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Order Behavior In High Frequency Markets

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ORDER BEHAVIOR IN HIGH FREQUENCY MARKETS

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ABSTRACT

In Part 1, I study the characteristics of short orders in stock markets. Fleeting orders are quick limit orders that remain on the limit order book for only a few seconds before being canceled, and are significantly different than more patient, static, limit orders that are added to the limit order book and await execution. I investigate the impact that fleeting orders have on spread and depth measures of market quality, and how fleeting orders differ from static orders. Attention is also given to the extent that total depth can be decomposed into the two components of fleeting and static depth. The results suggest that static orders have a positive impact on both spread and depth. However, fleeting orders have little impact on total liquidity. The results suggest that fleeting orders contribute noise to markets, and do not positively impact the spread and depth components of liquidity. This result is robust to the simultaneous issue that order submission strategies depend on current market quality conditions. In Part 2, I investigate the link between orders and trades in equity markets. A substantial body of research on limit order markets investigates the characteristics of orders and the characteristics of trades. However, there has been little research on how the characteristics of orders impact the characteristics of trades. I investigate the impact that marketable orders and limit orders have on the resulting trade characteristics. In addition, we test theoretical predictions on how market characteristics, like time of day and depth, impact order and trade characteristics. Lastly, in Part 3, I investigate the causes, and effects of intraday flash crashes. Breakdowns in financial markets occur when the market is not able to facilitate its principal responsibilities of liquidity provision and price discovery. In this paper we look at flash crashes, a special type of market breakdown. These crashes are generally non-fundamental in nature, and the market making responsibilities of liquidity and price discovery are only temporarily suspended for a short period before rebounding to pre-crash levels. This paper analyzes intraday flash crashes, primarily focusing on three aspects of flash crashes: crash frequency, crash triggers, and the impact on market quality once the crash has seceded.

DEDICATION

This dissertation is dedicated to my wife, who encouraged and supported me through this process, and to my parents who have always motivated me to always give my best effort.

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LISTS OF APPENDICES

PART 1: MORE DEPTH TO DEPTH: LIQUIDITY OF FLEETING AND STATIC ORDERS

I. INTRODUCTION

Exchanges and institutional traders devote considerable resources into decreasing the latency of transmitting market messages and increasing the speed of order placement (Gao, Yao, and Ye (2013)). Efforts to decrease latency include placement of traders' proprietary trading computers next to exchange servers, known as co-location, as well as development of trans-city networks (Garvey and Wu (2010)). These networks include fiber optic cables, lasers, radio waves, and microwave towers used to connect traders in New York City and other cities such as Chicago and London.[1] There is not a universally held opinion on whether these advances positively or negatively impact market quality (Jones (2013)). One externality of high speed markets is the increase in the order-trade ratio, which coincides with a decrease in the average duration of an order (Hasbrouck and Saar (2009), Hendershott, Jones, and Menkveld (2011)). Many orders are placed for microseconds and then quickly canceled, which are often referred to as fleeting orders. Quick, fleeting orders are receiving an increase in attention in the microstructure literature because of the potential impact on market quality (Hasbrouck (2013), Baruch and Glosten (2013)). Whether or not fleeting orders and low-latency orders improve market quality is the focus of this paper.

I compare the characteristics of fleeting orders against longer duration orders to study market quality in low-latency markets. Much of the literature on market quality in low-latency

[1] Spread Networks has a fiber optic line that connects Chicago to New York City (Laughlin, Aguirre, Grundfest (2014)). Hibernia Networks manufactured a high capacity trans-Atlantic fiber optic path between New York and London. McKay Brothers offers microwave towers to connect traders across different locations around the world. Anova Technologies delivers high-frequency data through laser and radio networks.

markets looks at the type of traders placing the order (i.e. algorithmic and/or high frequency traders) rather than the characteristics of the order, leading to conflicting conclusions on whether to classify algorithmic and high frequency traders as helpful or harmful to financial markets. Studies such as Hendershott, Jones, and Menkveld (2011), Menkveld (2013), Hendershott and Riordan (2013), and Brogaard, Hendershott, and Riordan (2014) provide evidence that high frequency and algorithmic trading help improve market quality, while studies such as O'Hara (2011), McInish and Upson (2012), Kirilenko, Kyle, Sadami, Tuzun (2014), and Gerig (2015), provide examples of potential harmful effects. The question of interest regarding market quality is not *who* places the orders, rather *what* orders are being placed, since a class of traders can pursue different order strategies, which either benefit or harm markets, at different times. I take a different approach on the subject in that I look at the orders being submitted, irrespective of the trader, and investigate how the order type impacts market quality. The empirical tests look at not only top-of-book measures (such as spread and price impact), but also depth measures, which may be more appropriate measure in high-frequency markets (O'Hara (2015)). In nearly all of the tests, static orders positively impact spread and depth, while fleeting orders have little or no positive impact on market quality and liquidity.

Empirically, I separate fleeting orders, which only provide liquidity for two seconds or less (Hasbrouck and Saar (2009)), from static orders, which provide liquidity for greater than two seconds.[2] Using order-level data from NASDAQ OMX, I recreate the limit order book for the NASDAQ exchange. In addition, and in an effort to disentangle the effects of fleeting orders from the effects of static orders, I also recreate two artificial limit order books, one that comprises

[2] Two seconds is arguably too long of a cutoff of fleeting orders in a low-latency market. However, given the results of the paper, reducing the measure to one second, or even sub-seconds, would only strengthen the results and implications of the paper.

fleeting orders, and one that comprises patient orders. By artificially separating the limit order book into these two components, I am able to measure and compare market quality (i.e. depth, spread, price impact) of fleeting and static orders.

This approach provides a number of contributions to the literature on liquidity, limit orders markets, and high frequency trading. First, separating the order types allows for a direct comparison of the market quality of fleeting orders, which provide liquidity only for a few seconds, against the market quality of static orders, which are submitted to the limit order book for longer durations. Since both human and algorithmic traders can pursue strategies of submitting static orders and fleeting orders, separating the two order types effectively tests the impact of the order type on market quality rather than the class of trader's impact on market quality.

A second contribution of my study is that I show depth can be separated into two components, patient depth and fleeting depth, wherein each component has a unique and varying impact on total depth and liquidity. A partitioned view of depth is more appropriate in low latency markets. Traditionally, depth is defined as the total number of shares available to trade at prices at (or near) the best bid and offer at a specific point in time. This simple definition does not, however, distinguish between starkly different types of order and trading strategies. Limit order traders can trade patiently (e.g. Glosten (1994), Handa and Schwartz (1996), and Rosu (2009)), or aggressively, as shown by recent high frequency trading papers (e.g. Hasbrouck and Saar (2009) Menkveld (2013), Baruch and Glosten (2013)).

Although my study is the first to empirically decompose depth into fleeting and static components, the existing work on limit order markets suggest that depth is composed of orders from various types of traders. Theoretical literature suggests that limit order traders pursue a number of strategies. Glosten (1994) considers patient limit order traders to be uninformed investors who make a market for impatient traders who submit market orders. Impatient traders may be either informed or noisy. In Glosten's model, limit order traders are patient and supply liquidity to impatient traders. In a different setting suggested by Rosu (2009), in which all participants are informed traders, limit orders are also submitted by patient traders. However, Rosu assumes that each trader is a liquidity trader, and information is constant and known by all market participants. In this framework, all agents incur waiting costs. Limit orders are submitted by traders with low waiting costs, and traders with high waiting costs submit market orders. However, not all limit orders are assumed to be patient. In Rosu's model, if depth in the limit order book is high and the spread is at a minimum, then impatient traders will either submit market orders, or submit quick, fleeting, limit orders. Fleeting orders are orders that are added and quickly canceled, which are starkly different than patient limit orders that supply liquidity. Theoretical work by Baruch and Glosten (2013) show that fleeting orders are the result of liquidity supplying traders preventing their stale prices from being picked off. To avoid pickoff risk, a liquidity providing trader will cancel stale quotes and replace them with newly priced quotes. Theories by Rosu, and Baruch and Glosten suggest that liquidity and depth are composed of both patient and fleeting orders. In related empirical work, Hasbrouck and Saar (2009) observe that one third of limit orders are canceled within two seconds. Further, Hasbrouck (2013) documents flickering and volatile best bid and best offer quote prices that may be the result of high frequency traders rapidly submitting and canceling nonmarketable orders. I build upon these studies by empirically showing the impact that patient orders and fleeting orders each have on total liquidity.

The third contribution of this study is that I investigate previously untested assumptions and implications from the theoretical literature on fleeting orders and low-latency limit order markets. A major obstacle in the analysis of fleeting orders is the difficulty in constructing the limit order book, and the difficulty in distinguishing between the impact that a fleeting order and static order has on total depth, which the approach in this study overcomes. In Rosu's (2009) model, traders may switch between limit orders and market orders depending on the state of the limit order book. Fleeting orders increase when the depth in the limit order book is high. I test Rosu's model by looking at the structure of the limit order book and composition of fleeting and static orders. I also test theoretical predictions from Baruch and Glosten (2013), who provide a number of implications on flickering quotes. In their model, flickering quotes exhibit different properties depending on the number of traders in the market. They show that although there may be fleeting orders that lead to flickering quotes, when there are many traders submitting flickering quotes, depth will appear to be static.

Although some traders may not initially decide on whether to submit a fleeting or static order, in retrospect the majority of orders are fleeting. Due to the ex-post definition of fleeting orders, there is concern of endogeneity. Simultaneity issues may arise if a trader's order submission strategy depends on current market conditions. A liquidity supplying trader who submits an order may be managing pick-off risk by monitoring the markets for information. As market conditions change, as evidenced by changes in the limit order book, the trader will dynamically respond to the new market conditions by deleting outstanding orders and submitting new, appropriately-priced orders. Theoretical work by Baruch and Glosten (2013) support this view. Additionally, empirical work shows that high speed traders have the ability to respond to changing market conditions (i.e. Hendershott and Riordan (2013)). The simultaneity issue is that current market quality is impacted by order submissions (which is true by construction), while at the same time market conditions may impact a trader's order submission strategy. I use two-staged least squares (2SLS) regression to simultaneously model the two endogenous relations. The results are robust, further strengthening the conclusions regarding the impact of fleeting and static orders on market quality.

The paper outline is as follows. I will first review the theoretical predictions of how fleeting and static orders should impact total liquidity. I then describe the data, and major empirical methods used. The fourth section compares the impact that fleeting and static orders have on total market quality. The fifth section tests theoretical predictions regarding fleeting orders and how they should behave. Finally I conclude.

II. BACKGROUND

Prior research does not explicitly define depth as being comprised of two separate components of static and fleeting depth. Previous studies do, however, suggest traders pursue multiple strategies when supplying liquidity. On one hand, theoretical work suggest limit order traders may patiently supply liquidity. These traders make a market for impatient traders by placing orders and waiting for execution (i.e. Glosten (1994), Foucault, Kadan, and Kandel (2005), Handa and Schwartz (1996)). On the other hand, limit order traders may also submit fleeting orders to increase the probability of execution when the limit order book is full (Rosu (2009)) or to manage undercutting exposure (Baruch and Glosten (2013)). These studies suggest depth in low-latency markets is not the composition of uniform orders. Rather, depth is composed of two categories of orders: static depth and fleeting depth. Static depth is defined as orders that are placed, and patiently await execution, while fleeting depth is defined as the depth that is provided by traders who submit and quickly cancel orders. Each type of depth has a different impact on total liquidity.

STATIC DEPTH

Traditional theories of limit order markets assume patient liquidity providers place limit orders while marketable orders are placed by impatient liquidity demanders. In the model of Glosten (1994), limit order traders are risk averse market makers. These traders patiently place orders to provide liquidity. In the Foucault, Kadan, and Kandel (2005) framework, impatient traders submit market orders and patient traders submit limit orders, providing liquidity for the impatient traders, suggesting that patient traders improve liquidity. In the Rosu (2009) model, all traders have waiting costs, and the aggressiveness of the trader is determined by whether the trader's waiting costs are high or low. In equilibrium, impatient traders submit market orders, while patient traders submit limit orders and wait for execution from an impatient trader. Unless the limit order book is full, Rosu shows the new limit orders will be placed aggressively within the bid-ask spread.[3] Orders that patiently await execution should be a positive component of depth, and orders that are placed inside the spread should improve liquidity measures such as quoted and effective spread. These studies provide theoretical support that patient depth, which is composed of static orders, should be a positive component of liquidity. I refer to this as the static depth hypothesis.

Hypothesis 1: Static depth has a positive impact on total market liquidity

FLEETING DEPTH

Fleeting orders are orders that are submitted and canceled almost immediately. Although fleeting orders are typically limit orders, the characteristics of these orders are different from limit orders in the traditional sense (Hasbrouck and Saar (2009)). Theoretical studies such as Rosu (2009) and Baruch and Glosten (2013) highlight a number of reasons that traders pursue fleeting order strategies. A special case of the Rosu theoretical model, when depth is high and the spread is at a minimum, traders will enter into a game of attrition where fleeting orders are used to entice the opposite side of the limit order book to submit a market order. Limit order traders only submit fleeting orders when the limit order book is full, and the orders are always submitted within the

[3] Rosu (2009) defines the limit order book as being full when the bid-ask spread is at a minimum, nonzero tick size. The model also assumes that there is a maximum number of limit orders allowed on the limit order book, which is not true empirically. I consider a 'full' limit order book to be when the spread is low and depth is high.

spread. Empirically, this suggests that fleeting orders are more likely for limit order books experiencing high depth or low spreads.

