Passive Informed Trading Around Earnings Announcements

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Abstract: Using a sample of NASDAQ firms, we investigate informed trading in the limit order book prior to earnings announcements. Consistent with recent limit order theory, and in contrast to classic adverse selection models, we show that liquidity improves during periods of asymmetric information, which is attributed to the liquidity supply of informed traders. For earnings announcements with high absolute returns, we find that the quoted spread is low, bid and ask depth is highly correlated, the implied cost to trade is low, and the information-share of the limit order book is high, relative to earnings announcements with low absolute returns.

Key Words: Informed Trading, Limit Order Book, Earnings Announcements
JEL: G10, G14

With the implementation of Regulation NMS, U.S. stock markets are significantly more integrated and computerized. The role of supplying liquidity and market making is now filled by Algorithmic Traders (AT) and High Frequency Traders (HFT) (Menkveld, 2013), where the dominance of AT in the market making function is driven by three main factors: high speed communication networks, co-location of computer systems at the market centers reducing transmission latencies, and the access to real-time, market center generated data feeds that show the supply and demand of order flow in the form of the limit order book (LOB). AT's not only monitor the market and order flow, but also monitor, via computers, news feeds and social media feeds for information and announcements.[1] While a traditional human market maker might be able to effectively monitor the order and information flow of several stocks, computerized AT's are able to monitor hundreds and perhaps thousands of equities simultaneously. The ability to monitor more stocks effectively increases the AT's information set and, therefore, the accuracy of pricing stocks since many equities are informationally related (Jiang et el, 2009).

Theoretical models on limit order markets and market making provide a variety of predictions on how informed investors trade. Classic demand-driven trading models, such as Grossman and Stiglitz (1980), Kyle (1985), Glosten and Milgrom (1985), Easley and O'Hara (1987), and Admati and Pfleiderer (1988), are developed where a central human market maker observes the demand for order flow and subsequent imbalance, and supplies liquidity on a single exchange. Conversely, liquidity is demanded by uninformed and informed traders. In this setting, informed traders place market orders to capture profits from their information, creating a significant source adverse selection risk for market makers. In the presence of informed traders,

[1] As an example of AT computer monitoring, on April 23, 2013, the stock market adversely reacted to a fake twitter post from AP indicating that the White House had been bombed. The market dropped 134 points in a matter of seconds.

market makers respond by widening spreads, decreasing depth, and increasing price impacts. These demand driven models indicate that liquidity will decrease prior to events with high information asymmetry, such as earnings announcements.

However, in modern markets, the dynamics of trading have significantly shifted. While classic demand-driven models still provide valuable insights into liquidity and price discovery, many of the market structure assumptions used in the models are no longer valid. Post Regulation NMS, volume is fragmented between 13 active market centers, with significant quote competition among them (Upson and Van Ness, 2017). Informed traders are faced with market makers that are informationally efficient regarding order flow, material announcements, and who react in time frames best measured in microseconds or nanoseconds. The extent that informed traders can earn profits from their information is rooted in the ability to successfully hide their information when trading. If informed traders reveal directional information regarding an asset's value, market makers will quickly respond by adjusting prices, potentially removing profits from the informed trader.

As an alternative to classic demand models, recent LOB theory provides insight into the settings in which informed traders may choose to supply liquidity through limit orders rather than demand liquidity though marketable orders. Holden and Chakravarty (1995) develop a model where informed traders maximize profit by using a combination of market and limit orders. Kaniel and Lui (2006) present a model in which informed traders will use resting limit orders when the expected time horizon until the information is revealed to the market is long. Goettler, Parlour, and Rajan (2009) use a dynamic modeling method to investigate the use of limit orders by informed traders. Their model indicates that informed traders supply liquidity through limit orders when the asset value is less volatile but use market orders when the asset value is more volatile. As informed traders place orders in the LOB, depth at and away from the top-of-book becomes informative about the true value of the asset.

The model of Rindi (2008) shows that informed traders will use resting limit orders under two conditions. Informed traders prefer to supply liquidity since they have little or no adverse selection risk. First there must be effective protections against insider trading, since informed traders cannot compete with the knowledge of insiders. Second, there must be low transparency in the order book; the limit order must not identify who places the order. The requirement of low transparency prevents uniformed traders from becoming informed through the observation of order flow in the limit order book. We believe that U.S. markets meet these two requirements.

In the Rindi (2008) model, an implied self-identification constraint exists where the informed traders themselves, through their own order submissions, cannot indicate the direction of their information. However, when placing limit orders, informed traders can select non-directional order placement strategies that signal an increase in information asymmetry. A signal that there is higher information asymmetry for the target stock can reduce competition for the liquidity provision from AT and HFT liquidity suppliers. For example, informed traders can reduce the spread for companies they target. A reduction in spread is non-directional but reduces the cost of trading to liquidity demanders, which might increase execution volumes. Our research, to our knowledge, is the first to focuses on non-directional signals in the LOB.

Supply-driven and demand-driven theoretical research provide offsetting predictions of liquidity in the presence of informed traders. Demand-driven models, where liquidity supply is driven by market markers, predict that liquidity decreases in the presence of information as a means to manage adverse selection risk. Supply-driven models suggest the opposite. As informed traders supply liquidity, depth increases and spreads improve.

Using earnings announcements as our setting, in this paper we compare supply-driven and demand-driven theories of informed trading. The analysis focuses on liquidity and price discovery in the LOB around earnings announcements in the second half of 2014. Our sample consists of NASDAQ listed securities with a price greater than ten dollars but less than 300 dollars with earnings announcements contained in the IBES database. We use NASDAQ TotalView ITCH data to measure intraday trading, daily trading, and to calculate LOB metrics. As the theoretical predictions we test hinge on the presence of information, we identify high information events based on the value of the risk-adjusted return of the firm on the announcement day. For each calendar quarter of the sample, we rank announcements into terciles according to the magnitude of the announcement day returns and define the first (large negative returns) and third (large positive returns) terciles as high-shock events. We propose that these firms are targets of informed trading. As a control, the second tercile of announcements are defined as low-shock events.

Our findings indicate that informed traders increase the use of liquidity supplying limit orders to trade prior to earnings announcements. We show that prior to the earnings announcement the absolute spread for High Shock firms are lower than Low Shock firms, consistent with the supply-driven models of informed trading in the LOB. We believe that informed traders decrease spreads on High Shock firms, which is a non-directional signal of the of future returns, to increase the probability of order execution. Our findings hold after controlling for other determinates of the quoted spread and when relative spreads are used.

To meet the self-identification constraint requirement of Rindi (2008), the informed trader will minimize the directional signal to the market while maximizing the number of shares executed on the desired side of the market. This occurs when ask and bid depth are symmetrical.[2] We show

[2] Informed traders in the LOB face a Kyle (1985) type trade-off between the amount of information released to the market and the profits that can be attained thought trading on the information. AT's and HFT's cannot only observe

that the ask and bid depths are generally economically and statistically equal prior to earnings announcements for High Shock firms with the difference between ask-side and bid-side depth being less than 10 shares. For Low Shock firms prior to the announcement the difference between ask-side and bid-side depth averages about 100 shares. As a consequence of informed traders attempting to minimize the directional signal by keeping depth on both sides of the limit order book symmetrical, the correlation coefficient between ask-side and bid-side depth will be higher for High Shock firms. We find this is the case. The correlation coefficient between ask and bid depth is higher for High Shock firms compared to Low Shock firms prior to the earnings announcement. In addition, when the correlation of ask and bid depth is used as an explanatory variable for spreads, we find the coefficient is negative and significant at the 1% level.

Goettler et el (2009) show that informed traders will place resting orders not only at the top of the book, but, also in the book away from best prices. The self-identification constraint requirement of Rindi (2008) implies that depth-of-book orders, like top-of-book orders, will be symmetrical with resting orders on the opposite side of the book. To evaluate this implication we adopt the Cost of a Round Trip (CRT) order method applied by Irvine, Benston, and Kandel (2000) and Domowitz, Hansch, and Wang (2005). CRT measures the implied cost of purchasing a fixed number of shares from the ask side of the market and then immediately selling the shares on the bid side of the market. CRT is reported on a cost per share basis. If the depth of the LOB becomes more symmetrical, the CRT for High Shock firms should be lower. We find that the CRT for High Shock firms is both statistically and economically significantly lower. For an implied 500 share

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the LOB for order flow but also can test reactions by submitting orders to the market in an effort to detect the directional information of the informed trader. We are not saying that informed traders will blindly match opposite market depth, but that they will strategically place orders to minimize the directional signal while maximizing the number of shares offered and maximizing execution probabilities. These actions will result in an increase in the correlation of ask and bid depth, not perfect correlation.

order the CRT for High Shock firms is $0.03 lower, or $15 lower for the full order. For a 1,000 share order the CRT for High Shock firms is approximately $0.08 lower per share, or $80 lower for the full order. By placing resting orders in the LOB, informed traders reduce the cost of trading which can induce higher trading volumes allowing the informed trades to fill larger positions.

