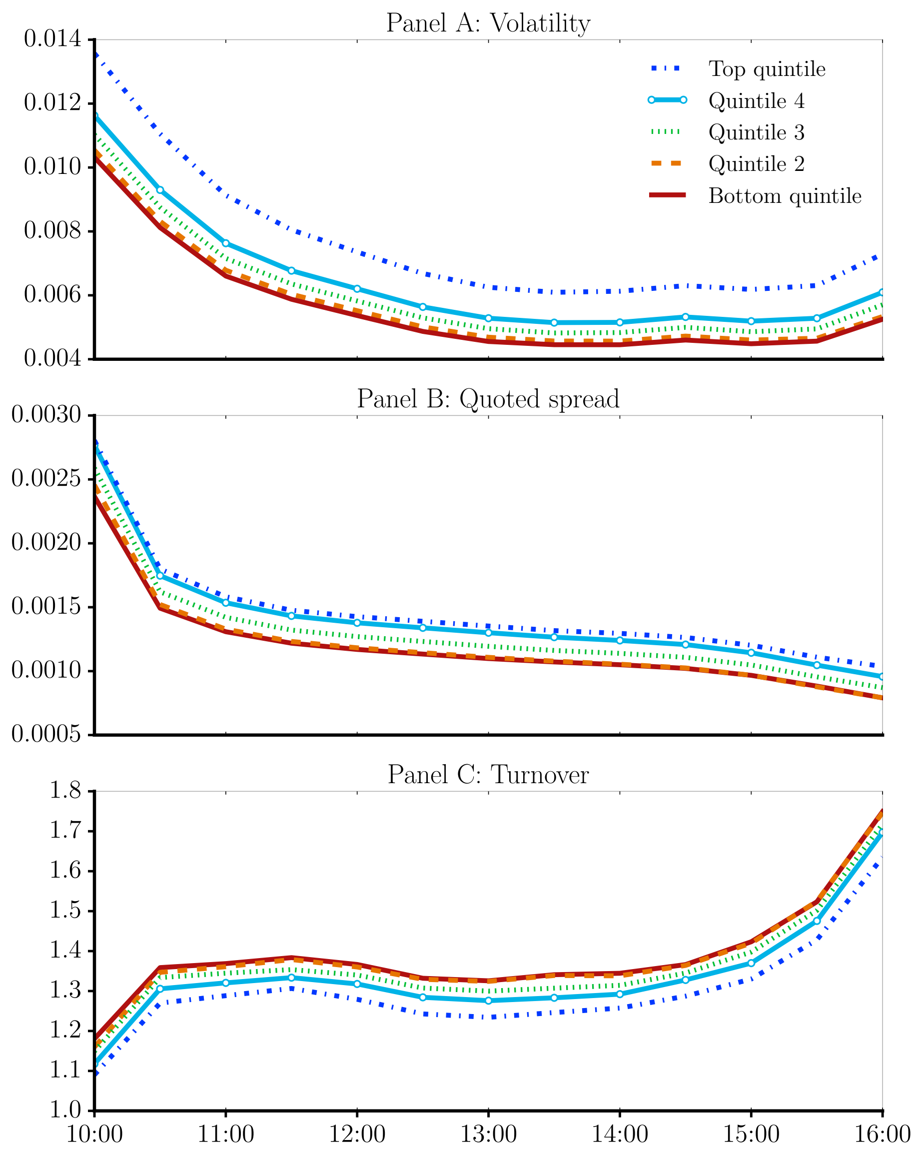


Figure 11. The Response of Abnormal Volatility, Abnormal Quoted Spread, and Abnormal Turnover to Earnings Surprises around Earnings Announcements

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 (7):