Baruch and Glosten (2013) develop a model where fleeting orders are the result of competing liquidity supplying traders. In Baruch and Glosten's model, traders submit competitive orders. However, limit order traders are exposed to time sensitive risk. To avoid time sensitive risk, traders withdraw outstanding orders and submit new orders quickly. The frequent adding and cancelling of orders will yield a flickering quote, but as the number of traders that pursue this strategy increase, the aggregate quotes in the market will have stable depth and appears to be static. Baruch and Glosten's theory suggests that during periods when there is high depth and many fleeting orders, the best bid and offer should appear static. The cumulative depth provided by fleeting orders should yield constant, forecastable, depth.

Both the theories by Baruch and Glosten (2013), and Rosu (2009) suggest that during periods of high depth and low spread, fleeting orders have a positive impact on total depth and liquidity. Rosu predicts that fleeting orders are price improving that are always submitted within the spread. Baruch and Glosten predict that fleeting orders are simply orders placed by liquidity supplying traders who are managing pick off risk. I refer to these theories collectively as the fleeting depth hypotheses.

Hypothesis 2: Fleeting depth has a positive impact on total market liquidity

Hypothesis 3: Fleeting orders are more likely when the spread is low and depth is high

Hypothesis 4: Fleeting orders are only placed within the bid-ask spread

III. DATA AND METHODS

The empirical analysis in this paper utilizes several different databases. Since measures of depth require construction of the limit order book, I use an order-level dataset, the NASDAQ TotalView-ITCH database, which includes order submissions, deletions, updates, and executions for orders placed on the NASDAQ exchange. With this order dataset I am able to reconstruct the limit order book. Additional stock information comes from the Center for Research and Securities Prices (CRSP) and daily trading characteristics come from the Securities and Exchange Commission (SEC) Midas database. The sample comprises the three months of trading days from August through October 2014.

A number of filters are employed. Since data for the exchange used in the study is owned by NASDAQ OMX, my sample includes only NASDAQ listed securities. On the NASDAQ exchange there are approximately 2,871 NASDAQ listed securities that trade during our sample period. In order to ensure that the liquidity measures used in this study provide meaningful results, additional filters eliminate stocks that do not trade at least 1,000 shares each day of the sample, as well as stocks that do not have a closing price of five dollars for each day of the sample (similar filters as Hendershott, Jones, and Menkveld (2011)), which leaves a sample of 1,186 actively traded securities. The limit order book is created dynamically so that every order, update message, and execution is implemented into the limit order book, which yields a best bid and offer that is accurate to the nanosecond. When creating the limit order book, I remove stub-quotes from the computations. Stub-quotes are orders that have an extremely low probability of execution

(Egginton, Van Ness, Van Ness (2014)). At the beginning of the trading day, the data reveals that many bid orders are priced at one penny, and sell orders may exceed $100,000. These orders have a low probability of execution, and may erroneously skew the measures of depth that are used in this study. For this reason I do not use orders that are less than three dollars, or orders that are greater than $5,000 when rebuilding the limit order book. [4] The created limit order book provides depth at the top of the book and beyond the top of the book when each new message during the trading day is received. Depth is accurate to the nanosecond.

Table 1 presents the characteristics of the stocks that are used in the sample. The average stock trades at a price of $37.26, has a market capitalization of $5.67 Billion, and has 626 trades totaling 1,120,198 shares traded per day. The average stock in the sample receives 18,734 fleeting orders and 16,115 static orders each day.

SEPARATING THE LIMIT ORDER BOOK

One difficulty for studies of market quality in low-latency markets is isolating the effects of multiple sources of liquidity improvement. For example, if market quality improves (spread decreases or depth increases) following the increase in algorithmic trading, as in Hendershott, Jones, and Menvkeld (2011), the improved liquidity may be partially due to non-algorithmic traders responding to increased competition induced by the algorithmic traders.

I employ a novel way to test the effects of multiple sources of liquidity improvement. I create three separate limit order books. The first limit order book is the 'true' limit order book, which represents the limit order book that traders see in real time. This limit order book includes all orders added, executed, updated, and deleted. I also create two artificial limit order books, a

[4] The data filters for the study eliminate stocks that do not have a closing price of five dollars. However, orders may still come in at any price. The cutoff of three dollars is to eliminate stub quotes from depth measures.

‘fleeting’ limit order book, and a ‘static’ limit order book. The fleeting limit order book is comprised of only orders that supply liquidity for two seconds or less, while the static limit order book is comprised of only orders that provide liquidity for greater than two seconds. The argument for studying depth in this manner is that both fleeting and static orders have an impact on total liquidity, but it is uncertain which type of order is driving the characteristics of the actual limit order book. With three limit order books I am able to see at each moment what is the market quality (spread and depth) of fleeting and static orders. Using these three limit order books I am able to isolate and test the effects of short-duration and long-duration orders on total market liquidity.

I present the characteristics of orders in Table 2. These statistics are averaged by stock by day, for each statistic used, and then descriptive statistics are taken from the average stock-day observations. The average order is for 202 shares, is on the limit order book for 9 minutes and 32 seconds (572 seconds), and is placed 23 cents from the top of the limit order book. There are approximately 32 orders for every trade. Static orders are placed on the limit order book for an average of 15 minutes and 50 seconds (950 seconds), and are placed 35 cents from the top of the limit order book. Static orders have approximately 25 orders to every trade. Fleeting orders are considerably less patient and more aggressive in pricing. The average fleeting order is on the limit order book for 240 milliseconds, and is placed 9 cents from the top of the limit order book. Although fleeting orders are more aggressive in their pricing, there are approximately 67 fleeting orders submitted for every fleeting order that executes.

Figure 1 reports the competiveness of fleeting and static orders. The first panel reports the ratio of fleeting orders to static orders at different price points away from the BBO. Negative numbers represent the distance from the best bid price for buy limit orders, and positive numbers represent the distance from the best offer for sell limit orders. The second panel reports the ratio of total depth (computed by summing the shares available for each order) at price points away from the BBO. From the first two panels, it is apparent that in general, fleeting orders outnumber static orders, with the exception being at the top of the limit order book. The third and fourth panels report the total number of fleeting and static orders, and the total depth provided by fleeting and static orders respectively. From these two panels it appears that most of the fleeting depth is at the top of the limit order book. All figures and summary statistics numbers are first averaged by stock, and then averaged across stocks.

LIQUIDITY MEAURES AND VARIABLES

A major focus of this paper is testing the differences in market quality provided by orders that are static against the market quality that is contributed from orders that are fleeting. To test the market quality of static and fleeting orders, I compute three spread measures used in Goyenko, Holden, Trzcinka (2009), as well as two additional depth measures, yielding five liquidity measure that are computed for each of the three limit order books described above. The limit order book computations yield a market quality measure for the nanosecond the limit order book is updated. For much of the empirical tests I average market quality measures to the minute. My full dataset yields the average spread and depth for each stock, each minute of the trading day for each of the limit order books computed.

The first measure is the quoted spread, the difference between the best bid and offer for stock j at time t. Quoted spread is defined as

$$Quoted\ Spread = p_{jt,ask} - p_{jt,bid}. \tag{1}$$

I compute the quoted spread using the true limit order book, as well as the quoted spread for the fleeting limit order book and the quoted spread for the static order book. Using each of the three limit order books yields three different measures of quoted spread: the true quoted spread, the quoted spread of fleeting orders, and the quoted spread of static orders.

I compute the effective spread for all three limit order books as

$$Effective\ Spread = 2 * \left|p_{j,t} - m_{j,t}\right|, \tag{2}$$

where the effective spread is twice the absolute distance from the price of a trade at time *t* to the midpoint of the BBO for stock *j*. The third common measure of market quality I use is the price impact that a trade has on the limit order book. In a highly liquidity market a trade will have a low price impact. Using the method of computing the price impact for three limit order books, I am able to see how fleeting orders and static orders react to information contained in trades. The price impact identifies the change in the BBO from the time of a trade to the BBO five minutes after the trade execution, which is considered the permanent component of the spread (Goyenko, Holdern, Trzcinka (2009)). I express it as a percentage of the original midpoint for stock *j* at time *t*. Price impact is defined as

$$Price\ Impact = 2 * \frac{\left|m_{j,t} - m_{j,t+5}\right|}{m_{j,t}}. \tag{3}$$

Measuring market quality only at the top of book does not fully reflect the market quality of a security. Traders wishing to execute large number of shares may be more concerned about the number of shares available to trade, rather than the cost to trade at the top of the limit order book. Therefore, limit order book depth is used as an additional measure of market quality. I use two depth measures, the first is the cost of a round trip trade (CRT), and the second is the depth-weighted average price (DWAP). The CRT is defined in Domowitz, Hansch, and Wang (2005), and reflects the ex-ante cost a trader would encounter by buying and selling *q* number of shares. I modify the notation of Domowitz et al. slightly, and express CRT as

$CRT =$

$$\left[\sum_{j=1}^{k-1} D_{j,ask}\, P_{j,ask} + \left(q - \sum_{j=1}^{k-1} D_{j,ask}\right) P_{k,ask}\right] - \left[\sum_{j=1}^{k'-1} D_{j,bid} P_{j,bid} + \left(q - \sum_{j=1}^{k'-1} D_{j,bid}\right) P_{k,bid}\right], \tag{4}$$

where k is the number of ticks that a sell order of q shares has to travel on the ask side of the limit order book before q shares are filled, k' is the number of ticks a buy order of q shares has to travel before being completely filled. The depth and price of tick j is represented by D_j and P_j. The first term of equation (4) is the cost to sell q shares, while the second term is the cost to buy q shares. The difference between the first and second term represents the total cost to buy and sell q shares of a security simultaneously, or the cost of a round trip trade of size q. Although Domowitz et al. consider 10 values of q between 1 and 2,701 in their depth simulations, I only consider five values due to computational constraints. I consider values of q equal to 100, 500, 1,000, 5,000 and 10,000 shares. Much of the empirical portions of this paper will focus on q values of 1,000 and 5,000. I express the CRT on a per share basis, which I define as the CRT_{SPREAD}, as

$$CRT_{SPREAD} = \frac{CRT}{q}. \tag{5}$$

CRT_{SPREAD} can be interpreted in the same manner as quoted spread, with the exception that CRT_{SPREAD} reflects more than the number of shares at the top of the limit order book. The CRT is computed for all the limit order books in the study. If static orders and fleeting orders have a positive impact on market quality, then the CRT_{SPREAD} should be low.

DWAP is the second measure of limit order book market quality that I use in this study. I calculate DWAP similar to Johnson and Upson (2013) as

$$DWAP = \frac{\sum_{i=1}^{I} P_i D_i}{\sum_{i=1}^{I} D_i}, \tag{6}$$

where there are I ticks on a given side of the limit order book, with a price of P_i and depth of D_i at tick i. I calculate the DWAP for both the bid and ask side of the limit order book, and take the difference to get the $\text{DWAP}_{\text{SPREAD}}$.

$$DWAP_{spread} = DWAP_{ask} - DWAP_{bid}. \tag{7}$$

In total, I have three spread measures for top of book market quality: quoted spread, effective spread and price impact, as well as two spread measures that reflect depth in the limit order book: CRT and DWAP. All five measures of market quality are computed for the true limit order book, the fleeting limit order book, and the static limit order book. After computing each of the five measures for each nanosecond, they are averaged to the minute level for much of the empirical analyses.

Panel A of Table 3 presents the liquidity measures for the average stock in my sample for the NASDAQ exchange. The average stock has a quoted spread of 6 cents, effective spread of 3 cents, and a negligible price impact. The CRT100 is the per share cost that a trader can expect to pay in transaction costs from simultaneously buying and selling 100 shares, and reflects depth beyond the top of the book. If there is greater than 100 shares in depth at the best bid and best offer, then the CRT100 will equal the quoted spread. If there is less than 100 shares at the best bid and best offer, the CRT100 will be greater than the quoted spread. The average stock in the sample has a CRT100 of 7 cents. It is not always possible to complete a round trip trade due to illiquidity. A trader wishing to buy and sell 100, 500, 1,000, 5,000, and 10,000 shares can expect to pay 7, 12, 20, 136, and 190 cents respectively. The average DWAPspread is 1,052 cents. The average CRT1000 is 3.22 times the quoted spread, the CRT5000 is 20.25 times the quoted spread, and the DWAP spread is 37.23 times the quoted spread.

In Panels B and C of Table 3 I report the liquidity measures for the fleeting and static limit order books. The quoted spread of the static limit order book is 7 cents, while the fleeting limit order book has an average quoted spread of 20 cents. A hypothetical roundtrip trade of 100 shares against the artificial static limit order book would cost an average of 8 cents per share, while the cost of a 100 share roundtrip executed against the artificial fleeting limit order book would cost 21 cents per share. A trade of 1000 shares on the static limit order book would cost 3.63 times the quoted spread on average, while a 1000 share trade on the fleeting limit order book would cost 3.87 times the quoted spread on average.