If informed traders use resting orders in the LOB to fill positions, then the price discovery component from the LOB should have a predictive effect on the earnings shock. Using the information shares method of Hasbrouck (1995) and following the methods of Cao et el (2009) we show that the information share of trades over the 5-day period prior to the announcement has little explanatory power to explain the cross sectional absolute values of announcement returns. However, we find that the information share component of the limit order book does have explanatory power over the same period.

The paper is organized as follows. Section I contains a brief literature review. Section II develops the testable hypotheses based on theoretical research in informed trading in the LOB. Section III reviews the sample, data, and methods applied in the study. Section IV presents our results and section V presents our conclusion.

I. Literature Review

Demand driven informed trading theory is generally based on a market with a central market maker whom observes order flow.[3] Informed traders place market orders to take advantage of their information and earn profits. Examples of these models are Grossman and Stiglitz (1980), Kyle (1985), Glosten and Milgrom (1985), Easley and O'Hara (1987), and Admti and Pfleiderer

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[3] Not all theoretical papers on informed trading are based on a single market or single market maker. Chowdhry and Nanda (1991) develop an informed trader model with multiple markets while Pagano and Roell (1996) compare auction and dealer markets.

(1988).[4] The informed traders' problem is how to submit orders to the market that maximize profit while minimizing the amount of private information released. In the context of earnings announcements, Lee, Mucklow, and Ready (1993) find that spreads increase and depth decreases prior to the announcement. This finding is consistent with the adverse selection problem of liquidity suppliers during periods of high information asymmetry and supports the demand driven informed trading models with a central market maker.

More recently, theoretical, empirical, and experimental work provide insights on the use of limit orders by informed traders.[5] Holden and Chakravarty (1995) develop a model where informed traders use a combination of limit and market orders to maximize profits. Kaniel and Liu (2006) model the use of limit orders when there is a long period of time before the information is revealed to the market. They present evidence based on TORQ data that informed traders do use limit orders. Boulatov and George (2013) develop a model which shows that informed traders will aggressively supply liquidity when limit orders can be hidden. Rindi (2008) examines the market rules that will influence the choice of informed traders to supply liquidity. She shows that informed traders will supply liquidity when 1) there are effective limitations and constraints on insider trading, and 2) there is low pre-trade transparency. Informed traders prefer to supply liquidity because they have low or no adverse selection risk. Goettler, Parlour, and Rajan (2009) (GPR henceforth) use a dynamic model to investigate the use of limit orders by informed traders. They suggest that informed traders might submit the bulk of limit orders to the market when the fundamental volatility of the asset value is low. However, if asset volatility is high, informed

[4] Our list of example models is not exhaustive. Many seminal works could be recognized. Our goal is only to give examples of the type of the literature. A more complete treatment of classical market microstructure theory is found in O'Hara (1998)

[5] A number of other theoretical papers examine the use of limit orders including Seppi (1997), Parlour (1998) Foucault (1999), Parlour and Seppi (2003), and Goettler, Parlor, and Rajan (2005, 2007).

traders will use market orders. In the context of this study, we believe the low volatility regime is before the earnings announcement. After the announcement the volatility of the asset increases as announcement information is processed.

Bloomfield, O'Hara, and Saar (2005) conduct an economic experiment for trading involving informed and uninformed traders. They find that the dynamics of liquidity supply are complex, however, they show that informed traders use more limit orders than do uninformed traders. Anand and Chakravarty (2005), using TORQ data, find evidence that informed traders tend to take liquidity in the morning but supply liquidity in the afternoon.[6] Collin-Dufresne and Fos (2015) investigate the impact of informed trading on measures of adverse selection and liquidity. They find evidence that informed traders use both market and limit orders.

There are also several relevant studies regarding trading prior to earnings announcements. Kim and Stoll (2015) study the information content of trading imbalances prior to earnings announcements and other informational events. They find that trade imbalances do not well reflect the information held by informed traders. If informed investors are on the limit order side of the market this could explain the finding. So and Wang (2014) investigate return reversals prior to earnings announcements. Using data form 1996 through 2011 they find a significant increase in return reversals prior to earnings announcements and use the return reversals as a proxy for increases in compensation to liquidity providers to demand liquidity. Using limit orders, informed traders can obtain execution volume from the variation in stock price.

While there are many research efforts devoted to informed and liquidity trading prior to earnings announcements, the use of the limit order book for informed trading prior to earnings announcements has not been investigated to our knowledge. We contribute to the literature by

[6] Anand and Chakravarty (2005) identify informed traders following Barclay and Warner (1993). They assign medium size trades to informed traders.

testing classic and modern theories of informed trading by investigating the use of limit orders prior to earnings announcements, and find significant evidence that informed traders do in fact use limit order prior to the announcement.

II. Hypothesis development

Rindi (2008) develops a model of informed trading in the limit order book. She shows that there are two requirements for informed traders to use limit orders. First, there can be no, or limited, insider trading. Since insiders will have superior information compared to external informed traders, informed traders will lose to insiders and therefore not trade. Second, there must be low pre-trade transparency. If uninformed traders can observe the placement of limit orders by informed traders then their informational advantage is expropriated by the uninformed. In U.S markets the SEC actively investigates and prosecuted insider trading which we believe effectively meets the first requirement of the Rindi (2008) model. Common data feeds such as the ITCH data feed, do not identify the source of the limit order initiator. We feel this meets the second requirement of Rindi (2008).

The Rindi (2008) model also implicitly limits informed traders from self-identification. For example, placing large limit buy orders at the bid will signal to the market that the firm is undervalued. Equivalently, aggressively undercutting the prevailing ask price can signal to the market that the firm is overvalued. However, informed traders may choose to create a non-directional signal to the market that there is increase information asymmetry for a given stock. Signaling an increase in information asymmetry for a given firm might have the benefit of decreasing completion for the liquidity provision by HFT's and AT liquidity suppliers. If HFT's and AT liquidity suppliers infer a higher information asymmetry to a firm, without knowing the future direction of the price move, they may become less aggressive with their limit order placement, reducing the competition for the liquidity provision.

GPR (2009) (observation 2) states the informed traders will, on average, set quotes. Kaniel and Liu (2006) show that with the time horizon is long, informed traders will use limit orders to trade. In addition, the spread of a stock is non-directional. A decrease or increase in spread does not signal the direction of a future price move. A decrease in spread will also decrease transaction costs which might increase trading volume from noise traders. Thus, we propose our first hypothesis.

H1: Spreads will be smaller for High Shock compared to Low Shock firms.

While this might be counter intuitive based on classical informed trading models such as Kyle (1985), Rindi (2008) shows the informed traders have lower adverse selection and inventory-bearing costs. They can therefore place more aggressive orders, narrowing the spread.

Further motivated by the limits on self-identification of Rindi (2008), limit order traders must be aware of their order submission strategies when filling their desired position. For instance, placing large limit orders on the ask (bid) side of the market for negative (positive) earnings announcement would signal to the market the expected direction of future stock prices from the imbalance of ask (bid) depth. However, matching the depth on the opposite side of the quote would reduce any such signal. As an example, suppose the informed trader is expecting a negative shock to earnings which would produce a negative return. Informed traders could place limit sell orders on the ask side of the market. If the bid depth decreases, informed traders may cancel orders on the ask side of the market to reduce a downward signal. If the bid depth increases, informed traders could place more orders on the ask side of the market, potential increasing counterparty execution.

This limit order strategy would result in an increase in the covariance between depth on the ask and bid side of the quote for companies with high earnings shocks.

This order submission strategy may also decrease the order aggressiveness of other liquidity suppliers. Ranaldo (2004) finds that liquidity suppliers place more aggressive limit orders when the opposite side book is thinner but become less aggressive when bid and ask depth is symmetrical or the spread is narrower. A more balanced top-of-book would increase the covariance of ask and bid depth but may also limit price undercutting by other liquidity suppliers. This implies the covariance for High Shock companies would be higher (or less negative) than Low Shock firms. A change in covariance is non-directional. Thus:

H2A: The covariance of ask and bid depth is higher for High Shock firms compared to Low Shock firms.

While hypothesis H2A evaluates top-of-book depth, we should also see an increase in depth-of-book covariance based on observation 2 of GPR (2009). However, as more price points are added to the analysis, the covariance structure becomes complex and difficult to interpret.[7] A higher correlation between the ask and bid depth in the book also implies that round trip trading costs are lower. If depth in the book has a higher covariance, then the implied cost of roundtrip trades (CRT) of High Shock firms should be lower than the CRT of Low Shock firms.

H2B: The cost of a round trip trade for High Shock firms will be lower compared to Low Shock firms.

Hypotheses H2A and H2B are univariate statements. However, there are other known determinates of spreads and transaction costs. If informed traders place orders in the LOB to fill

[7] Not only would the pair wise covariance between two price points on the ask and bid side of the market need to be considered, but the covariance between cross price points would need to be considered. The covariance structure would be similar to a portfolio of stocks. There would be N(N-1) covariance terms where N is the number of price points away from the top of book to be evaluated.

a position, then the correlation of ask and bid depth will also be a determinate of transaction costs in the cross section of firms. The correlation of ask and bid depth is mathematically independent of the spread.[8] We expect the correlation coefficient of book depth to be negative and significant.

H2C: In the cross section, an increase in the correlation of ask and bid depth will be negatively related to transaction costs.

