How Is Earnings News Transmitted to Stock Prices?

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ABSTRACT
Most corporate news occurs in the after-hours market, a very illiquid trading environment. We examine the relationship between liquidity and market efficiency around after-hours earnings announcements. Prices reflect earnings surprises through changes in quotes rather than through trades. Pre-announcement bid-ask spreads are wide enough to include the post-announcement closing price, eliminating the profits of informed liquidity-takers. Following announcements, ask (bid) prices adjust quickly to reflect positive (negative) surprises while bid (ask) prices are slower to adjust. These findings emphasize the importance of examining the adjustments in quotes and not in trade prices for appropriate inference about the price discovery process.

JEL Classification: G10, G12, G14, M41

Keywords: after-hours market, analyst coverage, analyst recommendations, disclosure, earnings announcements, liquidity, price discovery

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Most firms disclose news during the after-hours market (4 p.m. to 9:30 a.m.), an illiquid trading environment where trading costs are four times larger than during regular trading hours because of high asymmetric information and low trading volume (Barclay and Hendershott, 2003, 2004). Other corporate news events, such as analyst recommendations, also often come after hours. It is thus natural to question how stock prices incorporate news in such an illiquid environment and what is the appropriate empirical approach to examine price discovery in the after-hours markets.

In this paper, we use high-frequency order-level data on a recent five-year period for S&P 1500 firms to study the price formation process around earnings announcements in the after-hours market. We focus on earnings news because they are one of the most anticipated pieces of firm-level news, and almost all earnings are announced after hours. Our objectives are to understand how the illiquid nature of the after-hours market influences how quickly and through what mechanism stock prices incorporate earnings surprises (the “news”).

In the seminal model of (Kim and Verrecchia, 1994), price formation following earnings announcements is assumed to occur through trading has liquidity providers lack sophistication at process public information. However, with the rise in sophistication among liquidity providers, e.g., the growing presence of high-frequency traders, recent theoretical work models (e.g., Hoffmann, 2014) propose that price discovery to public news occurs quickly through limit orders, i.e., changes in quotes. Our paper sheds light on which of these paradigms explains after-hours price discovery following earnings announcements.

Having a better understanding of the mechanism of price discovery is key in identifying the right methodology to study price formation at high-frequency around after-hours corporate news events. The use of intraday data to examine the impact of corporate news on stock prices is becoming more common in accounting research. As argued by Li, Ramesh, Shen, and Wu (2015), it is challenging to disentangle the effects of various news on prices using daily data when multiple events occur on the same day. In a different context, early studies in the foreign exchange literature suggested that prices and fundamentals
high-frequency price formation around SEC insider trading filing releases (Rogers, Skinner, and Zechman, 2016, 2017), earnings announcements before and after changes in regulations (Dong, Li, Ramesh, and Shen, 2015), and analyst recommendations (Altunkılıç and Hansen, 2009, Li, Ramesh, Shen, and Wu, 2015).² Inferences about the price formation process documented in some of these studies are, however, incomplete. For example, Rogers, Skinner, and Zechman (2016, 2017) exclude about two-thirds of the news events from their principal analysis due to low trading activity because they occur outside of regular trading hours. Dong, Li, Ramesh, and Shen (2015) and Li, Ramesh, Shen, and Wu (2015) examine regular-hour and after-hours news events, but use trade prices to compute returns, which we show can lead to biased inference regarding the price formation process.

Our main results are that: (i) despite little to no trading following earnings announcements, prices reflect earnings surprises through changes in quotes by sophisticated liquidity providers and not through trades, (ii) pre-announcement bid-ask spreads are wide enough to include the post-announcement closing price; eliminating the profits of informed liquidity-takers, (iii) spreads narrow following announcements and do so asymmetrically: ask (bid) prices adjust quickly to reflect positive (negative) surprises while bid (ask) prices are slower to adjust, generating midquote price drifts. To our knowledge, this paper is the first to demonstrate that price discovery of earnings surprises generally occurs through changes in quotes and not through trading, consistent with recent models of price formation (e.g., Hoffmann, 2014).

Our findings have direct implications for future research on price discovery around after-hours corporate news events. First, low trading activity should not be used as a reason to filter out events because price discovery occurs through changes in quotes by sophisticated liquidity providers, not through trading. Trading is endogenous: a trade generally occurs if

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¹(i.e., macroeconomic news) were largely disconnected (e.g., Frankel and Rose, 1995). Andersen, Bollerslev, Diebold, and Vega (2003) reconcile this puzzle. Using intraday rather than daily observations, the authors show that foreign exchange rates do respond to unanticipated macroeconomic news.

²Early studies examining intraday price formation around earnings announcements include Patell and Wolfson (1984), Lee (1992), and Lee, Mucklow, and Ready (1993).
a trader detects a profitable trading opportunity, e.g., a mispriced (stale) quote. If quotes encompass the efficient price and spreads are wide, investors have no incentive to trade until the market becomes more liquid. Excluding events for which there is low trading can thus potentially bias inference about the importance of the news event on prices. Second, using trades to calculate returns is also problematic for the same reason. If price discovery occurs through changes in quotes, using trades will measure price adjustments with a lag. Hence, researchers should rely on quotes (midquote, bid, and ask prices) when examining intraday price discovery in the after-hours market. To highlight the importance of our results, we revisit the study of Li, Ramesh, Shen, and Wu (2015) who examine price formation around analyst recommendations using trade prices. We show that, without examining quotes adjustments, one’s inference about the price discovery process following after-hours analyst recommendations is incomplete.

Our empirical analysis first examines when price discovery happens following earnings surprises. Earnings news has long been associated in past studies with slow price formation at the daily horizon (e.g., Bernard and Thomas, 1989) often attributed to the limited attention of investors (e.g., DellaVigna and Pollet, 2009, Hirshleifer, Lim, and Teoh, 2009). The advent of algorithmic trading, however, has helped investors overcome frictions related to the monitoring of financial markets, quickening the speed at which prices reflect news (Hendershott and Riordan, 2013). Using daily returns for S&P 1500 stocks in a recent period (2011 to 2015), Martineau (2019) finds no evidence of price drifts following earnings announcement dates. We calculate buy-and-hold returns from the opening of the regular trading session to the end of the following regular trading session for stocks with earnings announcements. For most stocks, the complete one-day price response after conditioning on earnings surprises occurs in the after-hours market. We then zoom in the after-hours market and find that midquote price adjustments to news occur quickly but are followed by price drifts for stocks with large surprises. We show that midquote prices incorporate earnings surprises within 25, 35, and 40 minutes for S&P 500, S&P MidCap 400, and

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S&P SmallCap 600 stocks, respectively, with most of the price discovery occurring in the first 5 minutes. These findings show that researchers can rely on midquote prices to examine the impact of news on asset prices during the after-hours market.

A gradual adjustment in the midquote might indicate that there are profitable trading opportunities. Still, it is the ask and bid prices that indicate to liquidity takers whether it is profitable to trade on the earnings surprise. We show that bid-ask spreads are wide before announcements, in most cases already encompassing the post-announcement closing price at 4 p.m. of the following trading day. These large pre-announcement spreads indicate that liquidity providers face adverse selection, e.g., from traders who can process the news more rapidly. Following announcements, spreads gradually tighten around the post-announcement price, leaving no profits on average for informed liquidity takers that trade in the direction of the surprise. Moreover, the adjustment is mostly asymmetric: following a positive (negative) surprise, liquidity providers adjust the best ask (bid) price instantly to earnings surprise but only slowly adjust the best bid (ask) price. It is the slow adjustment in the bid (ask) price that generates midquote price drifts. The adjustment is also slower for illiquid assets (e.g., smaller firms).\(^4\) It is thus important to examine bid and ask price adjustments as simply considering an adjustment in midquotes does not adequately portray the actual speed of price discovery. To our knowledge, we are the first to document that price discovery following earnings announcements occurs through quote adjustments.\(^5\)

Liquidity-taking trades, however, are essential for price discovery to eliminate inefficient stale quotes that may remain, i.e., quotes posted in the order book before the arrival of news (Baldauf and Mollner, 2019, Dugast, 2018). Using the approach of Evans and Lyons (2002), we find that earnings surprises largely explain price variation at the announcement with a

\(^4\)Li (2016) develops a trading strategy following earnings announcements in the after-hours market and also documents a slow price adjustment in midquotes. Our paper shows why midquotes slowly adjust to earnings news.

\(^5\)Contrary to classical price formation models in which wider bid-ask spreads are indicative of faster price discovery (e.g., Glosten and Milgrom, 1985), our results signify that smaller spreads are associated with faster price discovery. These models assume that price discovery occurs through trading. Our findings show that quoted prices directly respond to the news.
$R^2$ of 6% compared to 3% for liquidity-taking order imbalance. Excluding trades against stale orders shows that the order imbalance has no explanatory power on the initial price adjustment to news. This result supports the notion that quoted prices directly respond to earnings surprises, but trading is necessary to remove any stale quotes. We also examine the profitability of trading for liquidity providers and find that they are profitable, further reinforcing the conclusion that liquidity providers are sophisticated at processing news.

Examining quotes and order imbalances provides an explanation for the existence of midquote price drifts at the opening of markets following large surprises. We show that these drifts are likely the result of price pressure coming from large liquidity-taking order imbalance going in the direction opposite to earnings surprises. To accommodate order flow, liquidity providers charge a price impact to manage inventory risk, which can generate price drifts unrelated to slow incorporation of news into stock prices.\(^6\)

The importance of examining the adjustment in quotes for the study of the price formation process expands beyond earnings announcements. Our last empirical exercise revisits a puzzling finding of Li, Ramesh, Shen, and Wu (2015). The authors use trade prices and document that after-hours analyst recommendation revisions are associated with greater price reactions than regular-hour revisions. We show that this difference is due to the use of trade prices. There is no difference in the price adjustment between regular-hour and after-hours recommendation revisions when using midquote prices.

Our paper is closely related to long-established literature associating the persistence in post-earnings announcement drifts to trading frictions, e.g., transaction costs (Bhushan, 1994, Ng, Rusticus, and Verdi, 2008), arbitrage risks (Mendenhall, 2004), and illiquidity (Chordia, Goyal, Sadka, Sadka, and Shivakumar, 2009). We show that price discovery in today’s financial markets generally occurs through quote changes by sophisticated liquidity providers and not through trading, and therefore, minimizing the importance of trading

\(^6\)This is consistent with the long-established microstructure literature linking price pressure to large order imbalances (e.g., Gromb and Vayanos, 2002, Hendershott and Menkveld, 2014).
frictions. Our results can explain, in part, why Martineau (2019) finds no evidence of post-earnings announcements drifts for S&P 1500 stocks over the same sample of our study.