In addition to the measures of liquidity, there are a number of other variables that I use in the study. Rosu (2009) makes predictions about the aggressiveness of an order. I define order aggressiveness similar to Griffiths, Smith, Turnball, and White (2000), who measure aggressiveness relative to the BBO. A buy order is most aggressive if it is higher than the ask price (i.e. crossing the market). A less aggressive order is placed within the BBO, and the least aggressive orders are placed less than the best bid. A similar scale of order aggressiveness is used for sell orders. I calculate minute volatility as the standard deviation of the midpoint at time *t.* Range is used as a measure of daily volatility, similar to O'Hara, Yao, and Ye (2014), which is the difference between the daily high and low price.

IV. THE IMPACT OF FLEETING AND STATIC DEPTH ON TOTAL LIQUIDITY

The empirical tests are broken into three broad categories. The first and second groups of tests are reported in this section. The first tests identify the impact that static orders and fleeting orders have on total depth, specifically addressing the hypotheses on whether fleeting and static orders impact total liquidity. These tests also compare the differences of fleeting orders against static orders. The second group considers the simultaneity issue that orders impact depth, while at the same time fleeting orders may be a function of depth. The third group of tests, reported in the following section, investigates the theoretical predictions or fleeting orders.

HOW DO FLEETING AND STATIC ORDERS IMPACT LIQUIDITY?

Many theoretical papers on limit order markets assume that patient liquidity providers improve liquidity by making a market for impatient traders who submit market orders (i.e. Glosten (1994), Foucault, Kadan, Kandel (2005)). These theories suggest that static orders should have a positive impact on total liquidity. Theory also suggests that fleeting orders, although less patient than static orders, may also have a positive impact on liquidity. Theory by Rosu (2009) and Baruch and Glosten (2013) consider fleeting orders to be price improving orders submitted by liquidity supplying traders. Rosu's (2009) model predicts that fleeting orders are placed within the bid-ask spread, suggesting that the market quality of the fleeting limit order book should improve liquidity measures at the top of the limit order book like quoted spread, effective spread, and price impact. Theory by Baruch and Glosten (2013) suggest that fleeting orders are liquidity providing limit orders placed by traders managing their pick-off risk. Although the orders may be fleeting, the trader will replace the order with a new order. If these traders are liquidity providing traders, then the cumulative market quality from fleeting orders should improve the market quality of the complete limit order book.

In Table 4, I report nine different liquidity measures for the total limit order book, as well as for the fleeting limit order book and static limit order book. The three top of book measures include the quoted spread, effective spread, and price impact. For the complete limit order book these are respectively 6.92 cents, 3.27 cents, and 26 basis points. Using the methods described in the previous section, I form two subsets of the complete limit order book. Using only static orders I form a static limit order book, and using fleeting orders I form a fleeting limit order book. I compute the same market quality measures for the two artificial limit order books as I do for the total limit order book. The quoted and effective spread for the static limit order book are respectively 7.08 cents and 3.50 cents, and for the fleeting limit order book they are respectively 21.18 and 7.43 cents. The price impact is negligible.

One of the objectives of this paper is to test the extent that static and fleeting depth each impact total depth. To test whether static orders have a positive impact on total liquidity I compare the liquidity measures of the static limit order book against the liquidity measures of the complete limit order book. If the static and fleeting limit order book have positive impacts on the complete limit order book, the differences should be insignificant. From columns 4 and 5 of Table 4, the quoted spread of the static limit order book is 0.16 cents larger than the total limit order book, and the effective spread is 0.23 cents larger. Both are statistically significant, but economically small. I repeat the test for fleeting orders, where the quoted spread is 14.26 cents larger and the effective spread 4.16 cents larger. The average fleeting quoted spread is 14 cents higher than the static limit order book, and the effective spread is 3.9 cents higher. These preliminary tests suggest that on average, the static limit order book contributes to a large portion of the total limit order book. Since the total spread measure is a form of a minimum function of static and fleeting orders, it is possible for the total spread measure to be less than either of the static or fleeting spread measure on average.

In Panel B I report the depth measures. In the analyses I focus on three main measures of depth. The first two measures are the cost of a round trip trade for a 1,000 share order and the cost of round trip trade for a 5,000 share order. Both of these measures can be interpreted in a similar way as the quoted spread. The difference being that the CRT measure reflects depth beyond the top of the limit order book. The third measure is the depth weighted average price spread (DWAPspread), which is the difference between the depth weighted bid price and the depth weighted ask price. I also express these measures as a ratio over the quoted spread.

Depth measures of liquidity are not as straight forward to interpret as the top of book measures of liquidity. Fleeting and static orders may selectively provide liquidity throughout the trading day, and as a result, at a given minute during the trading day there may not be enough fleeting or static depth to complete a trade. Therefore, interpretation of depth measures should be done in conjunction with the percentage of time when a round trip trade can be made. Panel B of Table 4 reports depth measures for the complete limit order book, static limit order book, and fleeting limit order book, while Panel C reports the percent of time during the day that a trader can successfully buy and sell q number of shares. From Panel B, the total limit order book depth reveals that a trader wishing to buy and sell 1,000 shares of the average stock can expect to pay 21.67 cents per share. In addition, Panel C reports that a trader is able to complete a 1,000 share trade 100% of the time for the average stock.

Comparing fleeting and static orders yields interesting results. From Panel B, The cost to trade 1,000 shares using exclusively static orders would cost a trader 25.43 cents per share, while a trade using exclusively fleeting orders is 5.53 cents cheaper, at 19.91 cents per share. Comparing cost alone, however, is not sufficient. Panel C reveals that the static limit order book is able to provide 1,000 shares of depth at the bid and offer side of the limit order book 100% of the time for the average stock. The fleeting limit order book, however, can only accommodate a 1,000 share order at the bid and offer side of the limit order book 29% of the time for the average stock (Panel C, row 3). The results suggest that for the average minute, for the average stock, fleeting orders are priced competitively, but are used selectively for providing liquidity to the market.

It is possible that some of these characteristics are driven by the time of the day, since markets are generally more active at the beginning and end of the trading day. Figure 2 presents some of the liquidity measures partitioned by time of day. Panel 1 shows that there are generally more orders submitted at open to close. The results in Panel B suggest that there is sufficient depth on the total limit order book and static limit order book to accommodate a 1000 share trade throughout the entirety of the trading day, but approximately only 30% of the time on the fleeting limit order book. The cost to trade, measured as the quoted spread and CRT1000 are highest in the morning, and significantly drop for the remainder of the trading day.

A concern these results is that fleeting orders are orders submitted primarily by algorithmic traders who primarily trade in large securities. [5] For example, Brogaard, Hendershott, and Riordan (2014) find that high frequency traders trade over $241 million in large capitalization securities, but only $4.8 and $0.48 million in medium and small capitalization securities. In Table 5, I report the CRT depth measures, partitioned by market capitalization quintiles. The CRT cost measure is

[5] Hasbrouck and Saar (2013) find their measure of algorithmic trading, strategic runs, is highly correlated with HFTs from the NASDAQ HFT database. Strategic runs are fleeting orders lasting 100ms.

presented, along with the percentage of time available to complete the trade in brackets. The results show that fleeting orders do supply more liquidity in high capitalization securities, but the amount of time is still much lower than static orders.

Thus far I have considered fleeting and static orders as independent factors that impact total liquidity. The true limit order book that is displayed in real time is created by traders submitting both fleeting and static orders simultaneously. I address the simultaneous impact that fleeting and static orders have on total liquidity while controlling for other major influences like time of day, price, minute volatility, and stock volatility. The main regression estimates the effect that fleeting and static liquidity have on complete liquidity. I run cross-sectional minute regressions of the following form:

$$Total_{i,t} = \beta_0 + \beta_1 Static_{i,t} + \beta_2 Fleeting_{i,t} + \beta_x X_{i,t} + \lambda_i + \lambda_t + \varepsilon_{i,t} \tag{8}$$

where *Total* is the liquidity measure for the total limit order book for firm *i* at minute *t*. I use both top-of-book liquidity measures (spread and price impact) and depth liquidity measures (CRT and DWAP). *Static* is the liquidity measure for the static limit order book, and *Fleeting* is the liquidity measure for the fleeting limit order book. The regression results for top-of-book liquidity measures are reported in Table 6, and depth liquidity measures are reported in Table 7. Control variables are represented by the matrix *X*, and include the log of the market capitalization for firm *i*, log of the daily closing price, the price volatility for minute *t* and the daily price range. I also include fifteen minute time-of-day fixed effects and firm fixed effects.

Table 6 presents the results from estimating equation 8 using top of book liquidity measures. The dependent variable in models [1] through [3] is the quoted spread, in models [4] through [6] it is the effective spread, and I regress price impact in models [7] through [9]. The two key variables in all equations is the static and fleeting measure of liquidity, which is the same liquidity measure as the dependent variable in each of the nine regressions. To account for minute volatility I include the volatility of the midpoint, and to capture daily volatility I use the stock's range, which is the daily high price minus the daily low price. I also control for stock prices and market capitalization. Each liquidity measure is computed with the fleeting and static measure independently, as well as the measures regressed together.

The results for top of book liquidity measures are fairly consistent. Both static and fleeting liquidity measures are usually positively associated with total liquidity. However, the static limit order book has a larger impact on total liquidity. On average, a one dollar increase in the fleeting quoted spread leads to a 12.11 cent increase in the total quoted spread (with the same holding true for a decrease in spread) while a one dollar increase in the static quoted spread leads to an 55.75 cent increase in the total quoted spread (with the same holding true for a decrease in spread). The Wald statistics report that the coefficients for the static and fleeting liquidity measures are significantly different from each other. From column 6, a one dollar increase in the fleeting effective spread will increase the effective spread of the total limit order book by 0.55 cents, and a one dollar increase in the static effective spread will lead to a 49 cent increase in the total limit order book effective spread (again, the same holding true for a one dollar decrease). There are similar results for the effective spread and price impact for static depth, but fleeting depth does not have a significant impact on total liquidity. Finally, from column 9, it appears that a one percent increase in the price impact of static orders increases the price impact of the total limit order book, while fleeting orders have little effect. The top of book liquidity results in Table 6 show that static orders are positively impacting the total limit order book, which provides support for Hypothesis 1, the static depth hypothesis. However, the fleeting limit order book has little impact on the total limit order book, which does not support Hypothesis 2, the fleeting depth hypothesis. I now turn to measures that account for liquidity beyond the top of the limit order book.

Table 7 presents the results from estimating equation 8 using depth liquidity measures. The specifications are identical to the models in Table 6, where depth measures are used in place of top-of-book measures. The dependent variable include the CRT1000 in models [1] through [3], the CRT5000 in models [4] through [6] and the DWAP spread in models [7] through [9]. In models [3], [6], and [9], total depth is regressed on static and fleeting depth. The results presented in model [3] show that a one dollar increase in the cost to trade 1000 shares on the static limit order book leads to a 83 cent increase in the total limit order book (with the same holding true for a one dollar decrease), while fleeting depth has no impact on the total limit order book. The results in Column [6] are even stronger, suggesting a one dollar increase in the cost of a round trip trade of 5,000 shares on the static limit order book will lead to nearly a 93 cent increase on the total limit order book. However, fleeting orders have little impact. Column 9 provides a marginal support that fleeting orders have an impact on liquidity, where a one dollar increase in the fleeting DWAP spread will lead to an increase in the total limit order book DWAP spread by 13.63 cents, which is significant at the 1% level.

The results displayed in tables 6 and 7 have interesting implications. Both the top-of-book and depth measures of liquidity show a consistent and strong relation between the static limit order book, which provides ample support for the static depth hypothesis, which states that static orders have a positive and significant impact on total liquidity. Static orders are consistently at the top of the limit order book, providing competitive prices for traders. Static orders also remain on the limit order book to allow traders to complete large roundtrip trades. Since there is a week and often insignificant relation between the fleeting limit order book and total limit order book, I find little support for the fleeting depth hypothesis. Fleeting orders have a small impact on top of book of liquidity measures, and in most of the model specifications fleeting orders do not contribute significantly to the depth of the total limit order book. It is important to note that although there isn’t a strong positive relation, there isn’t a strong negative relation either. This would suggest that fleeting orders may more appropriately be described as contributing noise to the markets, rather than contributing to depth and liquidity.

SIMULTANEITY OF FLEETING AND TOTAL LIQUIDITY

The results of the tests so far are assume an exogenous relation between fleeting orders and current spread and depth, since fleeting orders are defined ex-post. However, there is concern of endogeneity due to simultaneity. By construction, fleeting and static orders impact limit order book depth, and the results presented so far address this relation. But, it is possible that the current state of the limit order book will directly impact the behavior of orders, in particular fleeting orders. Hendershott and Riordan (2013) find that when spreads are narrow, algorithmic and high frequency traders are less likely to cancel outstanding orders. If fleeting orders are submitted by computers and algorithms, then the number of fleeting orders should be lower when spreads are narrow and current liquidity is high. Additionally, one could argue that traders initially submit orders with no intent of the order being a fleeting order. However, as market parameters and the limit order book changes, traders will revise their orders by canceling their current order and submiting new orders reflecting new information. This view is in agreement with theory by Baruch and Glosten (2013). I therefore attempt to control for this possible endogeneity problem.