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

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

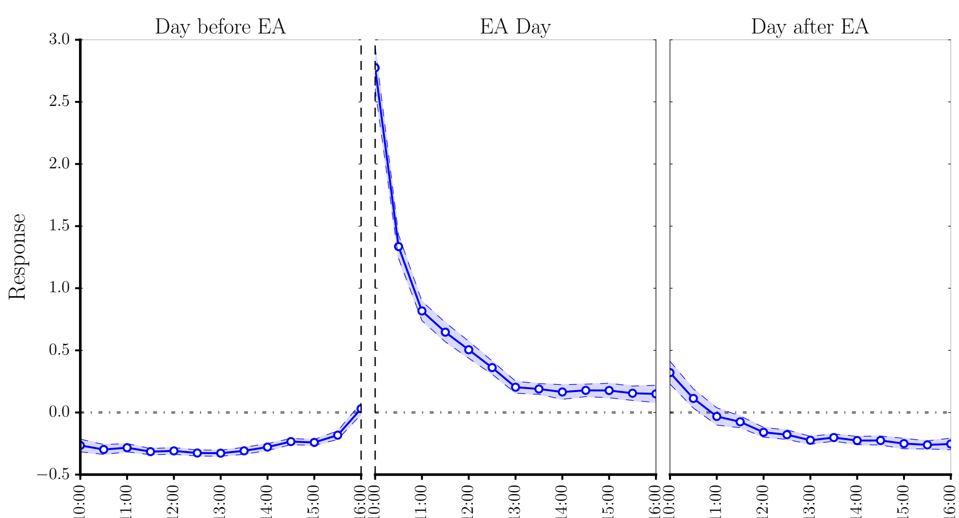
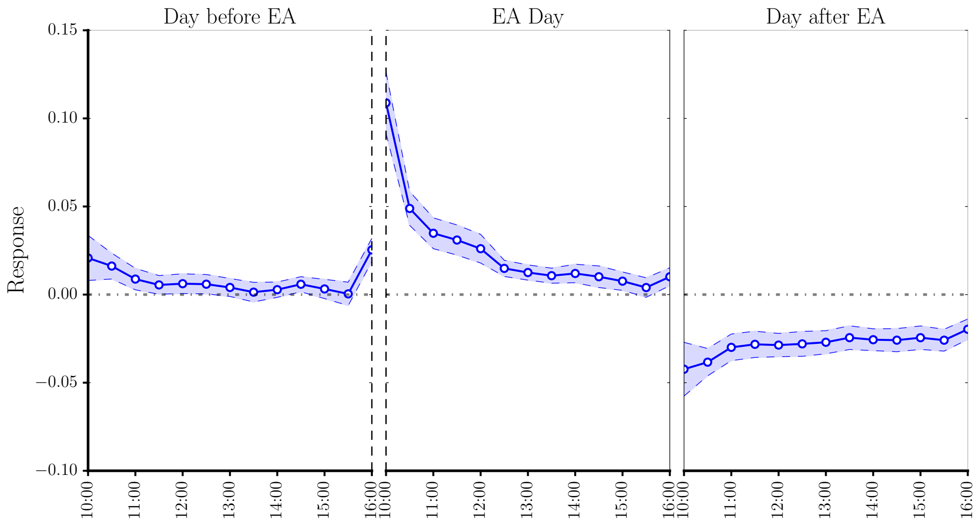


Figure 11. Continued.