The study of intraday price formation following earnings announcements dates back to Patell and Wolfson (1984), who find that profits of trading strategies based on forecast errors of earnings announced during regular trading hours dissipates within 10 minutes. Examining firms that began disclosing earnings overnight, Francis, Pagach, and Stephan (1992) find that price discovery occurs during the following trading day and not overnight. More recently, Jiang, Likitapiwat, and McInish (2012) show that a significant fraction of the total price variation over a trading day following earnings announcements for S&P 500 stocks now occurs overnight. To do so, they compare returns from the announcement to the opening of markets to the returns from the announcement to the closing of markets. They attribute the response of overnight returns to trading. In contrast to this last study, we focus on the price discovery process within the after-hours (or overnight) market. Doing so allows us to investigate the mechanism and the speed of price discovery directly. Despite little to no trading in the after-hours market, price discovery takes place at the announcement because it is driven by sophisticated liquidity providers.

Our paper contributes to recent empirical research on high-frequency price formation. Rogers, Skinner, and Zechman (2017), Bolandnazar, Jackson Jr., Jiang, and Mitts (2018), and Hu, Pan, and Wang (2017) examine price reactions to early public news dissemination to a select group of subscribers before the general market and find quick price adjustments. Brogaard, Hendershott, and Riordan (2018) show that continuous stock price changes (not conditioned on the arrival of news) during regular trading hours are predominantly driven by quote adjustments by high-frequency traders and not by trades. Our study fills a gap in the price discovery literature by documenting whether liquidity providers participating in the illiquid environment that is the after-hours market can process and quickly adjust bid and ask prices to news for a wide cross-section of stocks.
1. **Earnings Announcement Sample and Data Description**

The time coverage of this study is from January 1, 2011 to December 31, 2015.\(^7\) We describe below the earnings announcement sample and the high-frequency data and present an overview of the trading environment in the after-hours market.

1.1. **Earnings announcement sample**

We first select from the Center for Research in Security Prices (crsp) stocks with share code 10 or 11 that belong to the S&P Composite 1500 index with NYSE, NASDAQ, or NYSE MKT (formerly the American Stock Exchange) as their primary listing. Each stock must have total assets and market capitalization data at the end of December of the previous calendar year in Compustat. The S&P 1500 combines three leading indexes—the S&P 500 (largest 500 stocks), the S&P MidCap 400, and the S&P SmallCap 600—to cover approximately 90% of the total U.S. equity market capitalization.

We identify quarterly earnings announcements for our 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 Bradley, Clarke, Lee, and Ornthanalai, 2014), we use earnings news timestamps in RavenPack to improve the accuracy. We match 85% of the earnings announcements in I/B/E/S with the earnings news releases in RavenPack. For the missing 15%, we rely on the timestamps in I/B/E/S.

Since the turn of the century, almost all firms now announce their earnings during the after-hours market (Michaely, Rubin, and Vedrashko, 2013). Therefore, we focus only on after-hours earnings announcements (between 4 p.m. and 9:30 a.m. ET), which represent 99.1% of earnings announcements for S&P 1500 firms between 2011 and 2015.\(^8\) We exclude

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\(^7\)This period allows us to highlight the implications of hidden limit orders to price discovery in the after hours market, which is not possible with more recent data due to policy changes by stock exchanges with respect to the revelation of the direction of hidden limit orders. See Section 2 of the Internet Appendix for more institutional details regarding data on signed hidden orders.

\(^8\)We do not address earnings news announced during regular trading hours because market conditions are vastly different than for announcements in the after-hours market. Moreover, some of these regular hours announcements
weekend announcements (six observations) and all earnings announcements between October 26, 2012, 4 p.m. and October 31, 2012, 9:30 a.m. because Hurricane Sandy forced stock markets to close for two trading days (111 observations). After imposing these filters, the remaining sample contains 25,304 earnings announcements. We lose 39 additional observations when merging with the TRTH dataset described in the next subsection. Our final sample is composed of 25,265 firms-earnings announcements for 1,637 unique firms. The fraction of earnings announcements in our sample occurring on each day of the week, Monday to Friday, is 10, 23, 27, 34, and 6%, respectively.

We use analyst forecasts from I/B/E/S to compute earnings surprises. For each earnings announcement, we follow Hartzmark and Shue (2018) and calculate the earnings surprise as the scaled difference between actual and expected earnings:

$$Surprise_i = \frac{\text{EPS}_i - E[\text{EPS}_i]}{P_i},$$

where $\text{EPS}_i$ is the earnings per share of earnings announcement $i$, and $E[\text{EPS}_i]$ is the expectation of earnings per share, proxied by the consensus analyst forecast. We scale the surprise using the stock price five trading days before the announcement. We define the consensus forecast as the median of all analyst forecasts issued over the 90 days before the earnings announcement date. If an analyst revises their forecast during this interval, we use only the most recent forecast. Finally, we winsorize earnings surprises at the 1st and 99th percentile.

Table 1 presents descriptive statistics on sample firms, earnings announcements, and earnings surprises. The number of earnings announcements for firms in each S&P index (500, MidCap 400, SmallCap 600) is 8,964, 6,684, and 9,617, respectively. An S&P 500 firm are the result of errors. For example, Google mistakenly announced its third-quarter earnings on October 18, 2012, at 12:30 p.m. instead of 4:30 p.m., which resulted in a three-hour trading halt.

9We choose earnings surprise over the simple random-walk approach because past research shows price drifts are more persistent following earnings announcements when surprises are calculated using analyst forecasts (see Livnat and Mendenhall, 2006). Moreover, Walther (1997) finds that sophisticated market participants put more weight on analyst forecasts than random walk forecasts.

10Scaling the earnings surprise by the stock price is common in the literature (see, e.g., Doyle, Lundholm, and Soliman, 2006, Livnat and Mendenhall, 2006, DellaVigna and Pollet, 2009, Patton and Verardo, 2012).
has on average about three times more analyst forecasts (14 analysts) than an S&P 600 firm (5 analysts), suggesting more information production about these firms. The table further shows that the inter-quartile range in earnings surprises for S&P 500, S&P 400, and S&P 600 stocks is 0.13, 0.17, and 0.30%, respectively, implying that small firms are more likely to have large surprises (in absolute terms) than large firms. In line with this intuition, the table also shows that S&P 600 stocks are almost twice as likely than S&P 500 stocks to have earnings surprises that belong in the top and bottom earnings surprise quintiles.

Figure 1 shows for each of the S&P index the distribution of earnings announcements in Panel A, the mean overnight returns (close-to-open returns) around earnings announcements in Panel B for a range of earnings surprises varying from minus one to plus one percent as well as the number of earnings announcements in Panel C, and the overnight mean returns in Panel D by earnings surprise quintile. Panel A shows that the majority of firms announce positive earnings, as shown in previous studies (e.g., Burgstahler and Dichev, 1997).\footnote{One factor contributing to why earnings surprises are more likely to be positive is that firm managers frequently engage in manipulation of analyst expectations to meet or beat analyst estimates (e.g., Dichev, Graham, Harvey, and Rajgopal, 2016).} Panel B shows an “S-curve” relationship between surprises and returns for earnings surprises.\footnote{The accounting literature attributes the non-linearity between returns and significant surprises to the dispersion in analyst forecasts preceding announcements (Kinney, Burgstahler, and Martin, 2002).} Nonetheless, the relationship is close to linear for earnings surprises between -0.75 and 0.75%, which represent about 93% of all events. Panel C shows that large stocks (S&P 500) have fewer observations in extreme earnings surprise quintiles compared to the smallest stocks (S&P 600) and Panel D shows a linear relationship between earnings surprise quintiles and overnight returns. Overall, this figure suggests that assuming a linear relationship is reasonable when evaluating the impact of earnings surprises on stock returns.

1.2. High-frequency stock prices and trading activity data

We use two high-frequency databases that contain stock prices and trading activity data. The first is the \texttt{trth} dataset, provided by the Securities Industry Research Centre of Asia-
Pacific (sirca), that includes all trade and quote data with millisecond timestamps for all U.S. exchanges, including alternative platforms such as dark pools. The second database is the NASDAQ order-level dataset known as NASDAQ TotalView-ITCH. This database provides trading activity for the NASDAQ exchange only but with greater granularity and trade details than TRTH, which enhances our analysis. We describe both databases in detail below.

### 1.2.1. Thomson Reuters Tick History (TRTH)

We obtain trades and quotes reported to the consolidated tape from TRTH. For each trade, we extract the price, quantity, execution venue, and trade qualifiers. We exclude any trade that is reported late or out-of-sequence. In addition to trades, we also obtain the prevailing national best bid and offer across all exchanges (NBBO), with quote qualifiers. We match TRTH data with the earnings announcement sample on CUSIP for an overall match rate of 99.9%. Over the 2011 to 2015 period, our sample stocks have 19 billion trades for a total market value of 161 trillion dollars.

### 1.2.2. NASDAQ order-level data

We complement the TRTH data with order-level data from NASDAQ TotalView-ITCH. The ITCH data contains all messages distributed through NASDAQ’s high-frequency feed, including messages that describe orders added to, removed from, and executed on NASDAQ for NASDAQ-, NYSE-, NYSE MKT-, NYSE ARCA-, and BATS-listed securities. We construct a

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13 Other studies that use NASDAQ ITCH include Hasbrouck and Saar (2013) and O’Hara, Yao, and Ye (2014).

14 TRTH provides two timestamps, Time and Exch Time (for trades) or Quote Time. Time corresponds to the time at which the information was recorded by Thomson Reuters’ servers with microsecond precision. Exch Time and Quote Time have millisecond precision and correspond to the consolidated tape timestamp. We use Exch Time and Quote Time, and fill in any missing values using the Time field.

15 Trade qualifiers provide valuable information, including whether a trade is at the opening or closing auction, if it has been reported late or out-of-sequence, if it is meant for next day settlement, or if it is a “Form T” trade. Brokers have to file a “Form T” with the Financial Industry Regulatory Authority (FINRA) to report trades executed outside of normal market hours. In our analysis of price discovery in the after-hours markets, we focus only on trades that are reported to FINRA and marked “Form T”. Each exchange is also uniquely identified, while trades reported by dark pools, automated display facilities, and broker internalization systems to Trade Reporting Facilities are grouped under the same ADF identifier.