This subsection reports two different approaches to test for potential endogeneity. The first robustness test I employ uses the prior period's fleeting and static liquidity on the current period's total liquidity. I run the following regression:

$$Total_{i,t} = \beta_0 + \beta_1 Static_{i,t-1} + \beta_2 Fleeting_{i,t-1} + \beta_x \boldsymbol{X}_{i,t} + \lambda_i + \lambda_t + \varepsilon_{i,t}, \qquad (9)$$

where *Total* is the measure of liquidity for the entire limit order book. Static and *Fleeting* are the liquidity measures for the static and fleeting limit order book for the one minute period prior. The logic of this test is that fleeting orders from the previous minute are a function of the complete limit order book at that time period. Using lagged measures of *Static* and *Fleeting* liquidity eliminates contemporaneous correlation, since there is no feasible mechanism for the prior period fleeting orders to be impacted by current period liquidity. Column 1 of Table 8 reports the results for the top of book measure, quoted spread. Column 2 report the results for the depth measure CRT 1000. The results for the quoted book are similar to the results displayed in Table 6, where a one dollar increase in the static spread increase the total spread by 33 cents, and the fleeting spread has little impact. The depth measures do not show any significant relation in this specification.

The second test I employ attempts to model the simultaneous impact of fleeting orders on depth, and the impact of depth on fleeting order submission strategies. In order to alleviate concerns regarding an endogeneity bias, I estimate the simultaneous equation using two-stage least squares (2SLS).[6] The system of equations estimated is:

[6] For robustness I regress the entire system of equations in a 3SLS framework. The magnitude and significance of the coefficients are virtually identical. For brevity only 2SLS results are reported.

$$\text{1}^{st}\ \textit{Stage}: \quad Fleeting_{i,t} = \beta_0 + \beta_1 FleetingSpread_{i,t-1} + \beta_2 TotalSpread_{i,t-1} + \beta_3 FleetingDepth_{i,t-1} + \beta_4 TotalDepth_{i,t-1} + \beta_x X_{i,t} + \lambda_i + \lambda_t + \varepsilon_{i,t} \tag{10}$$

$$\text{2}^{nd}\ \textit{Stage}: \quad Total_{i,t} = \beta_0 + \beta_1 Static_{i,t} + \beta_2 \widehat{Fleeting}_{i,t} + \beta_x X_{i,t} + \lambda_i + \lambda_t + \varepsilon_{i,t}, \tag{11}$$

where equation (10) is the first stage of the system estimated. In this system I regress the current period measure of fleeting order liquidity on the prior period liquidity measures of fleeting order and total limit order book liquidity. I use both spread and depth as exogenous variables. Since there is no economic mechanism in which prior period liquidity can be impacted by current period liquidity, and they are highly correlated with current period fleeting order strategies, all four variables satisfy necessary conditions to be used as instrumental variables. In addition to the four instruments, I include the matrix of control variables *X*.

The predicted value for fleeting liquidity is then used as on exogenous variable in the second stage of the regression, as shown in equation (11). In this stage I regress total liquidity on static orders and fleeting orders.[7] The results are presented in columns 3 through 9 of Table 8. I use multiple depth measures to test for robustness. A number of interesting results are presented when controlling for the possibility of fleeting orders responding to current liquidity characteristics. The strong impact of static liquidity on total market liquidity remains for both top of book measures (columns [3] through [5]) and depth measures (columns [6] through [9]). However, fleeting orders provide mixed results. There is evidence that fleeting order have a marginal positive impact on liquidity, which is evident in the effective spread, and the DWAP

[7] Static orders do not have the same concern of endogeneity that fleeting orders do. Economic and theoretical reasoning do not suggest that static orders constantly revise their order submission strategies in the way that fleeting orders do.

ratio, and there is evidence of a negative impact in price impact and the cost to trade 5000 shares. The remaining models show an insignificant relation between fleeting orders and the market quality of the limit order book. In general, the results and the implications are similar to those from Tables 6 and 7, which is that fleeting orders do not have a significant positive impact on liquidity. I therefore conclude that the results are not subject to simultaneity issue of traders adjusting their orders depending on the current market liquidity.

V. THEORETICAL IMPLICATIONS OF FLEETING LIQUIDITY

In this section I test the theoretical predictions on fleeting orders. Rosu (2009) predicts that fleeting orders only occur when the spread is low, and depth is high. Rosu also predicts that fleeting orders are only submitted within the bid-ask spread. Baruch and Glosten (2013) predict that when there are a many fleeting orders, the depth provided by fleeting orders should be static and constant.

First, I test the prediction of Rosu (2009) that fleeting orders only occur when the limit order book is full (spread is at a minimum nonzero tick size). Empirically it is unlikely for a limit order book to ever be classified as full, since this would require the exchange to set a cap on the number of orders allowed on the limit order book. Therefore I test this theory by comparing fleeting orders during periods of high depth relative to periods of low depth. I partition fleeting orders for a given stock-day into depth quintiles. I test Rosu's theory by comparing the ratio of fleeting orders to static orders during the minutes that experienced the highest depth against the minutes that experience the lowest depth. Panel A and B in Table 9 display the results for sorting on the cost of a round trip trade, while Panel C reports the results for sorting based off of quoted spread.

When partitioning depth according to the CRT1000, there are 1,981 more fleeting orders submitted during periods with high liquidity relative to low liquidity. The same holds true for static orders, where there are 2,095 more static orders submitted during periods of high liquidity. Comparing number of orders alone doesn't effectively test the theory, since by construction, there are more order submitted during periods of higher depth. Therefore, in order to better test the theory we look at the ratio of fleeting to static orders, since the theory suggests that traders will switch from patient orders to impatient static orders during periods of high depth. The third row in Table 9 shows that during periods of high liquidity there are approximately .74 fleeting orders to every static orders, but during low liquidity there are 1.09 fleeting orders to every static order. The difference is highly significant. These results are consistent when partitioning by CRT5000, and by spread. Since fleeting orders provide a larger proportion of order flow when depth is low, there is no support for Hypothesis 3. The results from Table 9 provide little evidence supporting the prediction of Rosu (2009) that fleeting orders only occur when depth is high.

A second prediction of Rosu (2009) is that fleeting orders are only submitted within the bid-ask spread, which is identified as Hypothesis 4 in this study. To test this theory I separate all orders into one of three categories: orders that improve the BBO (submitted within the spread), orders that match the BBO, and orders behind the BBO. I calculate the number of fleeting, static, and total orders that fit into these three categories. I also calculate the percent of fleeting orders, static orders, and total orders that are in these categories. Table 10 reports the results. Approximately 14% of fleeting orders, and 9% of static orders are submitted within the bid-ask spread, making 11% of total orders being price improving orders. In addition, over 39% of fleeting orders match the BBO. Static orders are a little less with 31% of the orders matching the BBO. Finally, 47% of fleeting orders are behind the BBO while 60% of static orders are behind the BBO. All differences are all significant at the 1% level. The results do not provide strong evidence for Rosu (2009), which is admittedly a strong prediction. Although not all of fleeting orders are submitted within the spread, over half of fleeting orders are competitive orders, with 53% being priced at the top of the book or better. The results from Table 10 provide marginal support for Hypothesis 4 that fleeting orders are priced within the bid-ask spread.

The final theoretical prediction I test is from Baruch and Glosten (2013), who predict that fleeting orders may lead to forecastable and constant depth. The theory suggests that when there are only a few traders submitting fleeting orders, quotes will flicker and depth will not be constant. However, as the number of traders submitting fleeting orders increase, depth will be constant and quotes will appear static. I test this theory by partitioning stock-days into three fleeting order partitions based on the number of fleeting orders. In each partition I calculate the volatility of the total quoted spread, the static quoted spread, and the fleeting quoted spread. If depth is constant and forecastable when there are many fleeting orders, then the volatility of the fleeting quoted spread should be low, and indifferent from the total quoted spread in the highest tercile of fleeting orders.

Table 11 reports the results of this test. Column 1 displays the lowest tercile of fleeting orders during a stock day. In the lowest tercile of fleeting orders, the quoted spread is 0.53 cents. However, during periods when there are large numbers of fleeting orders, the quoted spread increases to 3.25 cents. The theory of Baruch and Glosten (2013) suggests that the top of book depth and spread should be more constant when there are high numbers of fleeting orders and flickering quotes, however we find that depth becomes less forecastable and less constant. These results further support the notion that fleeting orders introduce noise into financial markets.

VI. CONCLUSION

This paper investigates market quality in low latency markets. One of the externalities of low-latency markets is fleeting orders, which are orders that only provide liquidity for a few seconds before being canceled. I compare the characteristics of fleeting orders against longer duration orders to study market quality in low-latency markets. Theory by Rosu (2009) and Baruch and Glosten (2013) suggest that liquidity providing traders may submit fleeting orders and static orders, and should have a positive impact on market liquidity. Empirically, I separate short duration (fleeting) orders from long duration (static) orders to isolate the impact that each type of order has on market quality. In addition to comparing fleeting orders against static orders, I determine how much each type of order contributes on total liquidity.

The results suggest that static orders have a large and significant impact on total liquidity. The best bid and best offer prices are largely determined by static orders. Additionally, static orders significantly contribute to the total depth in the market. I find little support that fleeting orders positively impact liquidity. Fleeting orders have little to no impact on the best bid and offer, and do not provide depth for traders submitting large trades. The results suggest that fleeting orders provide more noise than liquidity.

There is concern that fleeting orders and total market liquidity are endogenous. Fleeting orders by construction impact market liquidity, however, if fleeting orders are submitted by traders who monitor current market activity, then there is a simultaneity issue. I employ two-stage least squares to model the endogeneity. The results are robust to any issues of simultaneity.

This paper also tests previously untested implications of the theoretical literature on fleeting orders. Rosu (2009) predicts that fleeting orders are more likely when depth is high and spread is low. I find that there are more fleeting orders submitted when depth is high, as well as more static orders. However, the ratio of fleeting orders to static orders is higher when depth is low. Rosu (2009) also predicts that fleeting orders are only submitted within the bid-ask spread. I find that approximately 15% of fleeting orders are submitted within the bid-ask spread, which is not statistically different than the number of static orders submitted within the bid-ask spread. These results only partially support the theory by Rosu. Baruch and Glosten (2013) predict that large numbers of fleeting orders should have constant and forecastable depth. I find that during periods of high fleeting order activity, volatility of the best bid and offer for the total limit order book and fleeting limit order book increase, which does not support the theory by Baruch and Glosten, and adds to the notion that fleeting orders are introducing noise to financial markets.

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APPENDIX

APPENDIX 1: SUMMARY STATISTICS

Table 1: Firm Summary Statistics

This table presents summary statistics for the data used in the study. The firm summary statistics include price, trades, shares traded, and market capitalization, which are respectively the closing price, number of daily trades, number of shares traded, and the market capitalization for the average firm in our sample. Fleeting orders are the number of orders on the limit order book for two seconds or less, and static orders are the number of orders that provide liquidity for greater than two seconds for the average firm in our sample on the NASDAQ exchange. Data comes from CRSP, the SEC MIDAS dataset, and the NASDAQ Total-View ITCH order-level dataset.

	Mean	Median	St. Dev.	Min	Max
Panel A: Firm level daily summary statistics					
Price	37.26	25.76	59.34	5.00	1,309.42
Trades	626	266	1,355	13	71,735
Shares Traded	1,120,198	303,593	4,026,127	12,489	233,883,264
Market Cap (000s)	5,666,771	1,068,623	26,593,012	54,764	618,546,679
Fleeting Orders	18,734	5,413	48,408	221	911,343
Static Orders	16,115	7,506	23,304	732	234,066

APPENDIX 2: ORDER CHARACTERISTICS

Table 2: Order Characteristics

This table looks at the characteristics of orders. All orders are the characteristics of all orders collectively, while static orders are orders on the limit order book greater than two seconds, and fleeting orders are orders that are on the limit order book for less than or equal to two seconds. The statistics in each panel is first averaged by stock day, and then the descriptive statistics are taken from the average daily observation. Order size is the average size of orders added, duration is the time between an order being added and deleted from the limit order book. Distance is the difference between the order price and the top of the limit order book. Execution rate is the number of orders that execute divided by total orders. Order-trade ratio is the number of orders added divided by the number of orders executed. Averages are calculated by stock, and then averaged across stocks. Data comes from CRSP, the SEC MIDAS dataset, and the NASDAQ Total-View ITCH order-level dataset.