Panel B: Abnormal quoted spread response to earnings surprises



Panel C: Abnormal turnover response to earnings surprises

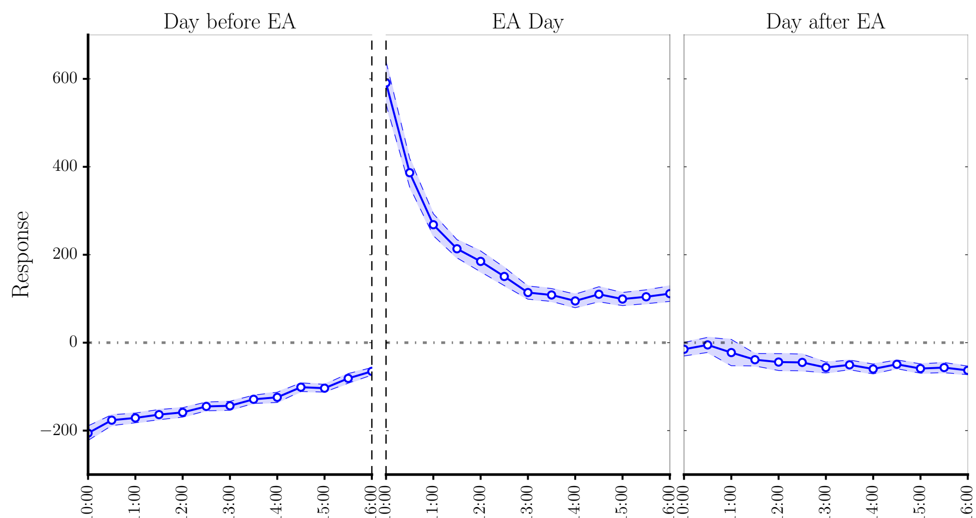


Table I
Descriptive Statistics

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 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 (non-visible limit orders). Panel D reports the trading statistics by trade size. EA corresponds to earnings announcements. 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
Market capitalization min	794	721	901	1100	1199
Market capitalization median	2924	2576	3147	4103	4115
Market capitalization 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 earnings announcements	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 announcement with after-hours 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
After-hours returns around announcements					
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

Table I
Continued.

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
% of trades against hidden	8	11	16	12	25	50	19	29	40
% of trade volume against hidden	8	12	18	8	25	60	21	41	59

Panel D: Descriptive statistics on trading size

	Number of shares per trade against displayed orders (%)			
	Less than 100	100-500	500-1,000	Greater than 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 (%)			
	Less than 100	100-500	500-1,000	Greater than 1,000
Market hours	27	71	2	1
After hours	27	63	7	4
After hours (EA)	22	61	8	8

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

	Trade size, in dollars per trade, against hidden orders (%)			
	Less than 1,000	1,000-5,000	5,000-50,000	Greater than 50,000
Market hours	15	52	32	1
After hours	15	39	43	3
After hours (EA)	11	36	47	6

Table II
Cumulative Daily Abnormal Returns following Earnings Announcements

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

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

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

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 and t is the announcement date of quarter q's earnings. 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]	CAR[2,5]	CAR[6,30]	CAR[31,61]	CAR[2,61]
Top quintile	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 quintile	-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 earnings surprises quintile and quintile 3

	AR[0]	AR[1]	CAR[2,5]	CAR[6,30]	CAR[31,61]	CAR[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]	CAR[2,5]	CAR[6,30]	CAR[31,61]	CAR[2,61]
Top decile	0.034	0.002	0.001	-0.004	0.00	-0.003
Bottom decile	-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]

Table III
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

Table IV
Logit Regression: After-Hours Trading and Information Quality

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	

Table V
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 IV. $NoTrade_{i,t}$ 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

Table VI
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 (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 IV. 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*

Table VI
Continued.

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

Table VII
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 ($Trd_{i,k}$). 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 B shows the results for stocks with more than 20 trades following earnings announcements and zooms in on the first trade bin of Panel B 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)
$S_{i,t}$	4.431*			2.518*	2.429*	2.445*
	(0.147)			(0.254)	(0.249)	(0.249)
$OI_{i,t}$		0.010*	0.002*		0.002*	0.002*
		(0.001)	(0.001)		(0.001)	(0.001)
$OI_{i,t} \times Trd_{i,t}$			0.005*		0.004*	0.004*
			(0.001)		(0.001)	(0.001)
$S_{i,t} \times Trd_{i,t}$				0.552*	0.540*	0.537*
				(0.088)	(0.087)	(0.087)
$S_{i,t} \times OI_{i,t}$						0.129
						(0.177)
$Trd_{i,t}$			-0.001*	-0.002*	-0.002*	-0.002*
			(0.000)	(0.000)	(0.000)	(0.000)
Intercept	-0.005*	-0.001*	0.002*	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Obs.	11255	11255	11255	11255	11255	11255
Adj-R^2	0.10	0.01	0.03	0.11	0.12	0.12

Table VII
Continued.