16 The NBBO quotes are protected from “trade-throughs” under SEC Rule 611 during regular trading hours only.
message-by-message limit order book, where the book is updated whenever a new message enters the NASDAQ exchange.\footnote{Compared to TRTH or to the Trade and Quote (TAQ) dataset, NASDAQ ITCH data does not suffer from liquidity measurement problems and errors in trade-quote matching as reported in Holden and Jacobsen (2014). However, processing this data and constructing the limit order book is computationally costly.}

Trades are not signed in TRTH (nor in TAQ); the researcher must infer if a trade is buyer- or seller-initiated using a trade classification algorithm.\footnote{Trade classification algorithms are not flawless (see Chakrabarty, Pascual, and Shkilko, 2015). Because liquidity is mostly hidden in the after-hours market, it imposes significant constraints on the effectiveness of these algorithms.} The main advantage of ITCH is that we can accurately sign all trades, except trades against hidden (i.e., non-displayed) limit orders after July 13, 2014. Hidden orders are essentially limit orders that are not visible to other traders and, as we show, are widely used by liquidity providers in the after-hours market. Hidden orders pose significant limitations to trade classification algorithms, and therefore, the use order-level data from ITCH is necessary. Moreover, we observe every initiated trade that arrives in NASDAQ ITCH, including the NASDAQ portion of Reg NMS ISO orders and odd-lot orders.\footnote{Odd-lot trades, which are executed trades with less than 100 shares, are not reported to the consolidated tape before December 9, 2013. Odd-lot orders can represent up to 60\% of the total trades (O’Hara, Yao, and Ye, 2014).}

After constructing the limit order book, we have for each trade the price, quantity, whether the trade was buyer- or seller-initiated, and information on the executed limit order such as the time it was posted to the order book or if it is hidden.

### 1.3. The after-hours market landscape

Given that all earnings announcements in our sample occur in the after-hours market, it is important to present an overview of the after-hours market trading environment. After-hours trading is wildly different than what market participants usually observe during regular trading hours regarding liquidity and fragmentation. Moreover, no liquidity providers have an obligation to participate during the after-hours market.

As documented in Barclay and Hendershott (2003, 2004), the after-hours market is much less liquid than regular trading hours. We find that after-hours trading accounts for only

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three percent of the total daily dollar trading volume. Of that figure, 83.3% of trading occurs after the market closes (4 p.m. to 8 p.m.) and 16.6% occurs before the market opens (4 a.m. to 9:30 a.m.).\textsuperscript{20} 97.3% of our stock-day observations contain at least one after-hours trade, but 96.7% contain less than 100 trades.

Figure A.1 in the Appendix presents an overview of the trading landscape and the share of fragmentation across different lit (e.g., NYSE and NASDAQ) and dark venues (e.g., dark pools and alternative trading systems) during regular- and after-hours trading for situations when earnings announcements do and do not occur. The key insight of this figure is that dark trading represents about 90% of the after-hours trade volume when there is no earnings announcement but falls to 30% when there is an earnings announcement. This is consistent with theoretical predictions of Menkveld, Yueshen, and Zhu (2017) that indicate trading will occur on lit venues following public news because of the need for immediacy by traders.

Table 2 presents descriptive statistics of trading during regular market hours, in the after-hours market, and in the after-hours market following earnings announcements. To capture the full view of market trading, the sample period for reported statistics starts on December 9, 2013, when the consolidated tape began reporting odd-lots (trades of less than 100 shares). We highlight two important insights from Table 2. First, there is little trading in the after-hours market, even when there is an earnings announcement. The median number of trades in the after-hours market with (without) an earnings announcement is 70 (17), 10 (7), and 7 (5) for S&P 500, S&P MidCap 400, and S&P SmallCap 600 stocks, respectively. Also, we find no trades in the after-hours market following earnings announcements for approximately 20% of events (untabulated). Of those events, 16, 34, and 50% are stocks that belong to the S&P 500, S&P 400, and S&P 600, respectively.\textsuperscript{21} The second main insight from Table 2 is that trades are larger in the after-hours market in terms of both shares and dollars.

\textsuperscript{20}The remaining 0.1% is comprised of trades that are flagged as Form T trades in the feed, but have a timestamp during regular trading hours.

\textsuperscript{21}The introduction of odd-lots reporting to the consolidated tapes after December 9, 2013 does not change the fraction of announcements with no trades in the after hours if we restrict our sample after December 9, 2013.
trade sizes raise the question: who is participating in the after-hours market? We cannot identify with our data who trades in the after-hours market, but Barclay and Hendershott (2004) show that adverse selection risk is higher in the after-hours market and retail traders are being discouraged from trading. Traders that do choose to participate are more likely to be informed and sophisticated. The larger trade sizes further indicate that trading is more likely to involve institutional traders.\footnote{Using the \textit{nasdaq-hft} dataset as studied in Brogaard, Hendershott, and Riordan (2014) that specifies whether a trade involves an high-frequency trader, we find that the fraction of trades (trade volume) involving an HFT varies from 24 to 36\% (22 to 34\%) for different size-tercile market capitalization firms in the after-hours market following earnings announcements. The dataset is limited to a sample of 120 stocks from 2008 to 2009. The results are tabulated in Table IA.2 of the Internet Appendix.}

2. Price Discovery in the After-hours Market

We begin the analysis of price discovery following earnings announcements by examining intraday price changes during regular trading hours around the after-hours period. We then dive into the after-hours market to more closely study the speed, dynamics, and mechanisms of price discovery.

2.1. Intraday price drifts during regular trading hours

When does price discovery occur following earnings announcements? To answer this question we plot in Figure 2 the average buy-and-hold abnormal log returns ($bhar$) using the midquote at 5-minute intervals, starting at the opening of markets on the trading day before the earnings announcement until the closing of markets on the following trading day by S&P index and earnings surprise quintile. We define $bhar$ for stock earnings announcement $i$ from time $\tau$ to $T$ ($\tau < T$) as

\begin{equation}
BHAR[\tau, T]_i = \sum_{t=\tau}^{T} r_{i,t} - \sum_{t=\tau}^{T} r_{m,t},
\end{equation}

where $r_{i,t}$ is the stock log midquote return and $r_{m,t}$ is the log midquote return of the stock market using the SPDR S&P 500 ETF on interval $t$. To mitigate the influence of large bid-
ask spreads at the opening of markets, we condense stock returns in the after-hours trading session to a single point, which includes the opening auction and the first 10 minutes of trading, calculated using the closing price at 4 p.m. and the midquote at 9:40 a.m.

The figure shows a clear demarcation in BHAR between earnings surprise quintiles. Moreover, these BHAR are mostly “flat” after the opening of markets across all S&P indexes. These flat BHAR suggest that most price discovery occurs before 9:40 a.m., i.e., during the after-hours market or at the opening at 9:30 a.m. However, we observe small price drifts for large surprises, especially for S&P 600 stocks, of approximately 50 basis points, which might indicate that price discovery still takes place following the opening of markets. We address this issue in Section 3 and show that these price drifts are most likely due to price pressure from liquidity-taking order imbalance going in the direction opposite of the earnings surprise and not to slow information processing by liquidity providers.

2.2. The speed and dynamics of price discovery in the after-hours market

We next zoom into the after-hours market to examine more closely the price formation process. Figure A.2 in the Appendix shows an example of stock price, trade volume, and added depth at the top of the order book around the earnings announcement of Apple Inc. scheduled at 4:30 p.m. on October 18, 2011 at a 1-minute frequency. There is little trading volume and depth in the order book before the announcement because liquidity providers refrain from adding liquidity before the arrival of the news. Following a negative earnings surprise at the announcement, prices react immediately to the news.

Focusing on price drifts around earnings announcements in the after-hours market, Figure 3 shows the buy-and-hold midquote returns from 5 minutes before to 60 minutes after earnings announcements, by earnings surprise quintile, for the full sample and by S&P index. We use midquotes and not trade prices because trades are endogenous to the presence of

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23So and Wang (2014) also show that liquidity providers anticipate earnings announcements and demand a higher rate of returns to provide liquidity.
a quote. Because bid-ask spreads can be very large, with the bid price sometimes equal to $0.01 and the ask price equal to $199,999, or simply non-existent, we exclude observations for which the relative spread, that is the absolute value between the ask and the bid divided by the midquote, is greater than 20%.²⁴ We choose 60 minutes as the end point because we want to limit the number of earnings announcements for which the BHAR extends beyond 9:30 a.m.²⁵ Figure 3 shows a clear demarcation in price drifts across earnings surprise quintiles for all S&P indexes. The largest price response to news occurs predominantly in the first 5 minutes, but we observe some price drifts that are more persistent for large earnings surprises and for S&P 600 stocks.²⁶

To examine the approximate time it takes for midquote prices to incorporate earnings surprises, we estimate the following regression equation:

\[ r_{i,t} = \alpha + \sum_{k=1}^{12} \beta_k \text{Surprise}_i \mathbb{1}_{k=t} + \epsilon_{i,t}, \]

where \( t \) denotes one of 12 5-minute intervals following earnings announcement \( i \), \( r_{i,t} \) is the stock log midquote return, and \( \mathbb{1}_{k=t} \) is an indicator variable equal to one if \( k = t \) and zero otherwise. Figure 4 shows the estimated \( \beta_k \) for the full sample in Panel A and by S&P index in Panels B to D.

The estimated coefficients show that 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. An earnings surprise of 0.2% (the full-sample earnings surprise inter-quartile range) leads to an initial increase in returns of 30 basis points. Panel A shows that price discovery for the full sample occurs over approximately 40 minutes (when the \( \beta_k \) becomes not statistically significant). The figure also shows that the speed of price discovery is slower for small stocks. We find that midquote prices incorporate earnings surprises, on average, in 25, 35, and 40

²⁴See the shaded area in Figure 5 for the fraction of stocks with relative spread that is less than or equal to 20%. Choosing a cutoff of 40% does not impact the overall results.

²⁵For 914 (3.6%) earnings announcements in our sample, the announcement is between 8:30 a.m. and 9:30 a.m.