	Firms	Mean	Median	St. Dev.	Min	Max
All Orders						
Order Size	1,186	202.01	120.40	460.38	44.28	12751.76
Duration (Seconds)	1,186	572.06	399.72	626.96	38.18	7103.52
Distance	1,186	0.23	0.16	0.25	0.02	2.88
Execution Rate	1,186	0.04	0.04	0.02	0.00	0.11
Order-Trade Ratio	1,186	32.01	26.30	29.50	9.16	688.10
Static Orders						
Order Size	1,186	199.02	120.99	267.81	43.70	4523.87
Duration (Seconds)	1,186	950.15	677.63	946.21	107.88	9113.05
Distance	1,186	0.35	0.24	0.39	0.03	4.78
Execution Rate	1,186	0.05	0.05	0.03	0.01	0.16
Order-Trade Ratio	1,186	24.88	20.06	17.03	6.13	176.12
Fleeting Orders						
Order Size	1,186	191.61	116.83	559.43	44.76	16151.78
Duration (Seconds)	1,186	0.24	0.23	0.11	0.02	1.18
Distance	1,186	0.09	0.05	0.14	-0.16	2.25
Execution Rate	1,186	0.03	0.02	0.01	0.00	0.11
Order-Trade Ratio*	1,185	67.67	43.43	264.76	8.96	8611.50

APPENDIX 3: DEPTH SUMMARY STATISTICS

Table 3: Depth summary statistics

This table presents summary statistics for the liquidity measures employed in the study. Panels A, B, and C report limit order book (LOB) summary statistics at the minute level for the average firm in our sample. Panel A is depth for the complete, or 'real', LOB. Panels B and C are two artificial LOBs, where Panel B reports the depth contributed from static limit orders, and Panel C reports the depth from fleeting limit orders. The depth measures include three top of book measures (quoted spread, effective spread, and price impact) and nine depth measures. Depth measures include the ex-ante per-share cost to buy and sell q number of shares (the cost of a round trade, CRT) and the difference between the depth-weighted average offer and the depth weighted average bid price (DWAP-spread). These depth measures are also reported as a ratio over the quoted spread. Data comes from CRSP, the SEC MIDAS dataset, and the NASDAQ Total-View ITCH order-level dataset.

Panel A: Complete limit order book minute level liquidity summary statistics

	Mean	Median	St. Dev.	Min	Max
Top of book liquidity					
Quoted Spread	0.06	0.03	0.38	0.00	518.31
Effective Spread	0.03	0.01	0.15	0.00	197.56
Price Impact	0.00	0.00	0.09	0.00	47.48
Depth Liquidity					
CRT100	0.07	0.03	0.39	0.00	519.79
CRT500	0.12	0.06	0.23	0.00	84.68
CRT1000	0.20	0.09	0.37	0.00	111.24
CRT5000	1.36	0.38	2.63	0.00	185.43
CRT10000	1.90	0.68	3.38	0.00	239.23
DWAP-Spread	10.52	7.30	14.47	0.10	521.24
CRT1000/Quoted	3.22	2.56	2.99	1.00	3497.18
CRT5000/Quoted	20.25	11.00	29.16	1.00	4470.76
DWAP/Quoted	37.23	40.37	10.67	1.00	50.00

	No Obs.	Mean	Median	St. Dev.	Min	Max
Panel B: Static limit order book minute level liquidity summary statistics						
Top of book liquidity						
Quoted Spread		0.07	0.04	0.13	0.00	48.33
Effective Spread		0.03	0.01	0.15	0.00	265.98
Price Impact		0.00	0.00	0.01	0.00	2.00
Depth Liquidity						
CRT100		0.08	0.04	0.15	0.00	49.09
CRT500		0.15	0.07	0.27	0.01	80.91
CRT1000		0.24	0.12	0.44	0.01	112.63
CRT5000		1.59	0.51	2.95	0.01	190.27
CRT10000		2.08	0.83	3.53	0.01	206.14
DWAP-Spread		10.70	7.39	14.47	0.01	423.48
CRT1000/Quoted		3.63	2.87	3.36	1.00	3,566.83
CRT5000/Quoted		22.80	13.21	31.61	1.00	4,411.69
DWAP/Quoted		35.16	38.10	11.48	1.00	50.00
Panel C: Fleeting limit order book minute level liquidity summary statistics						
Top of book liquidity						
Quoted Spread		0.20	0.10	1.30	0.01	1030.91
Effective Spread		0.07	0.03	0.36	0.00	271.35
Price Impact		0.00	0.00	0.00	0.00	0.63
Depth Liquidity						
CRT100		0.21	0.10	1.33	0.01	1030.91
CRT500		0.18	0.10	1.45	0.01	956.05
CRT1000		0.19	0.11	1.52	0.01	1081.63
CRT5000		0.13	0.07	0.53	0.00	66.96
CRT10000		0.22	0.07	1.06	0.01	31.94
DWAP-Spread		0.48	0.28	1.83	0.01	1030.91
CRT1000/Quoted		3.87	2.75	9.45	0.99	3504.19
CRT5000/Quoted		6.51	4.71	15.84	1.00	5651.43
DWAP/Quoted		4.78	3.22	4.33	0.01	50.00

APPENDIX 4: FLEETING AND STATIC DEPTH AGAINST TOTAL DEPTH

Table 4: Fleeting and Static depth against total depth

This table reports the differences of liquidity measures from the fleeting and static LOBs against total liquidity from the complete LOB. The total LOB includes all orders, while the static and fleeting LOBs are subsets of the complete LOB. The fleeting LOB is comprised of only limit orders that provide liquidity for two seconds or less, whereas the static LOB is only comprised of limit orders providing liquidity greater than two seconds. Columns [1] through [3] report the liquidity measures for the total, static and fleeting LOB respectively. Column [4] is the difference between the static and total LOB, while column [5] reports the difference between the fleeting and total LOB. Column 6 reports the differences between the fleeting and static LOB.

	Total LOB	Static LOB	Fleeting LOB	Total - Static	Total - Fleeting	Diff-in-Diff
	[1]	[2]	[3]	[4]	[5]	[6]
Panel A: Top of book liquidity measures						
Quoted Spread	0.0692	0.0708	0.2118	-0.0016	-0.1426	0.14
				15.4	409.62	-424.78
Effective Spread	0.0327	0.035	0.0743	-0.0023	-0.0416	0.039
				29.4	268.46	-247.51
Price Impact	0.0026	0.0002	0.0002	0.0024	0.0024	0.00
				-75.31	-73.65	-7.08
Panel B: Depth liquidity measures						
CRT1000	0.2167	0.2543	0.19907	-0.03766	0.0176	-0.0553
				258.26	-41	124.82
CRT5000	1.4926	1.6686	0.13732	-0.17601	1.3553	-1.5313
				173.55	-418.58	429.54
CRT1000 / Quoted	3.3566	3.7066	3.96038	-0.34995	-0.6038	0.2538
				311.43	215.91	-87.28
CRT5000 / Quoted	21.6723	23.5775	6.90505	-1.90528	14.7672	-16.6725
				173.48	-412.5	434.84
DWAP spread	11.1085	11.0191	0.49331	0.08936	10.6152	-10.5258
				-17.09	-2500.2	2523.85
DWAP / Quoted	37.5195	35.3364	4.79554	2.18308	32.724	-30.5409
				-172.38	-6848.8	6576.41
Panel C: Percentage of minutes able to buy and sell q shares						
q=100	1.00	1.00	0.99	0.00	0.01	-0.01
				-5.82	-53.37	53.27
q=500	1.00	1.00	0.42	0.00	0.58	-0.58
				-15.15	-282.69	282.51
q=1000	1.00	1.00	0.29	0.00	0.71	-0.71
				-15.29	-354.44	353.59
q=5000	1.00	0.98	0.04	0.02	0.95	-0.94
				-25.14	-1052.30	870.62
q=10000	0.81	0.78	0.02	0.03	0.79	-0.76
				-11.18	-424.68	387.16

APPENDIX 5: COST AND PERCENT OF TIME TO COMPLETE A ROUND TRIP TRAD

Table 5: Cost and percent of time to complete a round trip trade.

This table reports the cost of a round trip trade for trades of size q, separated by market capitalization quintiles. The percent of time a trader is able to complete a round trip trade is reported in brackets. The data are partitioned by market capitalization quintiles, where Q1 represents the smallest 20% of securities in the sample and Q5 represents the largest 20%. Column [6] reports the difference between the largest 20% and smallest 20%. * represents significance at the 1% level.

	Q1 Small	Q2	Q3	Q4	Q5 Large	Q5 – Q1	
	[1]	[2]	[3]	[4]	[5]	[6]	Test Statistic
			Panel A: Total Limit Order Book				
q=100	0.06	0.08	0.09	0.08	0.07	0.01	-8.84
	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[0.01]	-2.95
q=500	0.11	0.15	0.17	0.13	0.11	0.00	-0.03
	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[0.02]	-0.74
q=1,000	0.17	0.25	0.28	0.22	0.17	0.58	-10.09
	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[0.00]	0.00
q=5,000	0.91	1.66	2.12	1.96	0.93	0.00	-0.97
	[1.00]	[0.99]	[1.00]	[1.00]	[1.00]	[0.00]	0.00
q=10,000	1.66	2.62	3.76	3.61	2.24	0.00	-6.01
	[0.82]	[0.73]	[0.71]	[0.82]	[0.97]	[0.15]	-36.26

	Q1 Small	Q2	Q3	Q4	Q5 Large	Q5 – Q1	
	[1]	[2]	[3]	[4]	[5]	[6]	Test Statistic
Panel B: Static Limit Order Book							
q=100	0.06	0.09	0.10	0.08	0.08	0.02*	-8.99
	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[0.00]*	[-3.16]
q=500	0.12	0.18	0.20	0.16	0.13	0.01*	-2.79
	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[0.00]*	[-8.24]
q=1,000	0.20	0.29	0.33	0.27	0.20	0.01	-1.04
	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]	[0.00]*	[-8.21]
q=5,000	1.01	1.82	2.42	2.28	1.15	0.14*	-3.86
	[0.98]	[0.97]	[0.98]	[0.98]	[0.99]	[0.02]*	[-9.61]
q=10,000	1.72	2.68	3.83	3.76	2.47	0.75*	-11.92
	[0.79]	[0.70]	[0.68]	[0.78]	[0.95]	[0.17]*	[-36.21]
Panel C: Fleeting Limit Order Book							
q=100	0.20	0.27	0.28	0.24	0.22	0.02	-2.72
	[0.99]	[0.99]	[0.99]	[0.99]	[1.00]	[0.01]	[-16.35]
q=500	0.32	0.68	0.57	0.57	0.39	0.07	-3.09
	[0.21]	[0.31]	[0.35]	[0.54]	[0.78]	[0.57]	[-113.59]
q=1,000	0.57	1.37	0.81	1.02	0.49	-0.07	1.64
	[0.09]	[0.16]	[0.21]	[0.38]	[0.67]	[0.58]	[-111.47]
q=5,000	0.24	0.21	0.07	0.07	0.09	-0.15	13.44
	[0.00]	[0.01]	[0.02]	[0.07]	[0.13]	[0.13]	[-42.61]
q=10,000	1.04	0.67	0.08	0.06	0.07	-0.97	24.35
	[0.00]	[0.00]	[0.00]	[0.03]	[0.05]	[0.05]	[-26.14]

APPENDIX 6: THE CONTRIBUTION OF FLEETING AND STATIC TOP-OF-BOOK LIQUIDITY ON TOTAL TOP-OF-BOOK LIQUIDITY

Table 6: The contribution of fleeting and static top-of-book liquidity on total top-of-book liquidity

This table relates the static and fleeting limit order book to the complete limit order book. The dependent variable in models 1 to 3 is the quoted spread, models 4 to 6 is the effective spread, and models 7 to 9 is price impact for stock *i* and time *t*, averaged to the minute. The two key variables in all equations is the static and fleeting measure of liquidity (quoted spread, effective spread, and price impact). I include midpoint price volatility for minute *t* to capture minute volatility, daily price range to capture stock volatility, the log of the daily closing price, and the market capitalization, as control variables. Estimates are obtained by ordinary least squares, I report test-statistics computed with robust standard errors clustered at the firm level in parentheses. All models include firm fixed effects, as well as minute dummy variables to control for time of day liquidity patterns. Wald tests are conducted to check if fleeting and static liquidity is identical in its contribution to total liquidity, with f-tests reported at the bottom of the table. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Dependent Variable	Quoted Spread			Effective Spread			Price Impact		
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Intercept	-0.00	0.41*	0.01	0.07	0.22***	0.09***	-0.04	-0.04	-0.04
	(-0.057)	(1.959)	(0.036)	(1.441)	(4.607)	(3.908)	(-0.713)	(-0.688)	(-0.693)
Static	0.92***		0.56**	0.74***		0.49***	0.40***		0.39***
	(23.079)		(2.459)	(4.987)		(38.861)	(6.573)		(6.350)
Fleeting		0.13*	0.12		0.01***	0.01***		-0.04	-0.03
		(1.804)	(1.514)		(4.517)	(3.645)		(-0.884)	(-0.585)
Minute Volatility	-0.00	-0.00	-0.00	0.00**	0.00	0.00	0.00***	0.00***	0.00***
	(-1.336)	(-0.670)	(-1.522)	(2.231)	(1.070)	(0.750)	(7.885)	(7.419)	(7.377)
Range	-0.00	-0.00	-0.00	0.00	0.00***	0.00**	0.00***	0.00***	0.00***
	(-1.258)	(-0.565)	(-1.455)	(0.160)	(3.739)	(2.058)	(3.949)	(3.951)	(3.968)
Log Price	0.00	0.06***	0.01	0.01	0.03***	0.01***	-0.01	-0.01	-0.01
	(0.009)	(3.061)	(0.658)	(1.274)	(6.483)	(5.461)	(-1.189)	(-1.190)	(-1.168)
Market Cap	0.00	-0.03*	-0.00	-0.01	-0.02***	-0.01***	0.00	0.00	0.00
	(0.139)	(-1.801)	(-0.055)	(-1.361)	(-4.196)	(-3.575)	(0.870)	(0.852)	(0.848)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-test			582***			194***			16***
N	1071	1071	1071	1071	1071	1071	1071	1071	1071
R-Squared	0.0715	0.1619	0.1797	0.5432	0.0256	0.8889	0.0022	0.0021	0.0021