GPR, observation 2, states that informed traders will have a greater share of limit orders away from the top of the book. Kaniel and Liu (2006) show that informed traders will become more aggressive as the time horizon until the release of information decreases. We follow the basic method of Cao et el (2009) to find the information share of the limit order book. Specifically we use the top-of-book quote midpoint to proxy for the most aggressive limit orders, and the depth-of-book quote midpoint to proxy for information away from best prices. Our hypothesis is then:

H3A: The absolute value of the risk adjusted earnings return is increasing in the information share of the quote midpoint.

H3B: As the earnings announcement approaches, the information share of the depth-of-book will decrease in importance.

The information share of a price channel is non-directional, meeting the Rindi (2008) requirement of no self-identification. If informed traders are using the LOB to trade prior to earnings announcements, then the information share of the LOB should have cross sectional explanatory power in the ex-post return performance of the firm after the announcement. Hypothesis 3A is a statement of this outcome. Kaniel and Liu (2006) indicate that informed traders will become more aggressive as the release of information to the market approaches. In our

[8] To calculate the correlation of ask and bid depth we first find the time weighted ask and bid depth for each minute of a stock day. We then find the correlation between the two series. Since the spread is not part of the calculation it is possible to have high spread firms with high correlations of depth.

context, informed traders will place more orders at the top-of-book and less orders in the depth-of-book. This will lead to a drop in the impact of the information share if the depth-of-book.

III. Data and methods

A. Sample

Our sample contains earnings announcements contained in the IBES database from 1 July, 2014 through 31 December, 2014. We obtain firm level information from the Center for Research in Securities Prices (CRSP) database, and order and trade level data from the NASDAQ TotalView ITCH database. The ITCH database reports all orders submitted to the NADSAQ exchange, along with subsequent updates, executions, and deletions. Using this database, we are able to rebuild the limit order book to view depth beyond the best bid and offer. We restrict our sample to CRSP share codes 10 and 11 and require that firms have an average closing price between $10 and $300. As we utilize NASDAQ order level data, we restrict the firms to be listed on NASDAQ.

To create our sample of high and low shock events, we partition stocks into terciles based on the announcement day return, relative to the most recent closing price prior to the announcement. For firms with announcements after the market closes, the first trading day is the following day. For firms with announcements before the market opens, the first trading day is the same day. We risk adjust the daily return by subtracting the corresponding same-day market return We use the magnitude of close to close returns, rather than earning surprise, since additional information, such as forward looking statements and conference call results, is included in the close to close return but not included in the earnings surprise. We rank the risk adjusted announcement returns into terciles, and classify the first (large negative returns) and third (large positive returns) as high-shock announcements. The second tercile of announcement day returns is classified as Low-Shock announcements. As our sample covers two quarters, a firm may have multiple announcements assigned to different terciles.

The final sample includes 979 unique firms, which collectively have 1,686 earnings announcements during the sample period. Table I shows selective descriptive statistics of the firms contained in the analysis. When sorted according to the size of the return on the first day of trading following the announcement, there are 562 announcements we classify as a positive shock (which have an average first trading-day return of 7.0%), 562 events classified as a negative shock (which have an average first-trading day return of -7.3%), and 562 low-shock announcements where the first-day return is between the prior two. Prior the earnings announcement, all three event types have muted average daily returns. As the median firm has two earnings announcements during the time-period, the shock classifications are not mutually exclusive. We find 487 firms experience at least one positive shock, 504 firms experience at least one negative shock, and 478 firms experience at least one low-shock announcement. The mean (median) firm size in our sample is $5.26 billion ($982 million), with a daily volume of 996 (216) thousand shares traded, and a closing price of $35.84 ($27.18), as measured by the 45-days prior to the earnings events.

B. Methods

Our study draws on different components of the limit order book. To study transaction costs and liquidity, we compute the cost of a round-trip trade (CRT). To measure the limit order book implied price of a security, we calculate the depth-of-book midpoint. To calculate the information channel of the limit order book, we use the information shares method of Hasbrouck (1995).

B.1 Cost of a round trip trade

We adopt the Cost of a Round Trip (CRT) order method of Irvine et el (2000) and Domowitz et el (2005) as a measure of depth that incorporates the spread. The CRT method creates a theoretical cost of an order of a fixed size. We use fixed order sizes of 500 and 1,000 shares. Figure 1 shows an example of the CRT calculation based on a 500 share order. On the ask side of the market a 500 share order will execute 300 shares at a price of 20.00 and 200 shares at a price of 20.01 for a total price of $10,002. On the bid side of the market a 500 share order will execute 100 shares at 19.95, 300 shares at 19.94, and 100 shares at 19.93 for a total price of $9,970. We then divide the difference by the number of shares in the order for a cost per share of $0.064. The CRT is calculated every time there is a message submitted to the LOB in the ITCH data. The individual CRT values are time weighted to find the average for the day.

B.2 Depth of book midpoint

To evaluate the limit order book implied price of a stock, we calculate the depth-weighted midpoint. Although the quoted-midpoint is a commonly use metric for the value of a security, our analysis hinges on the information of limit order traders. Therefore, we supplement the quote mid-point with the depth-weighted midpoint as a measure of the stock's price. To compute this measure, we first calculate the depth-weighted bid and offer price as

$$DWAP_{bid/offer} = \frac{\sum_{\tau=1}^{T} P_\tau D_\tau}{\sum_{\tau=1}^{T} D_\tau}.$$

We then take the midpoint of the depth-weighted bid price and the depth-weighted ask price.

B.3 Information Share Method

If informed traders are using resting orders in the LOB to fill positions one might expect that the market will react to changes in the LOB as informational events. We investigate this question using the Information Shares method developed in Hasbrouck (1995). The method uses a vector autoregressive error correction model to decompose the random walk contribution from each price vector into the efficient price evolution process. We consider three price vectors for the analysis, the last trade price, the top of book quote midpoint, and the depth of book midpoint (From the previous section). We follow Hasbrouck (2003), Anand and Chakravarty (2007), and Goldstein, Shkilko, Van Ness, and Van Ness (2008), among others, in the use of transaction prices. Unless the resulting variance co-variance matrix is diagonal, the information share estimate for each price vector is not uniquely identified. We therefore average the upper and lower bounds as our point estimate of information share for a price vector.

IV. Results

A. Quoted Spreads

Our quoted spread analysis period includes the five days prior to the earnings announcement, the first day of trading after the announcement (t=0), and one day following the announcement. Using the NASDAQ TotalView ITCH data, which includes all orders and trades on the NASDAQ exchange, we rebuild the LOB and calculate the quoted spread using the NASDAQ BBO at each moment the BBO is updated. We time-weight the quoted spread and report the averages at the daily level. Our results are reported in Table II.

Panel A of Table II shows the absolute spread in dollars for Low and High Shock events. Rindi (2008) hypothesizes that informed traders are able to set tighter spreads because they have lower adverse selection costs. For all days in the analysis the absolute spread of High Shock events is statistically and economically lower than Low Shock events. On Day-5 the spread for Low Shock events is 0.122 while for High Shock firms the spread is 0.102. This difference is significant at the 1% level. Before the announcement, the difference in spread is largest on Day-2 where Low Shock firms have a spread of 0.130 and High Shock firms have a spread of 0.108 for a difference of 0.029 dollars. Consistent with Lee et el (1993) spreads widen for all firms as the announcement day approaches.

After the earnings announcement the spreads of High Shock firms remain smaller than the spreads of Low Shock firms. This result could be caused by several issues. Informed traders may still place resting order in the LOB and tighten the spread because of their lower adverse selection risk. Also, the reduction in information asymmetry in the post announcement period could result in lower spreads for High Shock firms because the announcement is more definitive and gives the market a better understanding of firm value.

Panel B of Table II shows the results for relative spread. The relative spread is measured as 2*(Ask-Bid)/(Ask+Bid) and is reported as a percent, which corrects for any spread effects due to the price of the stock. Our findings for the relative spread are the same as those of the absolute spread. Across the sample period, the relative spread of High Shock announcements are lower than the relative spread of Low Shock announcements. On the Day-1 the relative spread for Low Shock announcements is 0.453% while for High Shock announcements it is 0.349% with a difference of 0.103%. All differences are significant at the 1% level.

While our findings on the spread of High and Low Shock announcements is consistent with the Rindi (2008) model and support hypothesis 1, there are other variables known to impact the spread. In section D of the results we account other factors that could affect our results, such as firm size, stock price, order size, and trade intensity. After controlling for these factors our findings remain the same; spreads are smaller for High Shock firms.

To evaluate the robustness of this result, we consider an alternate setting. In the result presented in Table II, events are classified as high-shock and low-shock without any consideration of prior shock events. It is possible that there are unaccounted for characteristics of high-shock firms that naturally lend to tighter quoted spreads. To alleviate this concern, we consider an alternate test setting where we take the subset of firms experiencing a high-shock announcement immediately after the quarter of a low-shock announcement. We then compare these events against the control of low-shock events, where low-shock events are only considered if the previous quarter was a high-shock event. We test whether the difference is significantly different than zero. From this test, which is unreported in tabular form, but shown visually in Figure 2, we find no significant difference between high-shock and low-shock events up until about fifteen days prior to the announcement. From this point and up until the announcement, high-shock events have a lower quoted spread than the comparable low-shock events.