²⁶Figure IA.1 in the Internet Appendix shows the drifts for the 50 largest firms in the S&P 500 index. Price discovery for these firms is more immediate.
minutes for S&P 500, S&P 400, and S&P 600 stocks, respectively. Figure IA.2 in the Internet Appendix shows that it takes less than 10 minutes for the 50 largest firms in the S&P 500 index. Altogether, price discovery mostly occurs within the first 5 minutes. However, the presence of price drifts post-announcement appears to indicate that price discovery remains.

### 2.2.1. How do bid and ask prices adjust around earnings announcements?

Examining changes in midquote prices around earnings announcements provides only a partial view of the price discovery process. Because trades occur at the bid or the ask price, it is essential to examine how bid and ask prices adjust to earnings surprises to have a complete view of price formation.\(^{27}\) To do so, we calculate the following measures of profitability from the perspective of a seller:

\[
\begin{align*}
\text{Ask profit}_{i,t} &= \frac{\text{Ask price}_{i,t} - \text{Closing price}_{i,T}}{\text{Ask price}_{i,t}}, \\
\text{Bid profit}_{i,t} &= \frac{\text{Bid price}_{i,t} - \text{Closing price}_{i,T}}{\text{Bid price}_{i,t}}, \\
\text{Midquote profit}_{i,t} &= \frac{\text{Midquote}_{i,t} - \text{Closing price}_{i,T}}{\text{Midquote}_{i,t}},
\end{align*}
\]

where \(t < T\). *Ask profit* \(_{i,t}\) denotes the return for a liquidity provider that sells a stock at time \(t\) on earnings announcement \(i\) with a trade price occurring at the ask and “exits” its position at the closing of markets (4 p.m.) of the following regular trading hour session. Similarly, *Bid profit* \(_{i,t}\) denotes the return for a liquidity taker that sells a stock at time \(t\) with a trade price occurring at the bid. Finally, the *Midquote profit* \(_{i,t}\) denotes the profits for a trader that sells at time \(t\) with a trade price at the midquote. The approach specified in (4) to examine the adjustment in bid and ask prices and the spreads controls for price levels in the cross-section of stocks.

Figure 5 shows the cross-sectional average of the 1-minute ask, bid, and midquote profits

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\(^{27}\)Lee, Mucklow, and Ready (1993) were one of the first to examine quoted spread around earnings announcements during regular trading hours and document large quoted around announcements.
by S&P index and by earnings surprise quintile starting 5 minutes before to 60 minutes after earnings announcements. The red dashed line, the blue dash-dotted line, and the solid black line represent the ask, bid, and midquote profits, respectively, and their respective 95% confidence intervals. The gray shaded area represents the fraction of earnings announcements from our sample with quotes that have a relative spread below 20%.

Three important findings emerge from Figure 5. First, the figure depicts wide spreads around earnings announcements where the difference between the ask and bid profit lines can be as large as 6%, which suggests that liquidity providers face adverse selection before the arrival of news. Spreads are wider before announcements and narrow more slowly after announcements for small firms. Second, the narrowing of spreads is asymmetric, i.e., it is driven by one side of the quote as ask (bid) prices update almost instantaneously to the final ask (bid) price after positive (negative) news, and therefore, the bid (ask) side of the quote remains to adjust. It is the gradual adjustment on the other side of the quote that gradually pushes the midquote to the post-announcement price, consistent with our previous results. Finally, these wide spreads suggest that, on average, it is not possible for a liquidity taker to trade profitably following earnings announcements in the after-hours market (assuming the liquidity taker exits its position at 4:00 p.m.). To see this more clearly, notice that the ask (bid) profit lines are never significantly below (above) zero after the announcement. For example, for a surprise in the top quintile for an S&P 500 stock, a seller that sells at the ask (provides liquidity) during the first 60 minutes earns a profit of about 1%. A liquidity provider that buys at the bid earns 4% at the announcement and the profits decrease to 2% following the announcement; conversely, a liquidity taker that sells at the bid incurs the corresponding losses. Moreover, in most cases, the post-announcement closing price (at 4 p.m.) is already within the spreads before the announcement. Therefore, on average,
liquidity takers that are informed about upcoming surprises have no opportunity to trade profitably in the minutes leading to earnings announcements.

Overall, Figure 5 provide key insights into the price discovery process. In contrast to the model of Kim and Verrecchia (1994) in which trading is necessary to price discovery following earnings announcements, our findings show that quote adjustments are the main drivers of price discovery. One can simply use midquotes when examining the impact of after-hours news on stock prices. It is, however, necessary to further examine the dynamics in bid and ask price adjustments for proper inference of the speed of price discovery due to the asymmetric adjustments in quotes.

We believe that the asymmetric price adjustment is most likely due to the fact that spreads already include the next day closing price, and thus at the announcement, the true fundamental price is either closer to the ask (bid), and most of the adjustment remaining occurs on the bid (ask) side of the quote. The speed of adjustment, however, can be attributed to imperfect competition. The fact that asymmetries vary in firm size (a reasonable proxy for competition among liquidity providers), we can interpret the asymmetric adjustment as suggestive evidence of imperfect competition. To our knowledge, we are the first to document asymmetric adjustments in quotes (i.e., bid and ask prices) following the arrival of news and its implication on price discovery. Our results further suggest a departure from classical price formation models (e.g., Glosten and Milgrom, 1985) for which wide spreads are indicative of fast price discovery. These models assume that prices incorporate information through trading, but our findings suggests that prices directly respond to news through changes in quotes. We investigate the role of trades more thoroughly in the next section.

30 Other type of asymmetries have been previously documented. For example, Green, Li, and Schürhoff (2010) document that prices rise faster than they fall in the OTC bond market and this asymmetry varies with competitive conditions. Johnson and So (2018) show an asymmetric trading costs before earnings announcements. This asymmetry creates a predictable upward bias in prices that increases pre-announcement, and subsequently reverses.
2.3. The role of trading in price discovery

Our previous result suggests that, on average, price discovery should occur through quote adjustments alone because there appears to be no incentive for an informed liquidity taker to trade due to the large spreads. Nonetheless, we can directly test whether trading plays a role in price discovery at the time of the announcement. Also, other papers have shown that trading matters following news events. For example, Baldauf and Mollner (2019) show that the initial price adjustment of stocks following a specific macroeconomic news event (a false Twitter feed about a terrorist attack on the White House) occurred, in part, through trades “sniping” stale quotes (i.e., quotes that did not update to the arrival of the news), pushing prices closer to the new fundamental price. Therefore, trading can play an important role in price adjustments to news events by eliminating inefficient stale quotes. To examine the role of trading following earnings announcements, we follow Evans and Lyons (2002) and examine the explanatory power ($R^2$) associated with liquidity-taking order imbalance (a measure of buying and selling pressure) and earnings surprises to explain stock returns. Evans and Lyons (2002) estimate a structural model where changes in daily foreign exchange rates are determined by public information and aggregate order imbalances. Their model is applicable at high frequency and we use it to show whether stock prices respond primarily to news or order flow following earnings announcements. Formally, the change in log price following the arrival of news can be stated as

$$ r_{i,t} = \alpha + \beta_1 \text{Surprise}_i + \beta_2 OI_{i,t} + \epsilon_{i,t}, $$

where $\text{Surprise}_i$ is the earnings surprise for earnings announcement $i$, $OI_{i,t}$ is the order imbalance, and $r_{i,t}$ is the change in the stock log price (midquote) following the news over a 5-minute interval denoted $t$. We then examine the $R^2$ associated with the net order imbalance and earnings surprises in univariate regressions to explain the response of stock returns in the after-hours market at each 5-minute interval following the earnings announcement. If the explanatory power of $\text{Surprise}_i$ is higher than that of $OI$, then prices respond predominantly
to news and not order flow. We define net order imbalance (OI) as

$$OI_{i,t} = \frac{B_{i,t} - S_{i,t}}{B_{i,t} + S_{i,t}},$$

(6)

where $B_{i,t}$ and $S_{i,t}$ correspond to buyer- and seller-initiated trade volume for interval $t$ following earnings announcement $i$, respectively.\textsuperscript{31} Furthermore, we calculate OI from January 1, 2011 to July 13, 2014 because the NASDAQ limit order book data does not include signs for trades against hidden orders after that date. Because we only observe trade signs for executions on NASDAQ, we assume that the OI on NASDAQ is reflective of the aggregate OI across all exchanges.\textsuperscript{32}

Figure 6 shows the $R^2$ for three distinct sets of univariate regressions of stock returns on earnings surprises and on order imbalance. The regression is estimated at each 5-minute interval $t$ following earnings announcements for the full sample in Panel A and by S&P index in Panels B to D. Across all panels, earnings surprises explain close to 6% of the initial price response following the arrival of news, whereas order imbalance explains about 3%.\textsuperscript{33} Earnings surprises have almost no explanatory power after the initial response. In contrast, the explanatory power of order imbalance is stable at approximately 2 to 3%.

Figure 6 also shows the explanatory power of order imbalance computed by excluding trades against stale quotes, where we define stale quotes as those from limit orders posted before the announcement. Across our sample, we observe trades against stale quotes in the first 5 minutes for 10.4% of earnings announcements. 36% of these quotes are posted to the limit order book before the closing of markets (4 p.m.). When we exclude trades against stale quotes and recalculate the order imbalance measure, we find that the explanatory power of $OI$ in the first 5 minutes following the announcement drops considerably, from 3% to almost 0%. Thus, these results reinforce our previous findings indicating that prices incorporate

\textsuperscript{31}We obtain similar results using the number of buy and sell trades instead of trade volume.

\textsuperscript{32}Figure A.1 shows that NASDAQ’s market share of trade volume on earnings days in the after-hours market from 2011 to 2015 varies from 25 to 45% while NYSE’s share varies from 35 to 45%.

\textsuperscript{33}Figure IA.3 of the Internet Appendix shows the average order imbalance by earnings surprise quintiles. We find that order imbalance is positively correlated with earnings surprises in the first 5 minutes following the announcement.
earnings surprises mainly through quote adjustments, but that some trading is necessary to remove stale quotes. Consistent with recent theoretical limit order book models, price discovery following earnings news occurs through liquidity-taking market orders when the degree of mispricing is high, e.g., when there are stale quotes, and through limit orders when mispricing decreases (Hoffmann, 2014, Rosu, 2018, Dugast, 2018).