APPENDIX 7: THE CONTRIBUTION OF FLEETING DEPTH AND STATIC DEPTH ON TOTAL DEPTH

Table 7: The contribution of fleeting depth and static depth on total depth

This table relates the static and fleeting limit order book to the complete limit order book. The dependent variable in models 1 to 3 is the cost to buy and sell 1000 shares, 4 to 6 is the cost to buy and sell 5000 shares, and 7 to 9 is depth weighted average spread for stock *i* and time *t*, averaged to the minute. I include the daily range, the log of the closing price, and the market capitalization, as control variables. Estimates are obtained by ordinary least squares, test-statistics computed with robust standard errors clustered at the firm level are in parentheses. All models include firm fixed effects, as well as minute dummy variables to control for time of day liquidity patterns. Wald tests are conducted to check if fleeting and static liquidity is identical in its contribution to total liquidity, with f-tests reported at the bottom of the table. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Dependent Variable	CRT 1000			CRT 5000			DWAP Spread		
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Intercept	-0.43	1.51***	-2.52*	-4.92	-0.46	-0.42	22.49***	63.74***	25.62***
	(-0.647)	(2.879)	(-1.784)	(-1.301)	(-1.079)	(-1.587)	(2.685)	(2.723)	(2.741)
Static	0.82***		0.83***	0.88***		0.92***	0.67***		0.64***
	(48.344)		(17.393)	(110.69)		(56.817)	(11.309)		(12.758)
Fleeting		0.02***	0.00**		0.01	0.00		0.18***	0.14***
		(7.228)	(2.069)		(1.392)	(1.519)		(4.867)	(3.277)
Minute Volatility	0.00***	0.00***	0.00*	0.00***	-0.00**	-0.00***	-0.00***	-0.00***	-0.00***
	(5.853)	(4.316)	(1.904)	(3.646)	(-2.188)	(-3.506)	(-2.656)	(-6.746)	(-3.755)
Range	0.00***	0.01***	-0.00	0.00*	-0.02	-0.00	-0.01	0.17	-0.02
	(3.650)	(3.056)	(-1.361)	(1.756)	(-0.246)	(-1.570)	(-0.189)	(0.910)	(-0.452)
Log Price	-0.06	0.15***	-0.23*	-0.49	-0.01	-0.04**	1.75**	7.10***	2.08***
	(-0.865)	(3.336)	(-1.847)	(-1.307)	(-0.465)	(-2.014)	(2.385)	(3.398)	(2.697)
Market Cap	0.05	-0.12***	0.22*	0.46	0.04	0.03	-1.70**	-5.22**	-1.95**
	(0.725)	(-2.760)	(1.794)	(1.315)	(1.130)	(1.647)	(-2.398)	(-2.576)	(-2.527)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-test			170***			1433***			6**
N	1,089	1,089	1,089	1,089	576	576	1,089	1,089	1,089
R-Squared	0.8572	0.0855	0.8234	0.9465	0.1910	0.9714	0.5394	0.0189	0.5126

APPENDIX 8: Endogeneity and simultaneity of depth and fleeting orders

Table 8: Endogeneity and simultaneity of depth and fleeting orders

This table reports the estimates for models controlling for the simultaneity issues of fleeting and total depth. Fleeting liquidity may be determined by contemporaneous total liquidity, leading to endogeneity due to the simultaneous concern. Models 1 and 2 regress total liquidity on lagged fleeting and static orders, while Models 3 through 9 address the simultaneity issue through 2SLS. The first stage (unreported) regresses the fleeting and static liquidity measures for the current period and lagged period. The predicted estimates are then used in the second stage as an instrument for total liquidity. Test-statistics computed with robust standard errors clustered at the firm level are in parentheses. All models include firm fixed effects, as well as minute dummy variables to control for time of day liquidity patterns. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

	Lagged Cross Sectional		2SLS Model						
Dependent Variable	Total Quoted	Total CRT 1000	Total Quoted	Total Effective	Total Price Impact	Total CRT 1000	Total CRT 5000	Total CRT 1000 Ratio	DWAP Ratio
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Lagged	0.33***	-0.00							
Static	(11.11)	(-0.034)							
Lagged	-0.01***	-0.00							
Fleeting	(-4.40)	(-1.23)							
Static			1.13***	0.48***	0.23***	0.82***	0.92***	0.85***	0.69***
Liquidity			(7.860)	(62.582)	(2.849)	(39.773)	(120.068)	(15.612)	(201.267)
Predicted			-0.06	0.25***	-5.96***	0.00	-0.23***	-0.10	13.79***
(2^{nd} stage)			(-1.090)	(3.333)	(-11.733)	(0.504)	(-2.596)	(-1.188)	(74.187)
Minute	0.00***	0.00***	0.00**	-0.00	0.00***	0.00**	-0.00***	0.00	-0.00***
Volatility	(7.800)	(6.946)	(2.471)	(-1.632)	(22.447)	(2.019)	(-4.014)	(1.199)	(-26.848)
Range	0.00***	0.00***	0.00	-0.00***	0.00***	-0.00***	0.00**	0.04**	-1.30***
	(4.379)	(3.421)	(0.802)	(-2.718)	(21.726)	(-2.932)	(2.269)	(2.120)	(-34.130)
Log Price	0.0539***	0.14***	-0.0144	0.0010	-0.01***	-0.23***	0.15**	-1.43***	-1.71
	(2.765)	(4.209)	(-1.106)	(0.279)	(-3.752)	(-28.363)	(1.982)	(-40.863)	(-1.340)
Market Cap	-0.02	-0.11***	0.01	0.00	0.00**	0.21***	-0.13**	1.36***	-0.15
	(-1.486)	(-3.443)	(0.927)	(1.295)	(2.174)	(27.036)	(-2.021)	(13.701)	(-0.124)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,071	1,071	1,061	1,070	1,071	1,057	344	1,057	1,062
R-Squared	0.2745	0.0761	0.7998	-0.3528	-0.0197	0.8015	0.9206	0.5040	-9.9634

APPENDIX 9: DEPTH AND VOLUME QUINTILES

Table 9: Depth in volume quintiles

This table displays the number of fleeting and static orders at depth quintiles. Depth is first ranked at the minute level within a stock, and then averaged across stocks. Panel A ranks are formed according to the trading costs to simultaneously buy and sell 1000 shares of a stock. Panel B ranks are formed according to the cost to buy and sell 5000 shares of a stock. Panel C ranks are formed according to the DWAP spread, which is the difference between the depth-weighted average offer price and the depth-weighted average bid price. Q1 represents low levels of CRT and DWAPspread, which is indicative of high depth, while Q5 represents low depth. Column [6] reports the differences. * represents significance at the 1% level.

	Q1 High Depth	Q2	Q3	Q4	Q5 Low Depth	Q5 – Q1
	[1]	[2]	[3]	[4]	[5]	[6]
Panel A: Total CRT1000 Depth						
Fleeting Orders	4,524.63	4,541.41	4,065.35	2,952.98	2,543.19	-1,981.40
						-25.66
Static Orders	3,807.76	3,472.36	2,957.45	2,175.07	2,095.62	-1,712.10
						51.82
Fleeting/Static Orders	0.74	0.76	0.82	0.93	1.09	0.35
						39.95
Panel B: Total CRT5000 Depth						
Fleeting Orders	19.44	2,720.43	5,682.65	4,924.82	5,285.06	5,265.60
						56.78
Static Orders	35.45	2,677.60	4,534.64	3,882.17	3,388.14	3,352.70
						110.91
Fleeting/Static Orders	0.54	0.79	0.78	0.81	1.02	0.48
						18.53
Panel C: Spread						
Fleeting Orders	3,468.93	4,546.67	5,498.84	4,050.46	1,282.04	-2,186.90
						33.33
Static Orders	3,648.84	4,041.18	3,926.39	2,173.30	929.68	-2,719.20
						83.68
Fleeting/Static Orders	0.60	0.71	0.89	1.28	1.46	0.86
						84.08

APPENDIX 10: ARE FLEETING ORDERS ONLY SUBMITTED WITHIN THE SPREAD?

Table 10: Are fleeting orders only submitted within the spread?

This table reports the average daily aggressiveness of orders submitted in the limit order book. Order aggressiveness is separated into one of three categories, orders that improve the BBO, orders that match the BBO, and orders that are placed behind the best bid and offer. The best bid and offer are computed from the limit order book using NASDAQ Total-View Itch data. * indicates statistical significance at the 1% level.

	Improve BBO	Match BBO	Behind BBO	Difference	Test-statistic
	[1]	[2]	[3]	[1] – [3]	
# Fleeting Orders	1,298.13	8,466.71	7,181.76	-5,883*	79.61
# of Static Orders	763.95	3,742.62	8,894.91	-8,131*	135.58
# of All Orders	2,062.10	1,2211.43	16,078.59	-14,016*	110.15
% Fleeting Orders	0.14	0.39	0.47	-0.33*	354.73
% Static Orders	0.09	0.31	0.60	-0.50*	763.12
% All Orders	0.11	0.35	0.54	-0.42	576.81
%Fleeting – % Static	0.05*	0.07*	-0.13*		
Test-statistic	89.48	66.14	131.10		

APPENDIX 11: DO FLEETING ORDERS CREATE CONSTANT FORECASTABLE DEPTH

Table 11: Do fleeting orders create constant forecastable depth?

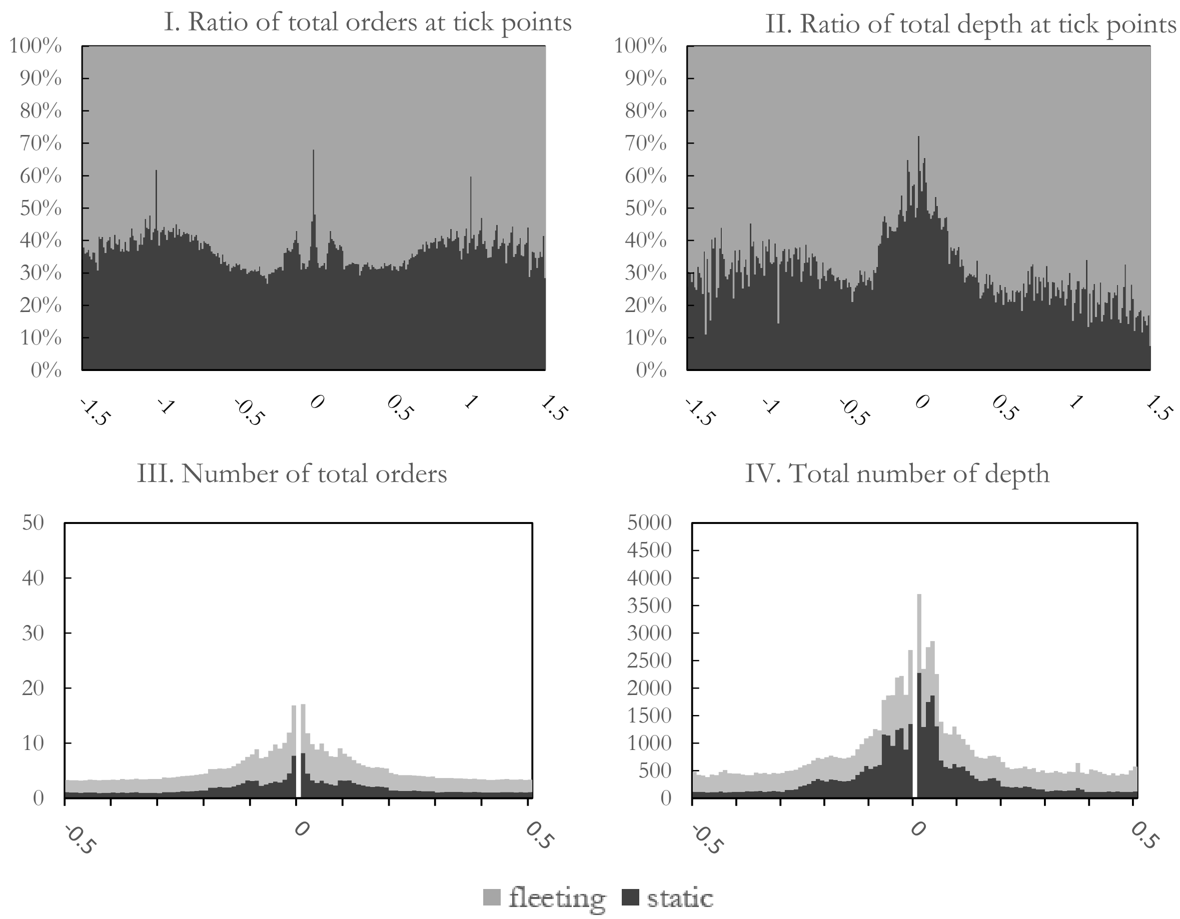
This table reports the volatility of the best bid and offer for the total limit order book, static limit order book, and fleeting limit order book. Terciles are formed within each stock, where days experiencing low fleeting order activity are in the first tercile, and days experiencing high fleeting order activity are in the third tercile. For consistency, ranks are formed within stocks and not cross-sectionally. * indicates significance at the 1% level.