B. Quoted Depth and Depth Correlation

Informed traders will always face the challenge of profitably trading from their information advantage, while minimizing the unintended consequence of alerting the market to the presence of information through their trading. If an informed trader signals the direction of a future price move, liquidity suppliers can quickly adjust prices, reducing the potential profits of the informed. A pure demand driven trading strategy that consumes liquidity would likely be detected by AT and HFT traders due to the automated monitoring mechanisms in place. Similarly, a large limit order placed by an informed trader could signal to the market the direction of a future price move.

Although signaling the direction of a future price move is not desired, there are advantages to signaling the presence of information asymmetry. If the trader can successfully submit a non-directional signal to the market that an informed trader is present, then competition for liquidity provision in the limit order book may decrease. AT's and HFT's may place fewer, less aggressive orders due to an increase in information asymmetry, improving the execution probabilities of resting orders from informed traders. The directional signal can be minimized by increasing the correlation between ask and bid depth, which is non-directional, but can signal increased information asymmetry.

Figure 3 shows a time series plot of the correlation of ask and bid depth for both High and Low Shock events. We calculate the correlation of ask and bid depth by first finding the time weighted average depth for each minute of the trading day, and then average to the daily level. High Shock events, shown by the solid line, have a higher correlation coefficient compared to Low Stock events, for all days around the earnings announcement. As the announcement approaches, the correlation of ask and bid depth increase for all announcement events in the sample. However, the correlation of ask and bid depth peaks for High Shock announcements on the day of the announcement. Low Shock announcements have the highest correlation on Day+1. The correlation of depth drops after the announcement peak for High Shock events. The plot indicates that earnings announcements do impact the correlation of ask and bid depth. In Table III we formally test ask and bid depth as well as depth correlation.

For each stock day in our sample, we calculate the time weighted average of depth at the NASDAQ BBO. We report the average depth at the ask and bid price for Day-5 through Day+1, and conduct a pared t-test for the difference between ask and bid depth. In Panel A of Table III we present results for the High Shock firms, while Panel B presents the results for Low Shock firms. For High Shock firms, the depth at the ask and bid prices are very similar on pre-announcement days. The maximum difference in the pre-announcement period is 9.3 shares on Day-2, which is statistically significant with a P-value 0.093. Ask and bid depths are less symmetrical for the Low Shock firms with the maximum difference of 165.7 shares, again on Day-2. For Low Shock firms ask depth is smaller than bid depth for all days, however, it is only statistically smaller on Day-5 and Day-2 with P-values of 0.078 and 0.074 respectfully.

For High Shock firms, after the announcement, we find a statistically significant difference of ask and bid depth where ask depth is greater than the bid depth. For Low Shock firms we find no statistical difference between ask and bid depth. Overall, the total depth of liquidity offered for High Shock firms is lower than the total depth offered for Low Shock firms; roughly 800 shares for High Shock firms and 1000 shares for Low Shock firms. Our spread findings of the previous section appear to be independent of the quoted depth at the best bid and offer.

Panel C of Table III shows the average correlation coefficients of ask and bid depth for High and Low Shock firms. We conduct a means difference t-test of the correlation. Prior to the earnings announcement we find a statistically significant difference in correlation on Day-1. The difference in depth correlation is highest on the announcement day with a Low-High difference of -0.034. We believe the higher correlation of depth and more symmetrical bid and ask depth for High Shock firms is an indication of informed trading in the LOB. By keeping ask and bid depth approximately equal, any directional signal to the market is minimized and the highest number of shares can be offered by the informed trader as a resting order. Although we only find a statistical difference on Day-1 we will present additional support of the impact of the correlation of depth in section D.

C. Cost of Round Trip orders

If informed traders are using resting orders in the LOB to fill a position, there is an incentive to encourage trading activity complete the position. As such, increasing liquidity and decreasing trading costs may encourage uninformed liquidity demanders to trade more. As spreads only consider top-of-book depth, we implement the CRT measure to account for liquidity beyond the top of the book. In this section we examine the CRT of 500 and 1,000 share orders. The CRT is presented on a cost per share basis and is time weighted for each stock day. GPR (2009) suggest informed traders place their orders at both the top of the book and also deeper in the limit order book to capture volume as the asset price moves. For example, if the informed trader believes that the earnings announcement will be positive, they will place limit orders at the best bid and prices below the best bid to capture volume from a temporary downward price move. However, this strategy is limited by the self-identification constraint of Rindi (2008). We believe that, similar to the correlation of the top of book depth, informed traders will balance the depth of book orders against the liquidity offered on the opposite side of the market. This will reduce the cost of round trip trading and reduce costs for uninformed liquidity demanders that wish to either buy or sell the stock.

Table IV shows the results of our CRT analysis. Panel A shows the results for a 500 share order while Panel B shows the results for a 1,000 share order. Uniformly the CRT for 500 and 1,000 share orders are economically and statistically significantly lower for High Shock firms compared to Low Shock firms. For 500 share orders the CRT is generally 0.03 dollars lower. This equates to a $15 reduction in round trip cost for a 500 share order. The cost reduction is higher for the 1,000 share order. The smallest difference between Low and High shock firms is on Day-3 and Day-4 at 0.08 dollars per share. This equates to a 0.08 dollars/share * 1,000 shares=$80 reduction in the round trip costs between Low and High Shock firms.

The average stock trades over 400,000 shares on the day of the earnings announcement. Using the cost reduction for the CRT 500, this equates to a $15*400,000/(500*2)=$6,000 cost reduction per stock day. We multiply the 500 shares by 2 since it is a round trip order. Since our sample contains 1,165 High Shock firms the cost reduction per day is an economically significant

$6.99 million per day. The analogous computation for the average, non-announcement day, yields a cost reduction of $3.93 million per day.

Uninformed liquidity demanders should be equally likely to buy or sell the asset for liquidity needs, and thus, as a group evaluate transaction costs from a CRT point of view. If informed traders increase the correlation of depth using resting orders, it will reduce transaction costs for uniformed liquidity demanders and possibly increase transaction volume. As indicated in Rindi (2008), informed traders have lower adverse selection costs and can therefore offer liquidity at lower prices and lower overall costs. This cost reduction is non-directional and improves the probability of execution for informed resting orders, while carrying the advantage of not leading to self-identification.

D. Regression Analysis

D.1 Regression Specification

Our analysis of the LOB metrics to this point have been univariate. We recognized that other variables that vary in the cross section of firms will have an impact of the univariate metric. In this section we use regression analysis to control for other variables. Our primary variable of interest is the correlation of ask and bid depth; *DepCorr*. Our primary contentions is that informed traders wish to minimize the directional signal to the market while offering the largest possible number of shares for execution. It may be technically possible for informed traders to use trading algorithms to exactly match any order cancelation or addition on the opposite side of the market and to create a correlation of depth that is close to 1. However, while it might be technically possible, such an algorithm would have two significant flaws. First, assuming that more than one informed trader is trading on the same basic information, the informed traders would have to perfectly coordinate their liquidity supply. While there are some clear legal problems with this level of collusion, there are also potential problems on the equitable distribution of profits and the real potential for cheating, see for example Holden and Subrahmanyam (1992). More importantly, sophisticated AT and HFT traders would be able to test and, in our view, detect the direction of this level of correlation, violating the self-identification constraint. In a very real sense, informed traders in the LOB still face a Kyle (1985) type tradeoff of how much signal they should place into the market to maximize profits.

We estimate the following regression by maximum likelihood for each of the individual five days prior to the earnings announcement. Jiang et el (2009) show that firms in the same industry SIC code have common liquidity reactions to informational events. We therefore estimate the regressions with clustered standard errors, clustering on industry SIC code. When then apply the Fama and Macbeth method to average the coefficients with a Newy-West correction to standard errors.

$$\begin{aligned} Liq_{i,t} = \alpha + \beta_1 DepCorr_{i,t} + \beta_2 VolImbal_{i,t} + \beta_3 LnMOsize_{i,t} + \beta_4 LnMcap_{i,t} \\ + \beta_5 InvPrc_{i,t} + \beta_6 VolTurns_{i,t} + \varepsilon_t \end{aligned} \tag{1.1}$$

Here *Liq* represents the LOB metric of absolute spread, relative spread, CRT500, and CRT1000.

DepCorr is the correlation of ask and bid depth at the top of book. *VolImbal* is the absolute value of (Buy Volume-Sell Volume)/Total Volume. *VolImbal* is included for two reasons. First, it is our contention that simple demand based trading strategies will be detected and adversely impact the liquidity provision of the LOB. These volume imbalances could be created by informed traders using demand based trading, or from natural variation in demand driven by uninformed liquidity traders. We will investigate the potential sources of demand based liquidity in the next section of the analysis. Second, volume imbalance is an observable metric in the ITCH data. If informed traders absorb the imbalance of the side of the market they want, but leave the imbalance unabsorbed on the side of the market they do not want, they will violate the self-identification constraint. Menkveld (2013) finds that HFT's inventory position leads to price pressure. If the HFT has negative (positive) inventory they will lower (increase) prices to induce buying (selling) to adjust their inventory position. However, by using a limit order strategy rather than a market order strategy, informed traders may be able to slow the inventory builds of AT and HFT liquidity suppliers, reducing the speed and magnitude of price reaction by AT and HFT liquidity suppliers due to their inventory builds.