2.3.1. The profitability of liquidity providers

Our previous results suggest that liquidity providers are sophisticated at processing and at adjusting quotes accordingly to earnings surprises. We should, therefore, expect that their executed orders are profitable because of large spreads and fast adjustments in quotes following announcements. Examining the profitability provides a robustness check for the interpretation of our previous results. Second, our analysis has ignored the implications of hidden orders for price discovery. We find that about 40% of executed limit orders on NASDAQ following earnings announcements in the after-hours market are hidden.\footnote{25\% (12\%) of trades execute against hidden orders when there are no earnings announcements in the after-hours market (regular trading hours). Chakrabarty and Shaw (2008) also find that the use of hidden orders increases on earnings announcement days.} For a hidden order to be executed, it must be placed within the spread as displayed quotes always have priority at the same price. Thus, it is possible that hidden orders are placed by unsophisticated liquidity providers and are executed at a loss. However, the literature often associates hidden orders with sophisticated traders.\footnote{For example, Harris (1996) and Bessembinder, Panayides, and Venkataraman (2009) argue that hidden orders are effective for mitigating adverse selection. Bloomfield, O’Hara, and Saar (2015) show in a lab experiment that informed traders might prefer hidden orders so as not to reveal how much they are willing to buy or sell and earn higher profits. Boulatov and George (2013) develop a theoretical model and show that the presence of hidden liquidity intensifies competition among informed traders and improves market efficiency. Yao (2017) further shows empirically that informed traders use hidden orders.}

For brevity, we explain how we measure profitability and detail our main analysis in Section A of the Appendix. We find that liquidity providers earn profits per execution of up to 61 bps for hidden orders and 20 bps for displayed non-stale orders, i.e., orders posted at or after the announcement, reinforcing the conclusion that liquidity providers participating
in the after-hours market are sophisticated at processing news.

3. Price Formation at the Opening of Markets

Our previous analysis conveys that price discovery takes place in the after-hours market and is mostly complete before the opening of markets. Results presented in Section 2.1 on the intraday buy-and-hold returns around earnings announcements suggest, however, that some price discovery following large earnings surprises might still take place following the opening of markets.\(^{36}\) We next investigate why there are some price drifts following the opening of markets and show the importance of examining quotes also following the opening of markets.

It is well known that trade volume following earnings announcements is abnormally high (e.g., Chae, 2005). Table IA.3 in the Internet Appendix presents a regression analysis that indicates that trade volume during regular trading hours is about 50% larger for S&P 500 stocks and 100% larger for both S&P SmallCap 400 and S&P MidCap 600 stocks when there is an earnings announcement. A large trade volume can signify that market participants interpret the earnings news differently and that more price discovery remains. Large trade volume can also be related to portfolio rebalancing following large price changes (Lehmann, 1990). This can cause liquidity providers to face significant inventory risk and a deviation in the efficient price because liquidity providers will charge a price impact for temporarily holding the position (Grossman and Miller, 1988, Hendershott and Menkveld, 2014).

To better understand these price drifts, we show in Figure 7 the average ask, bid, and midquote profits as defined in Equation (4) at the opening of markets, along with their respective 95% confidence intervals. We also show the 95% confidence intervals (the shaded area) around the mean of the order imbalance as defined in Equation (6) to examine if the trading pressure is in the same direction as the earnings surprise. Figure 8 shows the

\(^{36}\)In Section 5 of the Internet Appendix, we use the methodology of Biais, Hillion, and Spatt (1999) to examine the contribution of the opening auction to price discovery following earnings announcements. We find no evidence suggesting that the auction process contributes significantly to the price discovery of earnings surprises.
average cumulative order imbalance for the top and bottom two earnings quintiles following
the opening of markets.\textsuperscript{37}

Figure 7 shows that for large earnings surprises, there is a gradual convergence to zero
for the midquote profit line, especially for S&P 600 stocks. This suggests some price drifts,
which is consistent with Figure 2. These price drifts further suggest a trading strategy
potentially profitable for a liquidity taker. For example, for S&P 600 stocks, we observe an
ask profit line below zero following large positive surprises, which indicate that a trader that
buys an S&P 600 stock in the minutes after the announcement can earn a return of 25 bps.
However, liquidity takers, on average, do not trade in the same direction as the surprise. As
Figure 8 shows, the order imbalance accumulates in the direction opposite to the surprise.

Liquidity providers who absorb a large directed trade volume must balance their inven-
tory, and this can explain why there are some additional price drifts. Therefore, these drifts
are most likely unrelated to informational inefficiency. To see this more clearly, take for
example an S&P 600 stock with an earnings surprise in the top quintile. Liquidity providers
will have to absorb a large selling pressure and will, therefore, charge a price impact to
liquidity demanders (the sellers) by lowering the bid price while they accumulate inventory.
Consequently, they will also lower the ask price to help reduce their inventory leading to
negative ask profit according to our measure. Quote prices then adjust to their fundamental
value when the selling pressure subsides. The persistence in price drifts will depend on how
long the selling pressure lasts. Both Figures 7 and 8 convey that price pressure is more
prevalent for small stocks, consistent with Hendershott and Menkveld (2014) who find that
daily transitory volatility in stock returns due to price pressure is larger for the smallest
stocks.

The negative profits that we measure do not necessarily imply that liquidity providers

\textsuperscript{37}We ignore trades against hidden orders when calculating the order imbalance because we examine displayed bid-
ask spreads. Because spreads are much narrower during regular trading hours than during the after-hours market,
hidden orders are not used as much as in the after-hours market. The median fraction of the total volume against
hidden orders is 15, 17, and 20\% for S&P 500, S&P 400, and S&P 600 stocks, respectively.
actually loses money because they have a shorter time horizon when managing their inventory (Conrad and Wahal, 2019). We repeat the same analysis using the midquote one-minute later as the exit price and present the results in Figure 9. The figure shows that the ask and bid profit lines are wide at the opening of markets, suggesting large bid-ask spreads followed by a fast convergence in spreads as demonstrated by the profit lines converging close to zero. The ask and bid profit lines do not cross the zero y-axis and indicate that liquidity providers face no adverse selection on average when turning over their inventory at short horizon.

Overall, our findings suggest that incoming order flow is not informationally driven but most likely liquidity driven (e.g., portfolio balancing). The drifts at the opening of markets are more related to price pressure and inventory management by liquidity providers accommodating liquidity demand than slow information processing by liquidity providers. These results further emphasize the importance of examining bid and ask prices, as well as order imbalances, to understand price formation following the opening of markets.

3.1. Price discovery for stocks that do not trade in the after-hours market

For 20% of earnings announcements, there are no trades following the announcement until the opening of markets. One might expect that stocks that do not trade have additional price discovery following the opening of markets because, as we show in Section 3 of the Internet Appendix, these stocks are small with low analyst coverage and are less liquid (e.g., have lower turnover). In other words, these stocks are more opaque and have lower information quality, two characteristics that a large literature relates to slow price formation.\textsuperscript{38} Therefore, the mere fact that we do not observe a trade would suggest a greater likelihood of additional price discovery at the opening of markets. To examine this issue, we show in the Internet Appendix Section 6 that the impact of earnings surprises on 5 minutes returns following the opening markets is not significantly different between stocks with and without after hours.

\textsuperscript{38}For an overview of this literature, see Brennan, Jegadeesh, and Swaminathan (1993), Hong, Lim, and Stein (2000), Hou and Moskowitz (2005), Zhang (2006), and Boguth, Carlson, Fisher, and Simutin (2016).
trades. We conclude that trading is not a necessary condition for price discovery to occur and for prices to reflect earnings surprises.

4. Quote Adjustments Around Other News Events: Evidence from Analyst Recommendations

It is common in the literature to rely on trade prices to study price discovery. In this section, we illustrate the importance of examining quotes adjustments rather than the adjustment in trade prices for complete inference of the price formation process by revisiting a puzzling finding on analyst recommendations documented in Li, Ramesh, Shen, and Wu (2015). The authors find that after-hours recommendation revisions are associated with measurably greater overall price reactions than regular-hour revisions. They suggest that after-hours revisions have different information characteristics from regular-hour revisions and that analysts have incentives to issue recommendations after hours to benefit large institutional clients. We conjecture that the use of trade prices results in such a difference between regular-hour and after-hours recommendation revisions.

We retrieve analyst recommendation revisions for our sample of S&P 1500 stocks for the period of 2011 to 2015 from Ravenpack. The benefit of Ravenpack is that the analyst recommendation timestamps are accurate, in contrasts to I/B/E/S and First Call (Bradley, Clarke, Lee, and Ornthanalai, 2014). As in Li, Ramesh, Shen, and Wu (2015), we select news for which there is a change in recommendation, i.e., a revision. We retrieve a total of 19,720 analyst revisions. The fraction of revisions occurring during regular hour, after hours, and outside trading hours (8 p.m. to 4 a.m.) are 71.0, 24.8, and 4.2%, respectively. In Figure A.5 of the Appendix, we plot the total number of revisions from our sample by time of day. In contrast to earnings announcements, the majority of after-hours revisions are announced in the hours before the opening of markets. Regular-hour revisions largely

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39 Bradley, Clarke, Lee, and Ornthanalai (2014) show that the timestamp inaccuracy for recommendations released overnight to be the most problematic.

40 Ravenpack indicates which news consisted of a change in recommendation.
occur just after the opening of markets. Because many of the recommendations are issued following firm news events (e.g., earnings announcements) that generally occur after-hours (Altunkılıç and Hansen, 2009, Li, Ramesh, Shen, and Wu, 2015), it is anticipated that analyst revisions are released few hours just before or after the opening of markets. It is critical to understand when revisions occur because the dynamics in quotes will be largely influenced by how close (or how far) is the opening of markets (9:30 a.m.). As shown in Barclay and Hendershott (2004), quoted spreads are wide outside of trading hours and gradually narrows when approaching 9:30 a.m.\footnote{See Figure 2 in Barclay and Hendershott (2004).}

We begin by first examining cumulative returns using trade prices around positive and negative analyst revisions over a 200-minute window before and after the event. As in Li, Ramesh, Shen, and Wu (2015), if for a given time interval there is no trade, we impose a return of 0%. Figure 10 shows the average cumulative returns around analyst revisions for after-hours and regular-hour revisions in Panels A and B, respectively. We corroborate the findings of Li, Ramesh, Shen, and Wu (2015) and show significant price reaction and price drifts following after-hours revisions and no reaction for regular trading hours recommendations.