	Low Fleeting Orders	Medium Fleeting Orders	High Fleeting Orders	Difference	Test-statistic
	[1]	[2]	[3]	[1] – [3]	
Total BBO Std. Dev	0.0053	0.0119	0.0325	0.0272	27.60
Static BBO Std. Dev	0.0054	0.0123	0.0302	0.0248	93.94
Fleeting BBO Std. Dev	0.0765	0.0814	0.1087	0.0322	16.10
Fleeting – Static	0.0711	0.0691	0.0784		
Test-statistic	75.60	87.64	52.14		

APPENDIX 12: FLEETING AND STATIC ORDER PRICE COMPETIVENESS

Figure 1: Fleeting and Static order price competiveness

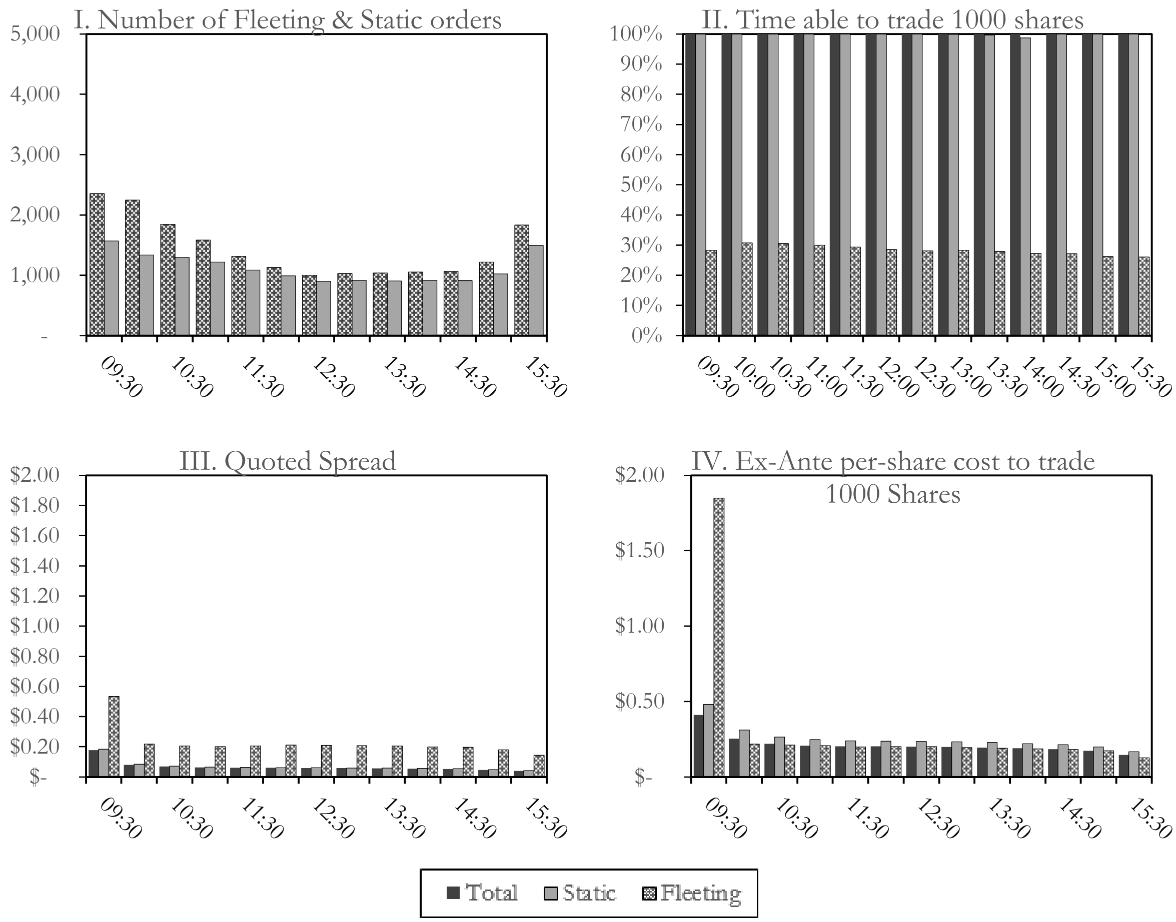
This figure presents the number of fleeting and static orders at price points relative to the Best Bid and Offer. Negative numbers represent the average distance of buy limit orders to the best bid, and positive numbers represent the average distance of sell limit orders to the best offer. The top panel presents the average raw number of fleeting and static orders relative to the BBO, at prices between 50 cents above and below the BBO. The bottom figure presents the ratio of fleeting and static orders at prices between 150 cents above and below the BBO.



APPENDIX 13: FLEETING AND STATIC LIMT ORDER BOOK BEHAVIOR THROUGHOUT THE TRADING DAY

Figure 2: Fleeting and Static limit order book behavior throughout the trading day

This figure presents characteristics of fleeting and static orders for the average stock by 30 minute periods throughout the trading day. The top left panel presents the number of fleeting and static orders submitted. The top right panel represents the percent of time able to buy and sell 1000 share trades for each of the limit order books. The bottom left is the quoted spread, and the bottom right is the cost to buy and sell 1000 shares.



PART 2: ORDER AND TRADE CHARACTERISTICS IN EQUITY MARKETS

I. INTRODUCTION

Many major U.S. exchanges and electronic trading networks are order driven markets. Traders place orders into one of two broad classes: limit orders, which are given priority following guidelines established by exchanges (i.e. price-visibility-time priority), or marketable orders, which execute at the prevailing prices set by limit orders. A trade-print is reported when a marketable order executes against an existing limit order. Many microstructure studies examine the properties of trades, and the characteristics orders.[8,9] However, given the extensive amount of research regarding orders and trades, it is uncertain how trade prints obtain their information and properties. Trades, in and of themselves, do not produce any information. Rather, properties of trades must stem from one of the two orders in which the trade originates. Marketable orders and limit orders are each submitted by independent agents with differing sets of information. The liquidity supplying trader will submit a limit order according to her beliefs regarding the asset's value, while a liquidity demanding trader (with an independent set of beliefs) will submit a marketable order. Therefore, if trades contain information or exhibit properties and patterns, the characteristics must be represented in either the limit order, market order, or both.

As an example, one documented characteristic of trade prints is the size of the trade. A number of studies make inferences regarding trading behavior based on the size of trade prints. Alexander and Peterson (2007) find that trades tend to have a higher than expected tendency to

[8] Barclay and Werner (1993), Chakravarty (2001), Alexander and Peterson (2007), O'Hara, Yao, and Ye (2014), etc.
[9] Biais, Hillion, and Spatt (1995), Foucault (1999), Chung, Van Ness, Van Ness (1999), etc.

occur on round numbers, and that these round trades have large price impacts. More recently, O'Hara, Yao, and Ye (2014) find that small, odd-lot trades contain a large amounts of price contribute, which they also suggest is evidence that informed traders strategically choose the trade size. One omission of studying trade prints alone, however, is that the trade print size is not exogenous, and information does not originate from the trade alone. The trade print size is merely an artifact of the union between a marketable order and a limit order, and is therefore some function of the size of the limit order and the size of the incoming market order. If an incoming market order is less than the posted depth at the NBBO, then the trade print will be equal to the size of the market order. However, if the market order size is greater than the posted depth, inferring information from trade print sizes become uncertain and unreliable.

Trade prints are simply a mechanical process, where market participants have no choice in choosing the characteristics of trades. Rather, market participants have control over the characteristics of the order they submit, and must make multiple simultaneous decisions when they submit their order. At the time of submission, they choose price, which ranges from marketable orders to passive limit orders, and they choose the size of the order. If traders submit limit orders, they also choose whether to wait for an incoming order, or to delete their existing order and resubmit a new order. Multiple order submission choices yield many different order classes. Prior studies look at different order classes including aggressive orders (Griffiths, Smith, Turnball, and White (2000), fleeting orders (Hasbrouck and Saar (2009)), and order sizes (O'Hara, Yao, and Ye (2014)). However, it is unknown if the characteristics between these order classes are similar.

The aim of our study is twofold. First, we compare the characteristics of trades against orders. Since trades result from the union of a marketable order executing against a posted limit order, characteristics of trades must stem from one of these two order types. We investigate which of the two order types has the larger impact trade characteristics. The second focus of our study is to look at how market conditions impact the prevalence and behavior of the different order classes.

II. HYPOTHESES

ORDER AND TRADE PRINT CHARACTERISTICS

Under normal market conditions, trade prints are the result of marketable orders executing against posted limit orders. The limit order is the supplier of liquidity, and the marketable order is the initiator of the trade. Therefore, the price, size, and information content of a trade must stem from one of the two orders from which it originated. The first question of our study is whether it is the trade initiating marketable order, or the liquidity supplying limit order, that primarily impacts the characteristics of trades. Theoretical models (e.g. Foucault, Kaden, and Kandel (2005) and Rosu (2009)) generally assume that limit order traders are risk neutral, which implies their orders execute is of little interest to them. However, recent empirical work suggests that limit order trades have a much larger role in the trading decision. Hasbrouck and Saar (2009) find that one third of limit orders are added and cancelled within two seconds, providing some evidence that limit order traders are aggressive in their strategies. We conjecture that if limit orders are aggressive and dynamic in their strategies, they are likely to have a large role on the resulting trades. Additionally, Johnson and Upson (2015) find that odd-lot trades usually are the result of odd-lot size limit orders. They also find evidence that limit orders are placed by fast, sophisticated traders.

H1: Limit orders primarily shape the characteristics of trades

We next turn our attention to how classes of orders compare against each other. Orders that are submitted by market participants do not neatly fall into the two order categories of marketable orders and limit orders. A trader is exposed to a number of decisions when placing an order, including the price to place the order, how long to let the order stand if does not execute, and how large of an order to submit. With regards to price, a trader may place the order aggressively by submitting a marketable order, or, if immediate execution isn't required the trader may place a limit order (Biais, Hillion, and Spatt (1995). However, even limit orders may be submitted with varying degrees of aggressiveness. A limit order's price may improve the current limit order book spread by being placed within the best bid and ask. A limit order may also match the best prices by being placed at the best bid (for buy orders) and best offer (for sell orders), or it may be placed deeper in the limit order book queue at inferior prices. Griffiths, et al. (2000) find that aggressive orders behave differently than less passive orders. They find that marketable orders that cross and lock the market have a high probability of execution, greater than 85% and as high as 99.85% depending on order size (see Griffiths et al.'s Table 1). With regards to time, recent evidence by Hasbrouck and Saar (2009) shows that some traders behave aggressively by submitting short-lived limit orders that are on the limit order book, which they refer to as fleeting orders. Fleeting orders are limit orders that are added, and quickly cancelled. Hasbrouck and Saar (2009) find that fleeting orders share similarities with liquidity demanding marketable orders. These many classes of orders highlight that traders with different expectations may behave differently.

We test to see if orders across different classifications are similar. Given that traders can place their orders aggressively with regards to both price and time duration, we hypothesize that aggressively priced orders (marketable orders and limit orders that result in execution) should be similar to orders that are aggressive in their timing strategies. We test this both by looking at size characteristics, as well as the fill rates of these orders.

H2: Fleeting orders, Executed limit orders, and marketable orders have similar characteristics

H3: Aggressive limit orders, and fleeting orders have higher fill-rates and order sizes compared to less-aggressive limit orders.

THE IMPACT OF MARKET CONDITIONS ON ORDER CLASSES

Theory suggests that the market environment impacts when traders will place their orders, as well as which orders to submit, highlighting that all orders are not uniformly distributed throughout the trading day. Traders will choose what type of order to submit depending on the nature of the limit order book. Parlour (1998) models a limit order market where the strategies of the market participants is dependent on the state of the limit order book. Limit orders that are added to a thick order book have a lower probability of execution, leading traders to submit more marketable orders. When depth is high at one side of the book, the likelihood of a limit order being submitted decreases on the same side of the book but increases on the opposite side of the book. We thus expect that more limit orders are submitted to the side of the limit order book with less depth. Foucault (1999) develops a dynamic theory on the trader's decision to submit limit and marketable orders. Foucault's theory predicts that the proportion of limit orders increases when volatility increases, and that the aggressiveness of orders will decreases with volatility. We expect to see a higher number of limit orders during episodes of heightened volatility.

H4: Traders submit limit orders when volatility is high, depth is low, and the spread is wide.

In the model developed by Foucault, Kadan, and Kandel (2005), all traders incur waiting costs; impatient traders have high waiting costs and patient traders have low waiting costs. Consequently, the impatient traders submit marketable orders and the patient traders submit limit orders. As the limit order book grows thick, the time to execution for limit orders increases and the probability of execution decreases. Traders that have a low tolerance for the cost of delaying execution will either submit more aggressive limit orders or submit marketable orders to reduce waiting times. Rosu (2009) also predicts that when the limit order book is thick, traders will either submit a quick fleeting order or a marketable order.

H5: Aggressive orders, market orders, and fleeting orders are more prevalent when volatility is low and depth is high.

Foucault, Kadan and Kandel (2005) predict that traders become more impatient over the course of the trading day. One of the costs traders are exposed to is the cost of delayed execution. Traders that have high costs of delayed execution are sensitive to the time of day and are aware of the time remaining until trading ends. Traders with high sensitivity to waiting costs will submit market orders, while traders with low sensitivity to waiting costs submit limit orders. Foucault, Kadan and Kandel predict that there is an increase in spreads and trading frequency toward the end of the day. We therefore expect an increase in aggressive limit orders, and a higher number of market orders relative to trades at the end of a trading day. Empirical literature, such as Chung, Van Ness, and Van Ness (1999) show that limit orders are increasing through the trading day, and drop of at the end of the day. We expect an increase in aggressive limit orders and an increase in marketable orders at the end of the trading day.