LnMOsize is the size of the marketable order submitted to the NASDAQ exchange. We follow the method Upson, Johnson, and McInish (2017) to find the marketable order size. Specifically, NASDAQ reports execution messages based on the size of the resting order in the LOB. To obtain the size of the marketable order we sum all executions at the same price in the same nanosecond. *LnMcap* is the natural log of the firm's market capitalization. *InvPrc* is the inverse of the closing price on the day of the analysis. *InvPrc* is dropped in the relative spread regression since it is incorporated on the left hand side in the calculation of relative spread.

VolTurns is the executed volume in shares on the analysis day divided by the number of shares outstanding in units of 10,000. We use *VolTurns* rather than volume executed because the LOB metrics and executed volume have a simultaneity issue. Changes to the LOB metrics can increase or decrease the cost of execution impacting execution volume but execution volume can impact the LOB metrics. One potential option to address the simultaneity between volume and LOB metrics would be a 2SLS regression if suitable instruments could be identified. Given the time dependent nature of information prior to earnings announcements, we believe that using lagged values as instruments would be invalid. An alternative solution is to use execution volume divided by shares outstanding since the number of outstanding shares is not simultaneously determined with LOB metrics. We believe *VolTurns* will still capture the relative market intensity in the cross section.

We re-estimate the regression equation and substitute a dummy variable for *DepCorr*. The dummy variable is *HiShk* which is 1 for High Shock firms and 0 otherwise. This specification directly tests if transaction costs are lower for High Shock firm while the use of *DepCorr* tests the impact of depth correlation in the cross section on transaction costs.

D.2 Regression Results

Our results are shown in Table V. Panel A shows the results for *DepCorr* while Panel B shows the results for *HiShk*. The coefficient of *DepCorr* is negative and significant in all of the LOB metric regressions. This indicates that an increase in the correlation of ask and bid depth is associated with lower spreads and lower costs of execution after controlling for other know variables of influence. For example, in the quoted spread regression the coefficient of *DepCorr* is -0.059 and is significant at the 1% level. While Ranaldo (2004) also find that spreads are tighter when ask and bid depth are more balanced, it is reported as a property of the market with no theoretical foundation. Mathematically, the correlation of ask and bid depth is independent of the quoted spread. In our context we believe that informed traders in the LOB are improving the correlation between ask and bid depth and reducing spreads to reduce execution costs to uninformed traders and increase execution volume while minimizing any directional signal to the market.

The coefficient of *DepCorr* is also negative and significant at the 1% level in the CRT500 and CRT1000 regressions. The authors concede that there will be at least some mechanical correlation between *DepCorr* and the CRT measure since a higher correlation between ask and bid depth indicates more balance between ask and bid depth, reducing the CRT. However, CRT is based on a fixed order size and when this fixed size is greater than the ask or bid depth, the balance of the order is filled from the depth of the book.[9] We believe that the significant and negative coefficient of *DepCorr* is evidence that informed traders reduce trading costs to entice uninformed liquidity traders to trade. Since informed traders have lower adverse selection risks they can reduced transaction costs to liquidity demanders as indicated by Rindi (2008).

The coefficient of *VolImbal* is positive and significant at the 1% level for all regressions. We interpret the positive coefficient in several ways. First, it is evidence that volume imbalances are easily detected by the market and that the reaction is to increase transaction costs. Second, if informed traders use demand based trading strategies the positive coefficient indicates that they will not only be detected, but increase the cost of acquiring the shares they seek. We acknowledge that informed traders may use a mixed strategy of demand and resting orders. Recall that *VolImbal* is the absolute value of the actual imbalance so that large negative and large positive imbalances will have the same absolute magnitudes.

Although *LnMOsize* is a control variable, we wish to comment on the negative and significant coefficient. *LnMOsize* is the natural log of the size of the marketable order. Several paper have found that smaller orders carry more information than larger orders (O'Hara et el 2015, Chakravarty et el 2012). Thus in a market that is so heavily monitored, uninformed liquidity demanders may signal their information content by submitting larger orders on average. The balance of the control variables are of the expected sign. *LnMcap* is positive, though only significant in the Relative spread regression. *InvPrc* is negative and significant in all regressions where the variable is applied. *VolTurns* is negative and significant indicating that the market responds to increases in trade intensity by adding more liquidity to the supply side of the market.

[9] In unreported results we recalculate the CRT without using top of book depth in the calculation, removing the mechanical correlation. Our results remain the same.

When we replace *DepCorr* with a dummy variable for High Shock firms, *HiShk*, our results remain the same. The coefficient of *HiShk* is negative and significant in all of the regressions indicated that transaction costs are lower for High Shock firms. Our results indicate that transaction costs are lower for High Shock firms even after controlling for other known determinates of transactions costs such as spreads.

Our regression results support and expand on our univariate findings. Quoted spreads, relative spreads, the CRT500, and the CRT1000 are lower when the correlation of ask and bid depth increase. We believe that this supports our contention that informed traders use resting orders prior to earnings announcements to fill at least some portion of their desired positions.

E. Information Share Analysis

E.1 Overview

A reasonable critique of our findings at this point is that the decreased spreads, the decreased transaction costs, and the increased correlation of ask and bid depth are a response by AT and HFT liquidity suppliers to an unobserved market variable and not a signal of informed traders placing resting orders in the LOB. In other words, informed traders may be using demand orders in such a way as to induce liquidity suppliers to reduce transaction costs on High Shock firms.

To address this identification issue we use the information shares methodology developed by Hasbrouck (1995) to investigate the information content of different price series prior to the earnings announcement of a firm. Three price channels are included in the information shares estimate; the last transaction price in a second, the top-of-book quote midpoint, and the depth-of-book quote midpoint. We follow the general process outlined in Cao et el (2008). The information shares method produces a maximum and minimum value. Following the literature, we use the average of the minimum and maximum values as a point estimate for the information share of a price channel. We estimate the information share for each stock day of the analysis.

E.2 Time Series Plot

Figure 4 shows the time series plot of the information share of each price channel segmented by High and Low Shock firms. Panel A shows the results for High Shock firms and Panel B shows the results for Low Shock firms. The figures show that the highest information share component is the top-of-book quote midpoint followed by the information share of transactions. The information share of the depth-of-book is lowest. However, the information share of the depth-of-book midpoint increases as the earnings announcement approaches and peaks during the announcement trading day. The information share of the quote midpoint is higher for high shock firms, roughly 0.44 compared to 0.41 for low shock firms. The information share of transactions decreases as the earnings announcement approaches and is smallest on the announcement trading day, but increases on trading days after the announcement.

E.3 Regression Results

Under traditional models of informed trading (Kyle, 1985; Glosten and Milgrom, 1985; Easley and O'Hara, 1987, and Admati and Pfleiderer, 1988) informed traders use market orders and meter their trading to control the release of information to the market. Our contention is that informed traders place limit orders in the LOB to fill their desired position. This hypothesis is supported by Kaniel and Liu (2006), GPR (2009), and Rindi (2008). If the former theories are correct under the current market conditions of high speed electronic trading, the information share of trades should have predictive power in the cross section of announcement day returns. If the later models are correct, the information share of the LOB should have predictive power in the cross section of announcement day returns. However, Kaniel and Liu (2006) show that informed traders will move to more aggressive orders as the release of information to the market approaches. If informed traders move from placing orders in the depth-of-book to the top-of-book a sign reversal is possible.

To test hypothesis H3A and B we estimate a regression using lagged values of the information share of each price channel on the absolute value of announcement day returns. Irvine, Lipson, and Puckett (2007) show that institutional traders significantly increase trading volume five days before an analyst releases an initial buy recommendation. Informed traders can obtain their information either through superior analysis or through the recommendation of analyst. Following Irvine et el we use the information share of a price channel five days prior to the announcement. We estimate the following regression:

$$AbsRtrn_i = \alpha + \sum_{j=-5}^{-1} \beta_j IS_{i,t-j} + \lambda Mcap_i + \varepsilon_i \qquad (1.2)$$

Where *AbsRtrn* is the absolute value of the risk adjusted stock return on the announcement trading day, $IS_{i,t-j}$ is the information share of the price channel; trades, quote midpoint, and depth-of-book midpoint. *Mcap* is the natural log of the market capitalization of the firm on the announcement day and acts as a control variable. We also estimate a logistic regression, replacing the *AbsRtrn* with a dummy variable that is 1 for High Shock firms and 0 otherwise. Our results are show in Table VI. Panel A shows the results for the *AbsRtrn* regression and Panel B shows the results for the logistic regression.