We next show in Figure 11 the dynamics in quote adjustments around after-hours revisions using measures of profitability from the perspective of a seller as specified in Equation (4) over a 200-minute window before and after the event. Panels A and B present the dynamics for positive and negative analyst revisions, respectively.\footnote{We present in the Internet Appendix Figure IA.10 the analysis over a longer window (400 minutes around the recommendation announcements). The figure shows how the closing and opening of markets influence the dynamics in the spread adjustments.} We also calculate profits using trade prices, i.e., \((Trade \ price_{i,t} - Closing \ price_{i,T})/Trade \ price_{i,t}\). If for a given time interval, there are no trades, we use the previous trade price (equivalent to assuming a return of 0%). The gray shaded area shows what fraction of observations at minute \(t\) that are during regular hour.
The figure shows that the dynamics in the trading profit (dotted purple line) around revisions closely maps the cumulative returns using trade prices presented in Figure 10. The dynamics in the midquote profit line present, however, a different story of the price formation process around analyst revisions. First, as opposed to the slow price formation following after-hours revisions shown in Figure 10 Panel A, there are no slow adjustments in midquotes following revisions, consistent to the price adjustment observed following regular trading hours revisions (see Figure 10 Panel B). Second, the adjustment in midquotes before revisions show a substantial price adjustment that is most likely related to the news before the revision. Consistent with our previous findings on earnings announcements, we observe asymmetric quote adjustments before analyst revisions (starting from the -100 minute mark). Before positive (negative) revisions, ask (bid) returns are flat and bid (ask) returns gradually increases (decreases).

Figure 10 confirm that the use of trade prices to calculate returns leads to incorrect inferences regarding the price formation process following after-hours revisions. Because there is often little to no trading, imposing a return of 0% underestimates the actual speed of price adjustments for after-hours revisions. If we limit ourselves to revisions issued between 5 p.m. and 8:30 a.m. (10,289 events) and examine a 60-minute window before and after revisions, 44% of these events have no trade and among those events with at least one trade, the median number of trades is 9. Therefore, imposing a return of 0% when observing no trades does not provide the correct price adjustment, because as we have shown, price discovery occurs through quotes. It thus primordial that researchers rely on quotes and not trade prices for complete inference of price formation following after-hours news events.

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43 We also present the profit lines dynamics as in Figure 11 for regular trading hours recommendations in Figure IA.10 of the Internet Appendix and we find no price adjustments in midquotes post-revisions.

44 We also confirm that after-hours analyst recommendations are most likely not causing a decline in asymmetric information, i.e., a narrowing of the spreads. The narrowing of spreads occurs as expected when approaching the opening of markets. Excluding analyst recommendations occurring after 8 a.m. shows a slower narrowing of spreads following revisions.

45 We choose a 60-minute window to remain in the after-hours and to minimize the likelihood of overlapping with a news event that occurred prior to the recommendation.

46 The use of trade prices for news events that occur during the day is not as problematic because the market is
5. Concluding Remarks and Recommendations

A recent trend in accounting research is to examine the impact of corporate news events on prices using intraday data. With the majority of firm-level news occurring in the after-hours market, a very illiquid trading environment with little trading activity, the after-hours market imposes various obstacles for complete inference of the price discovery process. Such obstacles are met in recently published accounting studies.

To better understand the relationship between liquidity and market efficiency in the after-hours market, we study price formation around earnings announcements. We show that stock prices efficiently reflect earnings surprises at the time of the announcement through changes in quotes by sophisticated liquidity providers despite little to no trading. Bid-ask spreads before announcements are wide enough to eliminate profits of liquidity-takers with private information about upcoming earnings surprises. Following announcements, spreads narrow and do so asymmetrically: ask (bid) prices adjust quickly and efficiently reflect positive (negative) surprises while bid (ask) prices are slower to adjust.

Our findings propose a guideline for future studies examining price formation at high-frequency. First, because there is little trading after hours following news events, we recommend researchers to use midquotes and not trade prices to calculate stock returns when quantifying the impact of news events on stock prices as price discovery occurs through changes in quotes and not through trading. The use of trade prices in periods of low trading activity can lead to incorrect inference with respect to how prices respond to news. Second, if researchers want to also understand the speed at which prices reflect news events, they must examine the changes in ask and bid prices to control for the asymmetric adjustment in quotes as using only the midquote underestimates the actual speed of price discovery. Finally, examining trades following news events are insightful when one wish to quantify the liquid and there are trades. We still, recommend researchers to use midquotes to avoid biases related to the bid-ask bounce when using trade prices (see Blume and Stambaugh, 1983).
speed at which stale quotes are executed.
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Figure 1. Distribution of Overnight Returns Around Earnings Announcements

This figure presents for each S&P index the number of earnings announcements and the mean overnight stock returns around earnings announcements (4 p.m. to 9:30 a.m.) for a range of earnings surprises varying from minus one to plus one percent in Panels A and B, respectively. Panels C and D show the number of earnings announcements and the mean overnight stock returns by earnings surprise quintile, respectively. Earnings surprises on the x-axis are in percent. The sample period is January 1, 2011 to December 31, 2015.
Figure 2. Cumulative Abnormal Returns Around Earnings Announcements

This figure shows the buy-and-hold cumulative abnormal returns (BHAR) from 9:40 a.m. on the trading days preceding after-hours sessions with earnings announcements until 4 p.m. on the following trading days. The BHAR values for the full sample, S&P 500, S&P MidCap 400, and S&P SmallCap 600 stocks are presented in Panels A to D, respectively. We define BHAR for stock-earnings announcement $i$ from time $\tau$ to $T$ as

$$ BHAR[\tau, T]_i = \sum_{t=\tau}^{T} r_{i,t} - \sum_{t=\tau}^{T} r_{m,t}, $$

where $r_{i,t}$ is the stock log return and $r_{m,t}$ is the log return of the stock market using the SPDR S&P 500 ETF on interval $t$. We use midquotes (mid-point between the best bid and best ask price) to calculate log returns at 5-minute intervals. We condense stock returns in the after-hours trading session to a single point, which includes the opening auction and the first 10 minutes of trading, calculated using the closing price at 4 p.m. and the midquote at 9:40 a.m. on the following trading day. Each line represents a different quintile sort for earnings surprises. The shaded areas represent pointwise 95% confidence bands around the average BHAR. The sample period is January 1, 2011 to December 31, 2015.
Figure 3. Cumulative Returns Following Earnings Announcements in the After-Hours Market

This figure shows the buy-and-hold returns (bhr) in the after-hours market from 5 minutes before to 60 minutes after the earnings announcement. The bhr values for the full sample, S&P 500, S&P MidCap 400, and S&P SmallCap 600 stocks are presented in Panels A to D, respectively. We define bhr for stock-earnings announcement $i$ from time $\tau$ to $T$ as

$$BHR[\tau, T]_i = \sum_{t=\tau}^{T} r_{i,t},$$

where $r_{i,t}$ is the stock log return for the 5-minute interval $t$. We use midquotes (mid-point between the best displayed bid and best ask price) to calculate log returns. Each line represents a different quintile sort for earnings surprises. The shaded areas represent pointwise 95% confidence bands around the average bhr. The sample period is January 1, 2011 to December 31, 2015.
Figure 4. Stock Return Responses to Earnings Surprises in the After-Hours Market

This figure shows the estimated response coefficients $\beta_k$ of the regression:

$$r_{i,t} = \alpha + \sum_{k=1}^{12} \beta_k Surprise_i \mathbb{1}_{k=t} + \varepsilon_{i,t},$$

where $t$ denotes one of 12 5-minute intervals following the earnings announcement, $i$ is a stock-earnings announcement, $r_{i,t}$ is the 5-minute log midquote stock return, $Surprise_i$ is the earnings surprise, and $\mathbb{1}_{k=t}$ is an indicator variable equal to one if $k = t$ and zero otherwise. The estimated $\beta_k$ for the full sample, S&P 500, S&P MidCap 400, and S&P SmallCap 600 stocks are presented in Panels A to D, respectively. The shaded areas represent pointwise 95% confidence bands. Standard errors are calculated using the Driscoll and Kraay (1998) method. The sample period is January 1, 2011 to December 31, 2015.
This figure shows the average ask profit (dashed red line), bid profit (dashed-dotted blue line), and midquote profit (solid black line) and their respective 95% confidence intervals by earnings surprise quintile (columns) and by S&P index (rows) -5 to 60 minutes around earnings announcements in the after-hours market. The profits are calculated from the perspective of a seller. We define the ask profit as \( \frac{(\text{Ask price}_{i,t} - \text{Closing price}_{i,T})}{\text{Ask price}_{i,t}} \), the bid profit as \( \frac{(\text{Bid price}_{i,t} - \text{Closing price}_{i,T})}{\text{Bid price}_{i,t}} \), and the midquote profit as \( \frac{(\text{Midquote}_{i,t} - \text{Closing price}_{i,T})}{\text{Midquote}_{i,t}} \), where \( t < T \). The closing price is the official closing price of the following regular trading hour session at 4 p.m. The gray shaded areas represent the fraction of valid quotes, which is the fraction of stock earnings announcement in our overall sample at each minute with a relative spread, \( \frac{|(\text{Ask}_{i,t} - \text{Bid}_{i,t})|}{\text{Midquote}_{i,t}} \), less than or equal to 20%. The earnings announcement occurs at time 0. The sample period is January 1, 2011 to December 31, 2015.
Figure 6. The Explanatory Power of Earnings Surprises and Order Imbalance with Respect to Stock Returns

This figure shows the $R^2$ from a univariate regression of log midquote stock returns on earnings surprises (solid blue line), stock returns on incoming net order imbalance (dotted red line), and stock returns on incoming net order imbalance excluding trades against stale quotes (dash-dotted black line) for each 5-minute interval following earnings announcements in the after-hours market. We define the order imbalance as

$$OI_{i,t} = \frac{B_{i,t} - S_{i,t}}{B_{i,t} + S_{i,t}},$$

where $B_{i,t}$ and $S_{i,t}$ correspond to buyer- and seller-initiated trade volume for interval $t$ following earnings announcement $i$, respectively. The results are presented for the full sample in Panel A and for the S&P 500, S&P MidCap 400, and S&P SmallCap 600 index in Panels in B to D, respectively. The sample period is January 1, 2011 to July 13, 2014.
Figure 7. Profitability Following the Opening of Markets for Displayed Quotes