Panel B: After hours - per trade bin

	Trade bin $k=1$				Trade bins $k>1$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$S_{i,t}$	3.761*	2.992*		2.922*	0.737*	0.302		0.226
	(0.127)	(0.140)		(0.138)	(0.096)	(0.196)		(0.193)
$S_{i,t} \times Trd_{i,k}$		0.500*		0.481*		0.119*		0.116
		(0.083)		(0.083)		(0.060)		(0.060)
$OI_{i,k}$			0.005*	0.004*			0.002*	0.002*
			(0.000)	(0.000)			(0.001)	(0.001)
$OI_{i,k} \times Trd_{i,k}$			0.003*	0.002*			0.003*	0.003*
			(0.001)	(0.001)			(0.000)	(0.000)
$Trd_{i,k}$		-0.002*	-0.001*	-0.002*		-0.000	-0.000	-0.000
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Intercept	-0.004*	-0.002*	0.001	-0.001*	-0.001*	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Obs.	11255	11255	11255	11255	10040	10040	10040	10040
Adj-R^2	0.11	0.12	0.02	0.13	0.01	0.01	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)
$S_{i,t}$	3.448*	1.825*		1.997*	1.278*	0.861*		0.825*
	(0.162)	(0.551)		(0.552)	(0.145)	(0.190)		(0.186)
$S_{i,t} \times Trd_{i,k}$		0.310*		0.246*		0.157		0.140
		(0.108)		(0.109)		(0.088)		(0.087)
$OI_{i,k}$			-0.010*	-0.009*			0.002*	0.002*
			(0.002)	(0.002)			(0.001)	(0.001)
$OI_{i,k} \times Trd_{i,k}$			0.004*	0.003*			0.003*	0.002*
			(0.001)	(0.000)			(0.000)	(0.000)
$Trd_{i,k}$		-0.002*	-0.001*	-0.002*		-0.000	-0.000	-0.000
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Intercept	-0.005*	0.004	0.006*	0.004	-0.003*	-0.002*	-0.001	-0.002*
	(0.001)	(0.002)	(0.002)	(0.002)	(0.000)	(0.001)	(0.001)	(0.001)
Obs.	5480	5480	5480	5480	5480	5480	5480	5480
Adj-R^2	0.11	0.11	0.04	0.14	0.03	0.03	0.02	0.05

Table VIII
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
Fraction displayed orders (%)	66	66	66	74	71	70
Fraction hidden orders (%)	34	34	34	26	29	30

Appendix

A. Post-Earnings Announcement Drifts since 1984

I plot in Figure A2 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.

B. 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.[41] 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.

[41] 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.

C. 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 A1 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.

D. Additional Figures

Figure A1. 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.

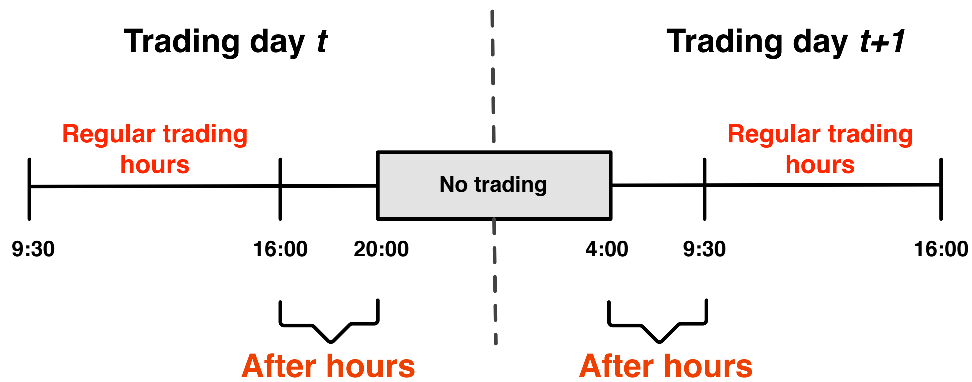


Figure A2. Historical Cumulative Abnormal Daily Returns around Earnings Announcements

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.