In Panel A, in the column labeled Trades we report the results for the lagged information share associated with trades against the absolute value of returns on the announcement day. The information share of a price channel represents the contribution of that price channel to price discover. Our results show that the information share of trades is not significant for any lag. It is possible that in modern electronic markets informed traders have become so good at hiding their trading intentions with demand orders that they reveal little relevant information regarding the future prices of equities. While this interpretation cannot be disproved, liquidity suppliers such as HFT's spend significant amounts of money to detect short term price moves and to anticipate the market. Menkveld (2013) shows the HFT's effectively monitor the market and react to changes in demand imbalances quickly. Brogaard, Hendershott, and Riordan (2014) show that HFT's facilitate price efficiency and trade in the direction of permanent price changes. These papers, among others, indicate that a pure demand driven strategy by informed traders is likely to be detected. However, Goettler et el (2009) and Kaniel and Liu (2006) allow for a mixed trading strategy of limit and marketable orders.

The column market Quote Midpoint is the information share regression results of lagged quote midpoint information shares against the absolute value of announcement day returns. Two of the five lagged values are significant at explaining variation in risk adjusted announcement day returns, lags four and lag two. Although lags three and one are not significant their p-values are 0.105 and 0.104 respectively. All coefficients are positive and jointly significant. We interpret these findings as supporting the model of Kaniel and Liu (2006), Rindi (2008), and GPR. Specifically that informed traders are using limit orders to fill positions prior to the announcement date. We believe that the market understands that informed traders are using the LOB and react to changes in the LOB increasing the price discover of the LOB. The increase in the information share of the LOB only indicates that a firm will be High Shock, but not the direction of the shock, meeting the self-identification restriction of Rindi (2008). While informed traders may still use market orders to fill positions, these results indicate that resting orders are also used.

A potential alternative explanation is that HFT's and liquidity suppliers are gleaning information from the order flow that is then reflected in the information share of top-of-book orders. However, this is inconsistent with the smaller spreads prior to the earnings announcement for High Shock firms. Why would HFT's decrease spreads in order to trade against informed traders? It is also not supported by the finding that the information share of trades is insignificant in predicting firm returns from the announcement.

Finally, in the column labeled Depth of Book Midpoint we show the information share results based on the LOB midpoint. Three of the five lagged information share variables are significant, lag three through lag one. However, lag one has a negative coefficient. Under Kaniel and Liu (2006) as the announcement date approaches, informed traders become more aggressive with their order placement, ultimately moving from resting orders to market orders. On the day prior to the earnings announcement, informed traders may place the majority of resting orders at the top of the book, decreasing the information content of the depth of the book or adopt a more mixed strategy of market orders and resting orders. The change of sign for the depth of book information share on the day before the earnings announcement supports this interpretation of the model and hypothesis H3B.

In Panel B of Table VI we present the results of a logistic regression where the dependent variable is 1 if the firm is High Shock and 0 otherwise. The informed trader limit order models do not explicitly indicate that the use of resting orders by informed traders will increase in the magnitude of the announcement shock. By applying a logistic regression we test a simple question if the information share of the LOB can identify High Shock firms. Similar to the findings in Panel A, the coefficients of the information share of trades is insignificant in identifying the announcement shock level of the firm. In addition, the coefficients are generally negative, indicating that the information share of trades better identifies the Low Shock firms. When the information share of the Quote Midpoint is used in the logistic regression two of the five lags are significant in identifying the shock level of announcement shock. The depth of book midpoint results indicate that the information share of the depth of book is insignificant in identifying the shock level of the announcement. The results of this regression do not support our hypothesis that informed traders are using limit orders in the depth of the book to fill positions, although the specification is sensitive to the definition of a High Shock firm. In general, the logistic regressions results offer some support that informed traders are using resting orders in the LOB to fill positions.

V. Conclusion

U.S. equity markets are highly monitored by Algorithmic Traders (AT) and High Frequency Traders (HFT) for the presents of informed traders attempting to trade on their information. Since markets are linked by high speed communication networks, offer exchange generated data feeds containing order book and order flow data, and allow co-located computer systems that reduce latency, informed traders have a distinct challenge in today's market to profitably trade on their information. We investigate if informed traders use resting orders in the Limit Order Book (LOB) prior to earnings announcements in an attempt to profit from their information.

Several theoretical papers including Holden and Chakravarty (1995), Kaniel and Lui (2006), Goettler, Parlour, and Rajan (2009), Boulatov and George (2013), and Rindi (2008) show that informed traders may prefer resting orders in the LOB rather than demand orders. Rindi (2008), Goettler, Parlour, and Rajan (2009), and Boulatov and George (2013) indicate that anonymity of order placements in the LOB is a key requirement. If informed traders are identified in the LOB they reveal their information simply by placing an order. We believe that the anonymity requirement also places a self-identification restriction on informed traders in the LOB. This implies that informed traders can only use non-directions order submission strategies in order to profit from their information. Placing a large resting order at the ask for a company with expected negative returns from the earnings announcement would signal the market that company is overvalued and violate the self-identification restriction.

We investigate the use of the LOB by informed traders prior to earnings announcements for a sample of NASDAQ listed stocks. Our sample is divided between High Shock companies, firms with high positive or negative returns on the announcement day, and Low Shock firms, with small returns on announcement days. We find that quoted spreads are lower for High Shock firms compared to Low Shock firms. Rindi (2008) shows that informed traders have lower adverse selection and inventory costs and therefore can place more aggressive orders. In addition, a decrease in spread is non-directional, meeting the self-identification constraint. Our spread findings are robust to the inclusion of other known determinates of spreads.

The informed traders' problem in the LOB is to minimize the directional signal to the market while maximizing the number of shares offered to maximize profits. In the LOB, the directional signal is minimized when ask depth is equal to bid depth. We posit that informed traders will increase the correlation of ask and bid depth in order to minimize the directional signal while maximizing the shares offered. By increasing the correlation between ask and bid depth, informed traders reduce transaction costs to uninformed liquidity demanders prior to the earnings announcement, possible increasing the probability of resting order execution. We find that the correlation of ask and bid depth is higher for High Shock firms and that the cost of round trip trading is both statistically and economically lower compared to Low Shock firms.

While informed traders are constrained in directional signals, they are permitted to signal a higher degree of information asymmetry for firms prior to earnings announcements. This signaling may reduce competition in the LOB from AT and HFT liquidity suppliers. In addition, if informed traders are using the LOB for order submission, the Hasbrouck (1995) information share of the LOB should increase. We show that the information share of the LOB does positively predict the announcement returns of firms, however, the information share of transactions does not. While informed traders may adopt a mixed strategy of demand and supply orders, we find that there is evidence that informed traders use the LOB to fill positions prior to earnings announcements.

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	Price	Depth
	20.02	100
	20.01	200
Best Ask	20.00	300
Best Bid	19.95	100
	19.94	300
	19.93	500

CRT for 500 shares = ((300*20.00+ 200*20.01)-(100*19.95+300*19.94+ 100*19.93))/500=0.064 per share.

Figure 1: An example of the Cost of Round Trip (CRT) order calculation for 500 shares.

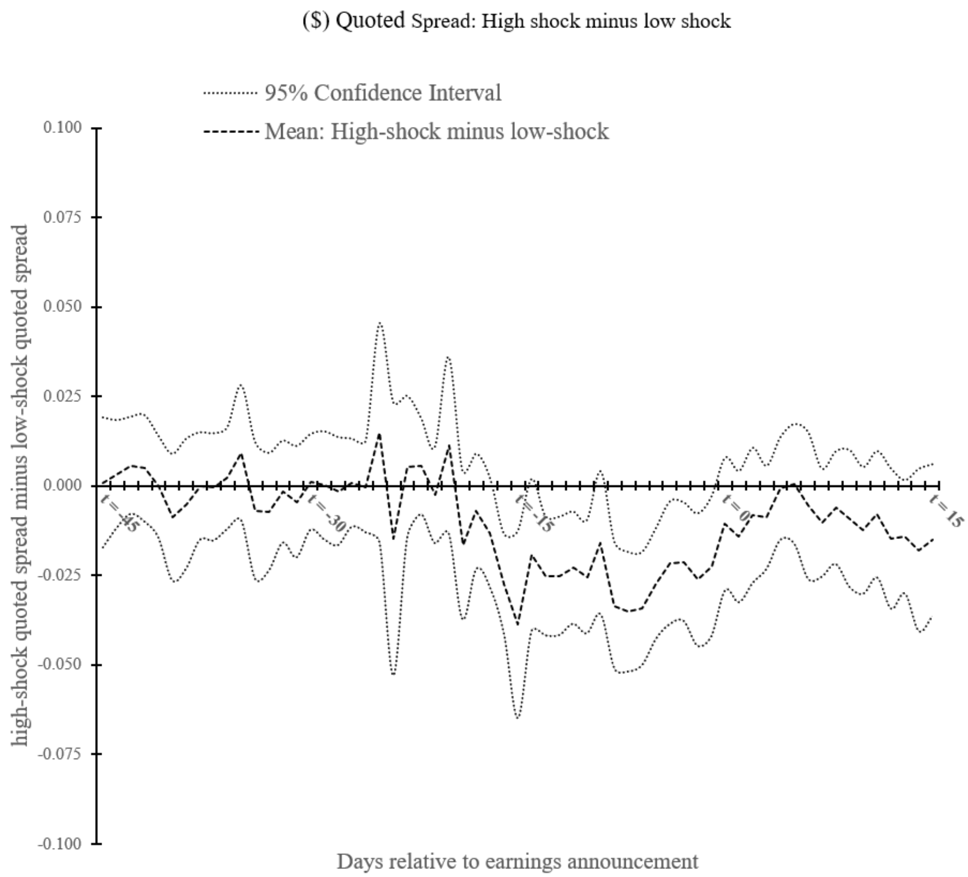

Figure 2: The difference between the quoted spread of a high-shock event and the quoted spread of a low-shock event. In this particular test design, high-shock events only include the subsample of earnings announcements where the previous shock was a low-shock. Conversely, low-shock events only include the subsample of events where the previous event was a high-shock event.