This figure shows the average ask profit (dashed red line), bid profit (dashed-dotted blue line), and midquote profit (solid black line) and their respective 95% confidence intervals by earnings surprise quintile (columns) and by S&P index (rows) from -2 to 120 minutes around the opening of markets (9:30 a.m.) following an earnings announcement that occurred in the preceding after-hours market session. We define the profits from the perspective of a seller and calculate ask profit as \((\text{Ask price}_{i,t} - \text{Closing price}_{i,T})/\text{Ask price}_{i,t}\), the bid profit as \((\text{Bid price}_{i,t} - \text{Closing price}_{i,T})/\text{Bid price}_{i,t}\), and the mid profit as \((\text{Midquote}_{i,t} - \text{Closing price}_{i,T})/\text{Midquote}_{i,t}\), where \(t\) are 1-minute intervals and \(t < T\). The closing price is the official closing price of the regular trading hour session at 4 p.m. The gray shaded area represents the 95% confidence intervals of the 1-minute net order imbalance defined as the difference between buyer- and seller-initiated market orders (in share volume) divided by the total trade volume, excluding trades against hidden orders. The opening of markets occurs at time 0. The sample period is January 1, 2011 to December 31, 2015.
Figure 8. Cumulative Order Imbalance Following the Opening of Markets

This figure shows the average cumulative order imbalance from 2 to 120 minutes following the opening of markets for stocks with earnings announcements in the previous after-hours trading session by earnings surprise quintile (excluding quintile 3). The cumulative order imbalance is calculated as

\[
Cumulative\ OI[2, 120]_i = \frac{\sum_{t=2}^{120} B_{i,t} - S_{i,t}}{\sum_{t=2}^{120} B_{i,t} + S_{i,t}},
\]

where \(B_{i,t}\) and \(S_{i,t}\) correspond to buyer- and seller-initiated trade volume and \(i\) is an earnings announcement. The shaded areas represent pointwise 95% confidence bands. We exclude trades against hidden orders in the calculation of the order imbalance. We begin 2 minutes after the opening of market to mitigate the impact of the opening auction. The results are presented for the full sample in Panel A and for the S&P 500, S&P MidCap 400, and S&P SmallCap 600 index in Panels in B to D, respectively. The sample period is January 1, 2011 to December 31, 2015.
Figure 9. One-Minute Profitability Following the Opening of Markets for Displayed Quotes

This figure shows the average ask profit (dashed red line), bid profit (dashed-dotted blue line), and midquote profit (solid black line) and their respective 95% confidence intervals by earnings surprise quintile (columns) and by S&P index (rows) from -2 to 120 minutes around the opening of markets (9:30 a.m.) following an earnings announcement that occurred in the preceding after-hours market session. We defined the profits from the perspective of a seller and calculate ask profit as \((\text{Ask price}_{i,t} - \text{Midquote}_{i,t+1}) / \text{Ask price}_{i,t}\), the bid profit as \((\text{Bid price}_{i,t} - \text{Midquote}_{i,t+1}) / \text{Bid price}_{i,t}\), and the midquote profit as \((\text{Midquote}_{i,t} - \text{Midquote}_{i,t+1}) / \text{Midquote}_{i,t}\), where \(t\) defines a 1-minute interval. The gray shaded area represents the 95% confidence intervals of the net order imbalance defined as the difference between buyer- and seller-initiated market orders (in share volume) divided by the total volume, excluding trades against hidden orders. The opening of markets occurs at time 0. The sample period is January 1, 2011 to December 31, 2015.
**Figure 10.** Cumulative Returns Using Trade Prices Around Analyst Recommendation Revisions

This figure shows the cumulative returns for positive (red solid line) and negative (blue dashed line) analysts recommendation revisions using trade prices 200 minutes before and following after-hours and regular-hour revisions in Panels A and B, respectively. If for a particular revision there is no trade for a minute interval $t$, we impose a return of 0% for that interval. We only consider analyst recommendations that correspond to a change in recommendation. The sample period is January 1, 2011 to December 31, 2015.
Figure 11. One-Minute Profitability Around After-Hours Analyst Recommendation Revisions

This figure shows the average ask profit (dashed red line), bid profit (dashed-dotted blue line), midquote profit (solid black line), and the trade profit (dotted purple line) and their respective 95% confidence intervals 200 minutes before and after positive (Panel A) and negative (Panel B) analyst recommendation revisions that occurred during the after-hours market. We defined the profits from the perspective of a seller and calculate ask profit as $(Ask \ price_{i,t} - Closing \ price_{i,T})/Ask \ price_{i,t}$, the bid profit as $(Bid \ price_{i,t} - Closing \ price_{i,T})/Bid \ price_{i,t}$, the midquote profit as $(Midquote_{i,t} - Closing \ price_{i,T})/Midquote_{i,t}$, and the trade profit as $(Trade \ price_{i,t} - Closing \ price_{i,T})/Trade \ price_{i,t}$, where $t$ defines a 1-minute interval and $t < T$. The closing price is the official closing price of the regular trading hour session at 4 p.m. The gray shaded area represents the fraction of observation at minute $t$ for which the observation is during regular trading hours. The sample period is January 1, 2011 to December 31, 2015.
Table 1
Sample Stocks, Earnings Announcements, and Earnings Surprises Descriptive Statistics

This table reports the sample stocks, earnings announcements, and earnings surprises descriptive statistics by S&P index for S&P 1500 stocks. The S&P 1500 combines three leading indexes: the S&P 500, the S&P MidCap 400, and the S&P SmallCap 600. Earnings surprise quintiles are defined over the entire sample of earnings announcements. The sample period is January 1, 2011 to December 31, 2015.

<table>
<thead>
<tr>
<th></th>
<th>S&amp;P 500</th>
<th>S&amp;P MidCap 400</th>
<th>S&amp;P SmallCap 600</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. observations</td>
<td>8,964</td>
<td>6,684</td>
<td>9,617</td>
</tr>
<tr>
<td>Market cap. (in million $)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>28,071</td>
<td>3,092</td>
<td>938</td>
</tr>
<tr>
<td>Median</td>
<td>12,637</td>
<td>2,730</td>
<td>789</td>
</tr>
<tr>
<td>Number of analysts</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>14</td>
<td>9</td>
<td>5</td>
</tr>
<tr>
<td>Median</td>
<td>13</td>
<td>8</td>
<td>4</td>
</tr>
<tr>
<td>Earnings surprise (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.08</td>
<td>0.06</td>
<td>0.07</td>
</tr>
<tr>
<td>St. Dev.</td>
<td>0.28</td>
<td>0.35</td>
<td>0.49</td>
</tr>
<tr>
<td>P25</td>
<td>0.00</td>
<td>-0.02</td>
<td>-0.07</td>
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<tr>
<td>P50</td>
<td>0.04</td>
<td>0.04</td>
<td>0.06</td>
</tr>
<tr>
<td>P75</td>
<td>0.13</td>
<td>0.15</td>
<td>0.23</td>
</tr>
<tr>
<td>Earnings surprise distribution (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Top quintile</td>
<td>15</td>
<td>18</td>
<td>26</td>
</tr>
<tr>
<td>Q4</td>
<td>21</td>
<td>20</td>
<td>19</td>
</tr>
<tr>
<td>Q3</td>
<td>26</td>
<td>22</td>
<td>13</td>
</tr>
<tr>
<td>Q2</td>
<td>25</td>
<td>20</td>
<td>15</td>
</tr>
<tr>
<td>Bottom quintile</td>
<td>13</td>
<td>19</td>
<td>27</td>
</tr>
</tbody>
</table>
**Table 2**

**Regular- and After-Hours Trading Descriptive Statistics**

This table presents statistics of trading activity during market hours, after hours, and after hours when a firm reports an earnings announcement (EA) by S&P index for S&P 1500 stocks. The S&P 1500 combines three leading indexes: the S&P 500, the S&P MidCap 400, and the S&P SmallCap 600. The sample period is December 9, 2013 to December 31, 2015 when odd-lots (trades with less than 100 shares) are reported to the consolidated tape.

<table>
<thead>
<tr>
<th></th>
<th>S&amp;P 500</th>
<th></th>
<th>S&amp;P MidCap 400</th>
<th></th>
<th>S&amp;P SmallCap 600</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Regular</td>
<td>After</td>
<td>After</td>
<td></td>
<td>Regular</td>
<td>After</td>
</tr>
<tr>
<td></td>
<td>hours</td>
<td>hours – EA</td>
<td>hours – EA</td>
<td></td>
<td>hours</td>
<td>hours – EA</td>
</tr>
<tr>
<td><strong>Number of trades</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>25th percentile</td>
<td>10,125</td>
<td>11</td>
<td>12</td>
<td>3,180</td>
<td>5</td>
<td>3</td>
</tr>
<tr>
<td>Median</td>
<td>16,900</td>
<td>17</td>
<td>70</td>
<td>5,123</td>
<td>7</td>
<td>10</td>
</tr>
<tr>
<td>75th percentile</td>
<td>28,494</td>
<td>31</td>
<td>623</td>
<td>8,675</td>
<td>10</td>
<td>59</td>
</tr>
<tr>
<td><strong>Trade size in shares (%)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;100</td>
<td>28</td>
<td>36</td>
<td>27</td>
<td>30</td>
<td>51</td>
<td>28</td>
</tr>
<tr>
<td>100-500</td>
<td>69</td>
<td>38</td>
<td>61</td>
<td>68</td>
<td>26</td>
<td>56</td>
</tr>
<tr>
<td>500-1,000</td>
<td>2</td>
<td>8</td>
<td>6</td>
<td>1</td>
<td>7</td>
<td>8</td>
</tr>
<tr>
<td>&gt;1,000</td>
<td>1</td>
<td>17</td>
<td>6</td>
<td>1</td>
<td>16</td>
<td>8</td>
</tr>
<tr>
<td><strong>Trade size in $ (%)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;1,000</td>
<td>10</td>
<td>14</td>
<td>7</td>
<td>14</td>
<td>27</td>
<td>13</td>
</tr>
<tr>
<td>1,000-5,000</td>
<td>35</td>
<td>24</td>
<td>31</td>
<td>50</td>
<td>29</td>
<td>41</td>
</tr>
<tr>
<td>5,000-50,000</td>
<td>53</td>
<td>44</td>
<td>56</td>
<td>36</td>
<td>30</td>
<td>41</td>
</tr>
<tr>
<td>&gt;50,000</td>
<td>2</td>
<td>19</td>
<td>6</td>
<td>0</td>
<td>14</td>
<td>5</td>
</tr>
</tbody>
</table>
Appendix for

How is Earnings News Transmitted to Stock Prices?
A. The Profitability of Liquidity Providers

To measure the profitability of liquidity providers associated with displayed and hidden orders, we calculate for each observed after-hours trade $j$ following each earnings announcement $i$, the realized spread measure, $r_{s_{i,j}}$, defined as

$$r_{s_{i,j}} = \begin{cases} \frac{(m_i - p_{i,j})}{p_{i,j}} \times 100, & \text{if trade } j \text{ is a passive buy,} \\ \frac{(p_{i,j} - m_i)}{p_{i,j}} \times 100, & \text{if trade } j \text{ is a passive sell,} \end{cases}$$

where $m_i$ is the crossing price at the opening of markets if there is an auction or the midquote in the order book at 9:30 a.m. otherwise and $p_{i,j}$ is the trade price. The realized spread is a measure of trading profit, but we note that it is a lower bound as NASDAQ also pays a rebate to liquidity providers, which we do not observe. We further winsorize the realized spreads at the 1st and 99th percentiles. We examine the profitability of liquidity providers for two time intervals: the first 5 minutes and from the 5th to the 60th minute following earnings announcements. For each of the time intervals following earnings announcement $i$, we compute the average realized spread, $\overline{r_{s_{i,k}}}$, across trades against limit orders of type $k \in \{\text{all order types, hidden, displayed, displayed stale, and non-stale displayed orders}\}$ by S&P index.