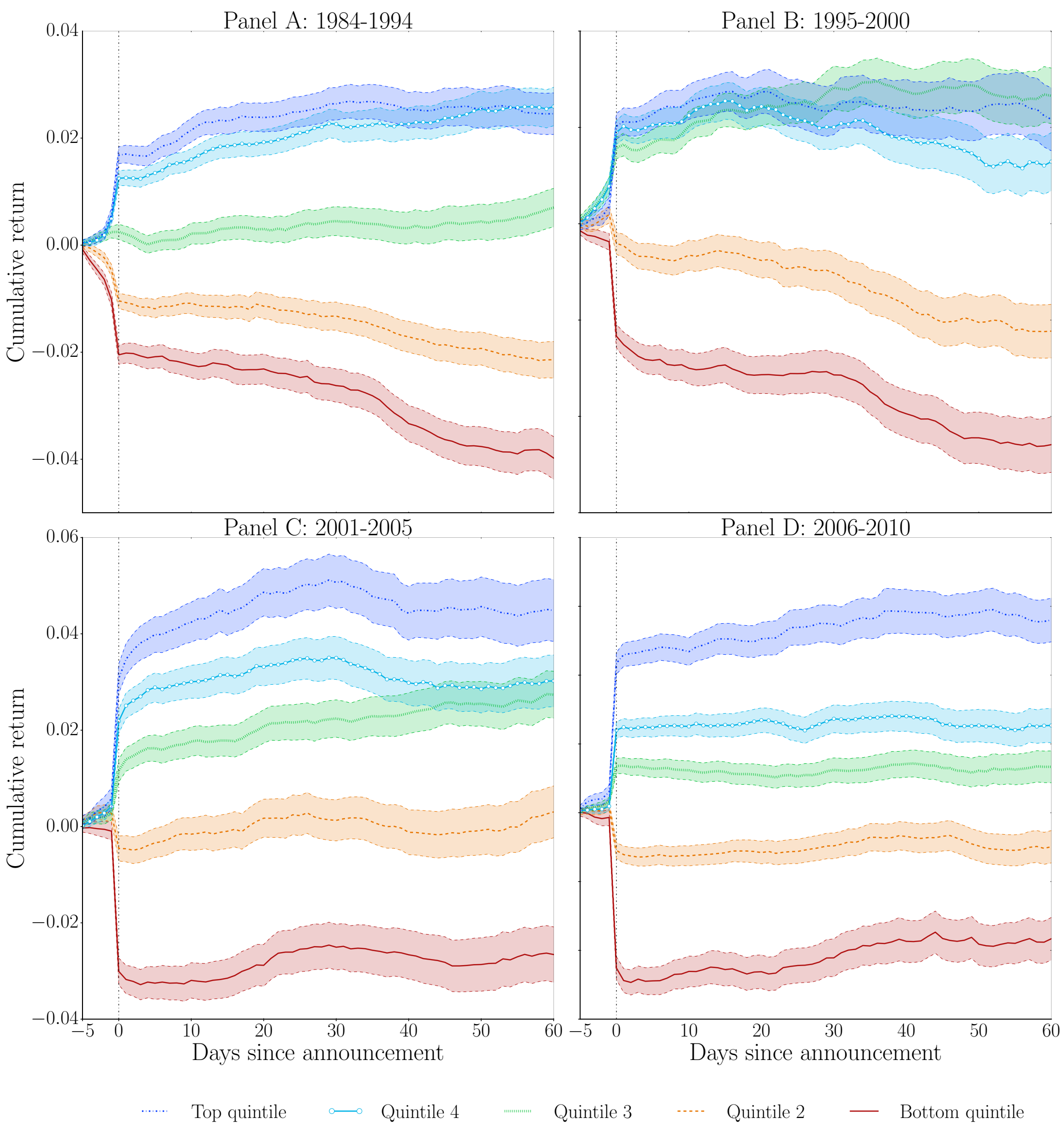


Figure A3. The Response of Abnormal Volatility, Abnormal Quoted Spread, and Abnormal Turnover to Earnings Surprises around Earnings Announcements

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 (7):