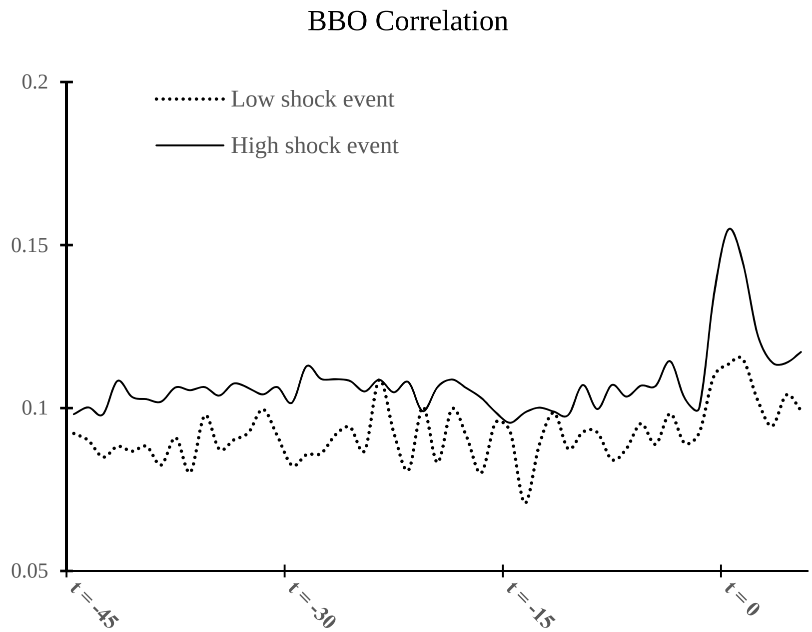

Figure 3: Time series plot of the time weighted covariance of ask and bid depth for high and low earnings shock firms. Day 0 is the day of the announcement.

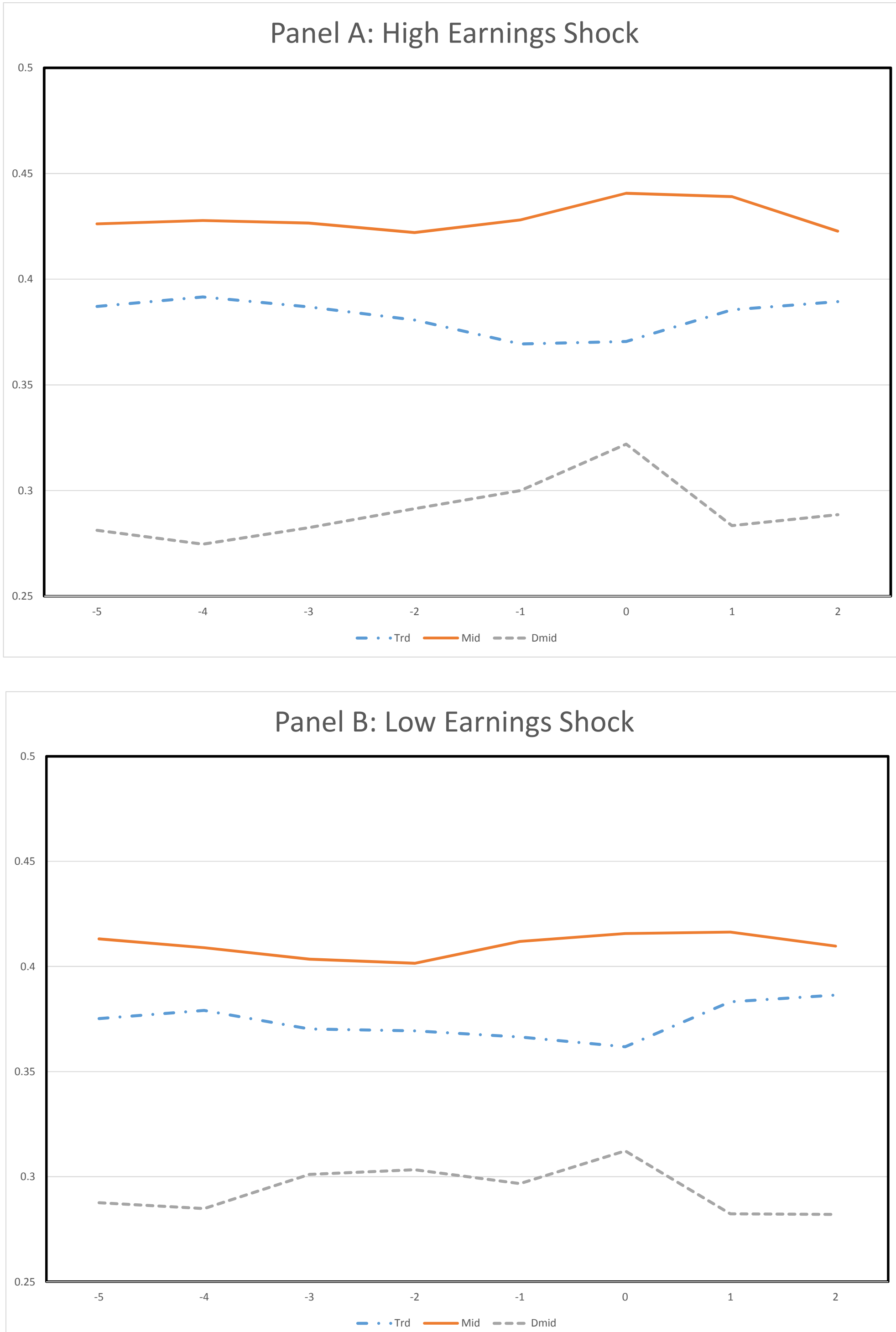

Figure 4: Panel A shows the time series plot of the information share of trades, the quote midpoint, and the depth of book midpoint for high shock firms. Panel B shows the time series plot of the information share of trades, the quote midpoint, and the depth of book midpoint for low earnings shock firms.

Table 1
Descriptive Stats

This table reports average daily summary statistics for Nasdaq-listed securities between July 2014 and December 2014. Securities are filtered to include firms with have an average stock price of between $10 and $300. Statistics are reported for the entire sample and for partitioned terciles according to the size of the earnings shock. Earnings shocks are defined as the stock return on the day of the announcement, risk adjusted by subtracting the value weighted return of the market. Range is the daily high price minus the daily low-price, as reported on the NASDAQ exchange. Midpoint volatility is the standard deviation of the mid-point at one-minute increments. Volume, which is reported in thousands, reflects trading activity on the NASDAQ exchange. The Positive and Negative Shock events are referred to as high-shock events, while neutral shocks are defined as low-shock events. These data are obtained from the Center for Research in Securities Prices (CRSP) and NASDAQ TotalView ITCH database.

Panel A: Firms and Unique Announcements

	Unique Firms	Earnings Events
Full Sample	979	1686
Tercile 3	474	562
Tercile 2	452	562
Tercile 1	474	562

Panel B: Summary Statistics: 45-Day average prior to earnings announcement

	Market Cap (Thousands)	Closing Price	Daily Return	Daily Range ($)	Midpoint Volatility ($)	Daily Volume
Mean						
Full Sample	5,262,951	35.84	0.000	0.024	0.190	996,278
Tercile 3	5,234,803	38.45	0.000	0.025	0.207	1,149,465
Tercile 2	6,236,176	34.08	0.000	0.022	0.162	907,565
Tercile 1	4,317,368	34.99	0.000	0.026	0.202	932,011
Median						
Full Sample	982,352	27.18	-0.001	0.020	0.132	216,751
Tercile 3	1,042,136	30.14	-0.001	0.020	0.146	253,609
Tercile 2	858,596	25.51	0.000	0.018	0.117	160,209
Tercile 1	1,030,766	26.22	-0.001	0.021	0.137	240,890

Panel C: Summary statistics: First trading day following announcement

	Market Cap (Thousands)	Closing Price	Daily Return	Daily Range ($)	Midpoint Volatility ($)	Daily Volume
Mean						
Full Sample	-	-	0.000	0.048	0.361	2,801,512
Tercile 3	-	-	0.070	0.053	0.441	3,396,175
Tercile 2	-	-	0.002	0.033	0.249	1,568,342
Tercile 1	-	-	-0.073	0.058	0.392	3,446,524
Median						
Full Sample	-	-	0.002	0.040	0.256	609,619
Tercile 3	-	-	0.054	0.047	0.327	860,965
Tercile 2	-	-	0.002	0.027	0.181	296,254
Tercile 1	-	-	-0.052	0.050	0.286	831,876