Table A.1 reports the mean $\overline{r_{s_{i,k}}}$ across all order types in Panel A, for hidden and displayed orders in Panel B, and for displayed stale and non-stale orders in Panel C. Panel A, Columns (1), (3), and (6) report that, in the first 5 minutes, liquidity providers on average earn profits of approximately $-5$, $-24$ and $-87$ bps for S&P 500, S&P MidCap 400, and S&P SmallCap 600 stocks, respectively, but only the profits for S&P 400 and 600 stocks are statistically significant at the 5 and 1% levels, respectively. Columns (2), (4), and (6) present statistically significant positive profits from the 5th to the 60th minute following earnings announcements varying from 7 to 18 bps across all S&P indexes. At first glance, these results appear to suggest that liquidity providers are providing liquidity at a loss to sophisticated liquidity-takers at the time of the announcement. However, these results ignore the heterogeneity in sophistication among liquidity providers. When examining the profitability associated with hidden and displayed orders in Panel B, we find that liquidity providers earn statistically significant profits on hidden orders in the first 5 minutes for S&P 500 stocks of 10 bps; in the following 55 minutes, they earn profits varying from 16 to 61 bps across all S&P indexes. However, displayed orders for S&P 400 and S&P 600 stocks remain associated with negative profits in the first 5 minutes following earnings announcements. Differentiating between stale and non-stale displayed orders, Columns (1), (3), and (6) in Panel C report that profits for non-stale orders are not statistically different from zero while profits for stale displayed orders are negative and statistically significant, varying from $-20$ to $-122$ bps in the first 5 minutes. In the following 55 minutes, Columns (2), (4), and (6) in Panel C show that displayed non-stale orders are profitable, with profits varying from 6 to 20 bps, whereas stale orders are not statistically different from zero.

Overall, our results on profitability present additional evidence that liquidity providers in the after-hours market following earnings announcements are generally sophisticated at adjusting quotes according to earnings news. Moreover, the fact that hidden orders are associated with positive returns confirms previous theoretical and empirical research suggesting that informed traders use hidden orders (Bloomfield, O’Hara, and Saar, 2015).
Figure A.1. Trade Volume and Fragmentation in the After-Hours Market

Panel A of this figure shows the monthly share of total aggregate traded dollar volume during extended trading hours before the market opens (blue dashed-dotted line), after the market closes (green dashed line), at the opening auction (purple dotted line), and at the closing auction (full orange line). Panel B shows the monthly market share of total volume executed on dark and lit venues. Panel C shows the monthly market share of after-hours volume executed on dark and lit venues. Panel D shows the monthly market share of after-hours volume following earnings announcements executed on dark and lit venues. The sample period is January 1, 2011 to December 31, 2015.
**Figure A.2.** An Example of a Price Response to an Earnings Announcement

This figure shows the stock price in Panel A, the buy and sell trade volume (in hundreds of shares) in Panel B, and the total added depth at the top of the limit order book (bid and ask, in hundreds of shares) in Panel C on NASDAQ for each 1 minute interval between 3:30 p.m. and 5:30 p.m. for the company Apple (ticker: AAPL) around its earnings announcement made at 4:30 p.m. on October 18, 2011. In Panel B, the positive blue bars are the buyer-initiated market orders and the negative red bars are the seller-initiated market orders.
This figure shows the median 1-minute relative spread 5 minutes before to 60 minutes after earnings announcements in the after-hours market for S&P 500 (red line), S&P MidCap 400 (dashed blue line), and S&P 600 SmallCap (dotted black line) stocks. Relative spread is defined as the difference between the best ask and bid prices divided by the midquote (the midpoint between the ask and bid prices). The earnings announcement occurs at time 0. The sample period is January 1, 2011 to December 31, 2015.
Figure A.4. Profitability Around Earnings Announcements for Displayed Quotes in the After-Hours Market for the 50 Largest Firms in the S&P 500 Index

This figure shows the average ask profit (dashed red line), bid profit (dashed-dotted blue line), and midquote profit (solid black line) and their respective 95% confidence intervals by earnings surprise quintile (columns) for the 50 largest firms in the S&P 500 index -5 to 60 minutes around earnings announcements in the after-hours market. We select the 50 largest firms in the S&P 500 based on their market capitalization at the beginning of each year. The profits are calculated from the perspective of a seller. We define the ask profit as \( \frac{(Ask\ price_{i,t} - Closing\ price_{i,T})}{Ask\ price_{i,t}} \), the bid profit as \( \frac{(Bid\ price_{i,t} - Closing\ price_{i,T})}{Bid\ price_{i,t}} \), and the midquote profit as \( \frac{(Midquote_{i,t} - Closing\ price_{i,T})}{Midquote_{i,t}} \), where \( t < T \). The closing price is the official closing price of the following regular trading hour session at 4 p.m. The gray shaded areas represent the fraction of valid quotes, which is the fraction of stock earnings announcement in our overall sample at each minute with a relative spread, \( \frac{|(Ask_{i,t} - Bid_{i,t})|}{Midquote_{i,t}} \), less than or equal to 20%. The earnings announcement occurs at time 0. The sample period is January 1, 2011 to December 31, 2015.
Figure A.5. The Number of Analyst Recommendation Revisions by the Time of Day

This figure shows the number of analyst recommendation revisions per 30-minute interval for S&P 1500 stocks from RavenPack. The sample period is from January 1, 2011 to December 31, 2015.
This table reports the mean realized spread across all trades against displayed, hidden, displayed non-stale, and displayed stale limit orders. We calculate the realized spread, \( r_{si,j} \), for each observed after-hours trade \( j \) following each earnings announcement \( i \), associated with different limit order types as

\[
    r_{si,j} = \begin{cases} 
    \frac{(m_i - p_{i,j})}{p_{i,j}} \times 100, & \text{if trade } j \text{ is a passive buy,} \\
    \frac{(p_{i,j} - m_i)}{p_{i,j}} \times 100, & \text{if trade } j \text{ is a passive sell,} 
    \end{cases}
\]

where \( m_i \) is the crossing price at the opening of markets if there is an auction or the midquote in the order book at 9:30 a.m. otherwise and \( p_{i,j} \) is the trade price. For different time intervals following earnings announcement \( i \), we compute the average realized spread, \( \overline{r_{si,k}} \), across trades against limit orders of type \( k \in \{ \text{all order types, hidden, displayed, displayed stale, and non-stale displayed orders} \} \) by S&P index. Panel A reports the mean \( \overline{r_{si,k}} \) across all order types, Panel B reports the mean \( \overline{r_{si,k}} \) for hidden and displayed orders, and Panel C reports the mean \( \overline{r_{si,k}} \) for displayed stale and non-stale orders for the first 5 minutes and from 5 to 60 minutes following earnings announcements. ** and * indicate a two-tailed test significance level of less than 1 and 5%, respectively, using standard errors clustered by date estimated by pooled regression. We also report the total number of \( \overline{r_{si,k}} \) observations (\( N \)) corresponding to each order type \( k \). The sample period is January 1, 2011 to July 13, 2014.

### Panel A: All order types

<table>
<thead>
<tr>
<th>S&amp;P 500</th>
<th>S&amp;P MidCap 400</th>
<th>S&amp;P SmallCap 600</th>
</tr>
</thead>
<tbody>
<tr>
<td>5-min.</td>
<td>5-60min.</td>
<td>5-min.</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>All order types</td>
<td>-0.051</td>
<td>0.074**</td>
</tr>
<tr>
<td>N</td>
<td>2,871</td>
<td>4,600</td>
</tr>
</tbody>
</table>

### Panel B: Hidden and displayed orders

<table>
<thead>
<tr>
<th>S&amp;P 500</th>
<th>S&amp;P MidCap 400</th>
<th>S&amp;P SmallCap 600</th>
</tr>
</thead>
<tbody>
<tr>
<td>5-min.</td>
<td>5-60min.</td>
<td>5-min.</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Hidden orders</td>
<td>0.100*</td>
<td>0.159**</td>
</tr>
<tr>
<td>Displayed orders</td>
<td>-0.038</td>
<td>0.065*</td>
</tr>
<tr>
<td>N hidden</td>
<td>1,625</td>
<td>2,665</td>
</tr>
<tr>
<td>N displayed</td>
<td>2,033</td>
<td>3,241</td>
</tr>
</tbody>
</table>

### Panel C: Displayed stale and non-stale orders

<table>
<thead>
<tr>
<th>S&amp;P 500</th>
<th>S&amp;P MidCap 400</th>
<th>S&amp;P SmallCap 600</th>
</tr>
</thead>
<tbody>
<tr>
<td>5-min.</td>
<td>5-60min.</td>
<td>5-min.</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Stale orders</td>
<td>-0.202*</td>
<td>0.049</td>
</tr>
<tr>
<td>Non-stale orders</td>
<td>0.019</td>
<td>0.058*</td>
</tr>
<tr>
<td>N stale</td>
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<td>659</td>
</tr>
<tr>
<td>N non-stale</td>
<td>1,801</td>
<td>3,206</td>
</tr>
</tbody>
</table>

** and * indicate a two-tailed test significance level of less than 1 and 5%, respectively, using standard errors clustered by date estimated by pooled regression.