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

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

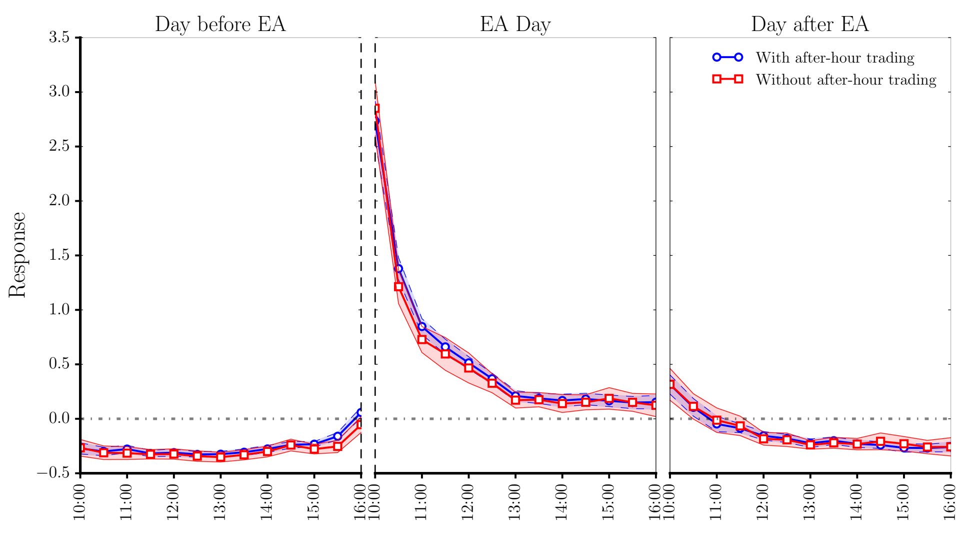
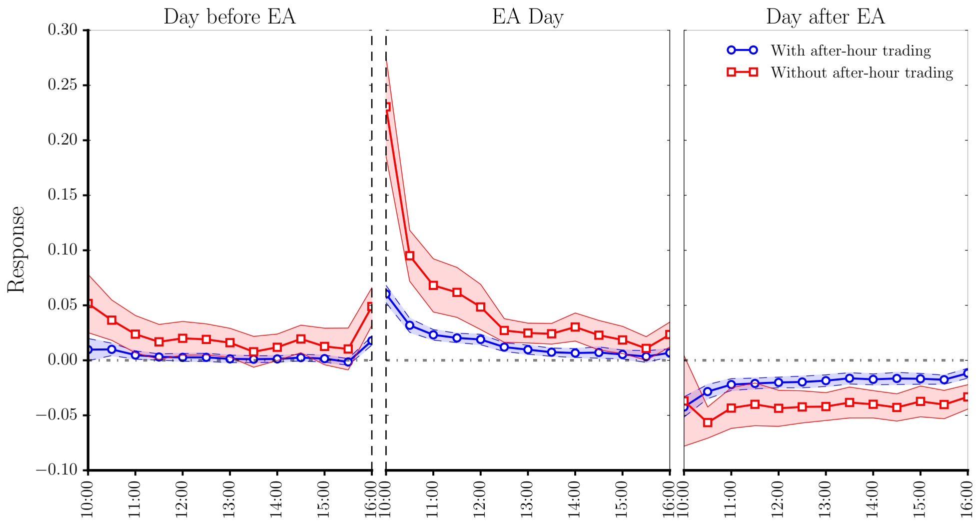
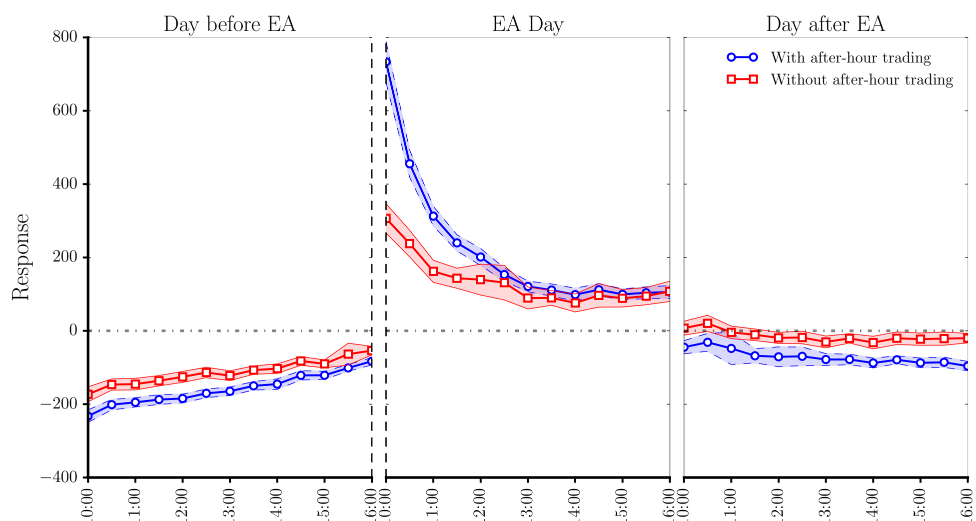


Figure A3. Continued.

Panel B: Abnormal quoted spread response to earnings surprises



Panel C: Abnormal turnover response to earnings surprises



E. Additional Result

Table A1
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