Table II

Quoted and Relative Spreads for High and Low Earning Shock Companies

We rank the sample of firms based on the firms return on the announcement day into terciles. First and third tercile groups are high earnings shock firms. The second tercile group is the low earnings shock group. We calculate the time weighted quoted spread in dollars and the time weighted relative spread in percent for each day. The relative spread is defined as 2*(Ask-Bid)/(Ask+Bid). We present the values for five days before the announcement day and one day after. We conduct a means difference t-test between the low and high (low-high) earning shock firms. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

	Day Relative to Announcement Day 0						
Earnings	Day-5	Day-4	Day-3	Day-2	Day-1	Day 0	Day+1
Panel A:Quoted Spread in Dollars							
High Shock	0.1027	0.1004	0.0996	0.1003	0.1041	0.1055	0.0895
Low Shock	0.1224	0.1237	0.1184	0.1296	0.1290	0.1384	0.1089
Difference	-0.0196**	-0.0232***	-0.0189***	-0.0293***	-0.0249***	-0.0329***	-0.0194***
Panel B: Relative Spread in Percent							
High Shock	0.0034	0.0034	0.0033	0.0033	0.0035	0.0035	0.0030
Low Shock	0.0043	0.0042	0.0043	0.0045	0.0045	0.0048	0.0041
Difference	-0.0010***	-0.0009***	-0.0010***	-0.0012***	-0.0010***	-0.0013***	-0.0011***

Table III

Ask and Bid Depth and Ask and Bid Correlation Evaluation

We rank the sample of firms based on the firms return on the announcement day into terciles. First and third tercile groups are high earnings shock firms. The second tercile group is the low earnings shock group. In Panels A and B we present the time weighted top of book ask and bid depth for high and low shock companies. We conduct a paired difference t-test between the ask and bid depths for high and low earning shock firms P-values are reported for this test. We present the values for five days before the announcement day and one day after. In Panel C we report the correlation coefficient of top of book ask and bid depth. Specifically we calculate the time weighted average ask and bid depth for each minute of the trading day and then calculate the correlation coefficient. We conduct a means difference t-test between the correlation of high and low shock firms and report the difference (low-high). ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

	Day Relative to Announcement Day 0						
Variable	Day-5	Day-4	Day-3	Day-2	Day-1	Day 0	Day+1
Panel A: High Shock Firms							
Ask Depth	393.1	400.3	399.4	395.1	404.0	445.9	487.2
Bid Depth	393.3	394.3	398.5	385.8	403.2	420.2	473.3
Difference	-0.2	6.0	0.9	9.3	0.8	25.7	13.9
P-Value	0.982	0.296	0.845	0.093	0.903	0.000	0.035
Panel B: Low Shock Firms							
Ask Depth	491.6	521.9	477.6	505.2	492.7	484.9	582.5
Bid Depth	557.0	598.1	582.1	670.9	622.1	539.2	630.8
Difference	-65.4	-76.2	-104.5	-165.7	-129.4	-54.3	-48.3
P-Value	0.078	0.169	0.152	0.074	0.324	0.298	0.363
Panel C: Correlation Coefficient of Ask and Bid Depth							
Low Shock	0.118	0.124	0.115	0.107	0.120	0.127	0.130
High Shock	0.132	0.136	0.125	0.116	0.142	0.160	0.154
Difference	-0.014*	-0.012	-0.009	-0.009	-0.022**	-0.034***	-0.024**
P-Value	0.057	0.103	0.133	0.146	0.023	0.000	0.017

Table IV

Cost of Round Trip Orders for High and Low Shock Firms

We rank the sample of firms based on the firms return on the announcement day into terciles. First and third tercile groups are high earnings shock firms. The second tercile group is the low earnings shock group. We examine the Cost of Round Trip Orders (CRT) for 500 and 1,000 share orders. The measure calculates the cost, based on the depth in the limit order book, to purchase a fixed quantity of shares on the ask side and then reverse the position immediately on the bid side of the market. The CRT is calculated each time an order of any type is submitted to the market. These costs are then time weighted to find an average for each stock day. The presented values are on a cost per share basis in dollars. In addition, we winsorize the full sample at the 99% level to control for outliers. We present the values for five days before the announcement day and one day after. We conduct a means difference t-test between the low and high (low-high) earning shock firms. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

		Day Relative to Announcement Day 0						
Earnings	N	Day-5	Day-4	Day-3	Day-2	Day-1	Day 0	Day+1
Panel A: 500 Share Cost of Round Trip Order								
Low Shock	574	0.24	0.23	0.24	0.24	0.25	0.26	0.23
High Shock	1,147	0.20	0.21	0.21	0.21	0.22	0.22	0.19
Difference		0.04***	0.03**	0.03**	0.03**	0.03**	0.04***	0.04***
Panel B: 1,000 Share Cost of Round Trip Order								
Low Shock	574	0.55	0.54	0.54	0.56	0.59	0.61	0.53
High Shock	1,147	0.46	0.46	0.46	0.47	0.51	0.51	0.43
Difference		0.09***	0.08**	0.08**	0.09***	0.08**	0.10***	0.10***

Table V
Transaction Costs and Trading

This table presents results on the impact of informed trading in the limit order book. We estimate the following regression in Panel A:

$$Liq_{i,t} = \alpha + \beta_1 DepCorr_{i,t} + \beta_2 VolImbal_{i,t} + \beta_3 LnMOsize_{i,t} + \beta_4 LnMcap_{i,t} + \beta_5 InvPrc_{i,t} + \beta_6 VolTurns_{i,t} + \varepsilon_t$$

DepCorr is the correlation coefficient between top of book ask and bid depth. *VolImbal* is the absolute value of volume imbalance between buy and sell volume divided by total volume. *LnMOsize* is the natural log of the average size of a marketable order. *LnMcap* is the natural log of the market capitalization of the firm. *InvPrc* is the inverse price. *InvPrc* is not included in the relative spread regression. *VolTurns* is the volume divided by the number of shares outstanding. We estimate the regression each day for the five days prior to the earnings announcement. We then apply the Fama-Macbeth method to average the coefficients with Newy-West adjustment to the standard errors. In Panel B we present results where the *DepCorr* variable is replaced with a High Shock firm dummy, *HiShk*, which is 1 for High Shock firms and 0 otherwise. We present results for the quoted spread, relative spread, the cost of a round trip trade of 500 shares, CRT500, and for 1,000 shares, CRT1000. * indicates 10% significance, ** is 5% significance, and *** is 1% significance.

Variable	Quoted Spread	Relative Spread	CRT500	CRT1000
Panel A: Correlation of Depth Regression				
DepCorr	-0.059***	-0.262***	-0.124***	-0.289***
VolImbal	0.190***	0.898***	0.344***	0.850***
LnMOsize	-0.099***	-0.201***	-0.202***	-0.470***
LnMcap	0.000	0.000***	0.000	0.000
InvPrc	-1.140***		-2.023***	-4.394***
VolTurns	-0.003***	-0.025***	-0.007***	-0.020***
Intercept	0.620***	1.284***	1.243***	2.865***
Panel B: High Shock Dummy Variable				
HiShk	-0.009***	-0.035***	-0.012***	-0.032***
VolImbal	0.198***	0.944***	0.362***	0.892***
LnMOsize	-0.111***	-0.245***	-0.226***	-0.527***
LnMcap	0.000	0.000***	0.000	0.000
InvPrc	-1.077***		-1.869***	-4.038***
VolTurns	-0.003***	-0.025***	-0.007***	-0.019***
Intercept	0.666***	1.466***	1.339***	3.090***

Table VI

Information Share and the Cross Sectional Returns of Earnings Announcements

We present the results from an OLS regression in Panel A where the dependent variable is the absolute value of the risk adjusted return for stock i on announcement day t. IS represents the lagged information share of the price channel. Regressions are estimated for each price channel; Trades, Quote Midpoint, and Depth of Book Midpoint. To control for heteroscedasticity White's standard errors are applied. In Panel B we estimate a Logistic regression where High Shock firms set to 1 and Low Shock firms are set to 0. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Variable	Trades	Quote Midpoint	Depth Midpoint
Panel A: OLS regression; Dependent Variable is the Absolute Value of Return			
ISt-5	0.003	0.006	0.005
ISt-4	-0.006	0.019*	0.011
ISt-3	-0.010	0.016	0.040***
ISt-2	-0.009	0.019*	0.022*
ISt-1	0.007	0.017	-0.022*
Market Cap	-0.003***	-0.003***	-0.005***
Intercept	0.067***	0.032***	0.051***
Adjusted R^2	0.003	0.010	0.013
N	1,721	1,721	1,721
Panel B: Logistic Regression; High Shock Firms Modeled			
ISt-5	-0.398	0.852*	0.748
ISt-4	-0.159	0.632	0.204
ISt-3	-0.251	0.621	0.401
ISt-2	-0.267	0.917**	0.245
ISt-1	0.221	0.242	-0.420
Market Cap	0.018	0.011	-0.015
Intercept	0.851***	-0.725**	0.315
Pseudo R^2	0.005	0.017	0.005
N	1,721	1,721	1,721