H6: Limit orders are more aggressive, and traders submit more market orders at the end of the trading day relative to limit orders.

III. DATA AND METHODS

DATA SOURCES

This paper uses data from several different sources. Our primary dataset is NASDAQ OMX TotalView-ITCH dataset. The dataset includes messages for orders that are added, deleted, updated, and executed on the NASDAQ exchange. Additional stock information for this study comes from the Center for Research and Securities Prices (CRSP). Since theories tested in this paper rely on measures of depth, we reconstruct the limit order book for each of the datasets. The limit order book is recreated by implementing the information from all add orders into a dynamic database. The database then automatically sorts the orders on price-time priority. When each order is added, the database reports the best bid, best offer, and depth of the limit order book for that security. As orders are updated, deleted, or executed, the database incorporates the new information according to the message type.

Our sample period includes the trading days from the months of August 2014 through October 2014. Since we use NASDAQ order level data, we filter our sample to only included NASDAQ listed securities. During our time period there are 2,871 NASDAQ listed securities. To adequately test our hypotheses, we reconstruct the limit order book and compute measures of depth (described in the next section). Many of the variables break down for illiquid securities, and as a result we employ a number of additional filters to ensure that the measures we employ are reliable. We require the securities in our sample to have closing prices above five dollars each day, and we eliminate from our sample stocks that do not trade at least 1,000 shares each day, which leaves a final sample of 1,187 stocks. When recreating the limit order book, we remove stub quotes, which are non-competitive orders placed on the limit order book. We classify stub-quotes as orders less than one dollar and greater than $10,000 (the minimum closing price in our study is $5 and the highest closing price is just over $1,000).

VARIABLE MEASURES AND METHODS

A majority of the analysis rests on comparing limit orders against marketable orders. The data in its original form only contains information for limit orders as they enter the limit order book, and then reports which limit orders executed and cancel. There are no entries for marketable orders. Following the method of Johnson, McInish, and Upson (2015), we sum all trade-prints that occur for the same stock in the same nanosecond, to gather information on the size of the marketable order.

Theory by Foucault (1998) and Foucault, Kadan, and Kandel (2005) both make assumptions that rely on the thickness of a limit order book (LOB). Measuring depth for a security in a concise manner is difficult. Unlike spread, which can be represented by a single number, depth is more indefinite. There is no single number that is universally used to represent the depth of a security. In order to test the theories of Foucault (1998) and Foucault, Kadan, and Kandel (2005) we construct two different measures of LOB thickness. The first measure of LOB thickness we construct makes use of the ex-ante cost of a round trip trade (*CRT*) defined in Domowitz, Hansch, and Wang (2005). This measure is the trading cost a trader will pay to buy and sell an order of q shares. Using similar notation as Domowitz, Hansch, and Wang the *CRT* is expressed as

$$CRT = \left[\sum_{j=1}^{k-1} D_{j,ask}\, P_{j,ask} + \left(q - \sum_{j=1}^{k-1} D_{j,ask}\right)P_{k,ask}\right] - \left[\sum_{j=1}^{k'-1} D_{j,bid}P_{j,bid} + \left(q - \sum_{j=1}^{k'-1} D_{j,bid}\right)P_{k,bid}\right]. \quad (1)$$

In equation (1), k is the number of ticks that a sell order of q shares has to travel on the offer side of the book before fully filling and k' is the number of ticks a buy order of q shares has to travel before completely filling. D_j is depth at a tick j and P_j is the price at tick j. The first term in equation (1) is the cost to sell q shares, and the second term is the cost to buy q shares. The difference is the total cost to buy and sell q shares. Although Domowitz, Hansch, and Wang consider 10 values of q between 1 and 2,701 in their depth simulations, computational constraints limit me to five values. We compute the *CRT* for values of q of 100, 500, and 1,000, 5,000 and 10,000 shares. Our results are similar for all measures of q, for brevity we only report results using a value of 1,000 for q.

The *CRT* is the ex-ante cost to buy and sell q number of shares, and the CRT_{SPREAD} is the per share ex-ante cost to buy and sell q number of shares. A trader who wishes to trade q shares would not look only at the quoted spread, rather the trader would look at the shape of the limit order book. If the number of shares being traded, q, is less than or equal to depth at the top of the book then the trader can expect to pay the quoted spread for each share of the order. If the order of size q is greater than the top of the book, the actual spread the trader will anticipate paying is greater than the quoted spread.

We separate the limit orders into various order classes to perform our analysis. Traders may pursue a number of different strategies when submitting limit orders, including the price to submit, as well as the how long to let the order stand before deleting. For convenience, we report all of the order classes used in our study in Table 1. The first three variables are common variables that are used in Microstructure studies. A trade-print is what is reported to traders on the consolidated tape, and is produced from a marketable order executing against a limit order. Marketable orders are liquidity demanding orders that are submitted by traders for immediate execution. A marketable order and a trade print will not always be the same. Although every trade print does stem from a marketable order, a single marketable order may execute against multiple limit orders, which would produce multiple trade prints. Limit orders are all liquidity supplying orders that are submitted to the limit order book. This broad class includes all the subsets of limit orders. We break down limit orders into five subsets (which may overlap in their classification). Executed limit orders are the subset of limit orders that result in execution. This subset excludes all limit orders that never execute. Fleeting limit orders are limit orders that are on the limit order book for less than two seconds, and may be removed either through deletion or execution. The remaining three limit orders are mutually exclusive. Improving limit orders are limit orders that are priced within the bid-ask spread. Matching limit orders are limit orders that are priced at the top of the limit order book. Passive limit orders are priced behind the top of the limit order book.

DESCRIPTIVE STATISTICS

Table 2 presents descriptive statistics of the orders and trades in the study. The average security has a closing price of $45.71, a market capitalization of $5.67 billion, and has a daily range (daily high minus daily low) of 92 cents. For each day in our sample, the average stock has 2,356 trade prints, which originate from 987 marketable orders, and 1,464 limit orders. The average total number of orders per stock, including orders that do not execute, is 33,150 per day, of which 18,632 are submitted for less than two seconds. We also include the average order and trade sizes. The average trade print, which is the union of a marketable and limit order, is 96.34 shares. The average marketable order is 168.40 shares, and the average size of executed limit orders is 118.81 shares. The average executed volume is 227,112 shares. The total number of order volume received for the average stock is just over seven million shares. The final summary statistic reported is the standard deviation of order and trade prices. Trades, marketable orders, and executed limit orders have low standard deviations, while all limit orders and fleeting orders have wide standard deviations.

In Figure 1 we present the intraday patterns of orders and trades averaged to the minute level. Panel A reports the number of orders and trade prints. Early in the trading day the average minute stock will receive approximately 100 trade prints, while throughout the trading day there are less than 20 trade prints. Marketable orders and executed limit orders follow a similar pattern. Early in the trading day there are approximately 140 limit orders submitted in a one minute period for the average security in our sample, and drops to about 60 steadily drops to about 60 midday. Panel B reports the trade print sizes and order sizes averaged to the minute. All order sizes, including limit orders, executed limit orders, and marketable orders all display consistent order sizes throughout the trading day of approximately 150-200 shares, with the exception of the final closing period of the trading day, where order sizes jump above between 200-500 shares per order. Trade prints are much smaller, with the average trade-print size being approximately 100 shares, and jumping to over 200 shares at the end of the trading day.

IV. RESULTS

In this section we test the hypotheses regarding the characteristics of orders and trades. We separate our analysis into two subsections. The first subsection tests the first three hypotheses. These tests identify how order characteristics impact trade characteristics, as well as how different classes of orders compare against one another. The second subsection investigates how market liquidity impacts the characteristics and order submission strategies of market participants.

COMPARING CHARACTERISTICS OF ORDERS AND TRADES

We begin our analysis by identifying the extent that the characteristics of marketable orders and limit orders each impact the characteristics of trades. The first hypothesis suggests that limit orders primarily shape the characteristics of trades. Our analysis focuses on two testable characteristics of orders and trades, the first is size and the second is price volatility. We hypothesize that trade print sizes are mostly determined by limit orders, and that any volatility that is present in the trade print price will also stem from the volatility of the original limit order price. Table 3 reports summary statistics and correlations of these major order and trade characteristics. Panel A reports summary statistics of the size and price volatility of marketable orders, as well as three classes of limit orders. There is approximately one marketable order for every two trades, and approximately one limit order that executes to every two trades. The average trade print is 96.37 shares, while the average size for marketable and executed limit orders is 168 and 118 respectively. One explanation for trade prints to be smaller than both marketable and limit order sizes is that orders at the top of the book cascade. A cascade occurs when the available liquidity at the top of the limit order book is smaller than the size of an incoming marketable order. The marketable order will consume all the liquidity from the order at the top of the limit order book, and then partially execute against the next best order in the limit order book. The order to trade ratio for marketable orders and executed limit orders also support this explanation. These results are similar to those found by Johnson, McInish and Upson (2015) who find that odd lot trade prints on the ticker tape stem from larger marketable orders.

Panel B of Table 3 reports the size correlations of trades, marketable orders, and multiple classes of limit orders. The size of trade prints are highly correlated with marketable limit orders and executed limit orders, however limit orders placed deeper in the limit order book have a weaker size correlation with trade prints. In Panel C of Table 3 we report the correlations of standard deviations. One of the characteristics of trade prints is volatility. Similar to size, the standard deviation of trade prints is highly correlated with marketable orders and executed limit orders, but has little correlation with limit orders placed deeper in the limit order book. Another interesting result is that limit orders which executed have little correlation with limit orders placed deeper in the limit order book, which may indicate that traders are more active in pricing at the top of the limit order book.

We continue the analysis in a multivariate framework, which is reported in Table 4. We regress trade characteristics on each of the separate order characteristics. Models [1] through [4] focus on size characteristics, and the remaining four models investigate the determinants of trade price volatility. In models [1] through [4] the independent variables include the size of marketable orders, limit orders, executed limit orders, aggressive limit orders, price matching limit orders, and passive limit orders, as well as control variables. In models [5] through [8] the independent variables of interest include the price standard deviation of marketable orders, limit orders, executed limit orders, aggressive limit orders, price matching limit orders, and passive limit orders, as well as four control variables. All variables are averaged by stock and day, leaving us with over 162,000 stock day observations. In all our models we include stock fixed effects.

Our most simple specification tests the characteristics of marketable orders and limit orders. For trade size this is expressed in columns 1 and 2 of Table 4, and for trade price standard deviation it is expressed in columns 5 and 6. Limit orders that execute primarily trade the characteristics of trade size, while trade price standard deviation is almost entirely driven by marketable order prices. We provider further tests by looking at subsets of limit orders, partitioned into three pricing categories, where an order may improve the BBO, match the BBO, or be placed behind the BBO. These specifications are shown in columns 3 and 4 for trade and order size, and columns 7 and 8 for trade and order price standard deviation. We find similar results, where trade print sizes are driven by limit orders which executed, and trade print price standard deviations are driven by marketable orders. In sum, we find mixed support for our first hypothesis which states that limit orders have a significant impact on the characteristics of trades.

The second and third hypotheses compare the characteristics of classes of limit orders and marketable orders with each other. Studies such as Hasbrouck and Saar (2009) and Griffiths et al. (2000) suggest that aggressive orders and marketable orders should have similar characteristics. We test to see if fleeting orders, limit orders which executed, and marketable orders, have similar characteristics. Table 5 reports the estimates for comparing the characteristics of order classes. Columns 1-4 reports our investigation of how different order classes compare in order size. The independent variable is order size, and the dependent variables include four indicator variables equal to one if an order fits the classification, zero otherwise. The indicator variables include marketable order, executed limit order, fleeting order, and aggressive limit order. In each specification we omit one of the indicator variables, which allows us to make comparisons of order size among order classifications. In each column, the coefficients of the non-omitted indicator variables are compared against the omitted classification. To test our second hypotheses, order classes that are similar to each other will have insignificant coefficients.

In column 1, we omit marketable orders. The average marketable order size, as indicated by the intercept, is 169 shares. The average size of executed limit orders is 50 shares smaller, and fleeting orders are 22 shares smaller. Aggressive limit orders appear to be insignificantly different, which provides evidence that marketable orders and aggressive limit orders, orders that improve the best bid an offer, have similar characteristics. We repeat the analysis, omitting executed limit orders in column 2. We find that limit orders which executed are significantly different than the other order classifications. In column 3 we omit fleeting orders, and in column 4 we omit aggressive limit orders. We repeat the analysis in columns 5-8, where order price volatility is the dependent variable, and the independent variables again include the four indicator variables of order classifications. Marketable orders and limit orders which executed have very similar price standard deviations. Although statistically different, the economic significance is low between the two order classifications. The greatest difference is among fleeting orders, which in all specifications much larger price standard deviations than the other three classifications of orders. Overall, the results from Table 5 provide mixed support for hypothesis 2. We find that marketable orders and aggressively priced limit orders are similar in size, marketable orders and executed limit orders are similar in pricing standard deviations, and that fleeting orders are priced very differently than the remaining order classes.

The third hypothesis we test in this subsection suggests that aggressive limit orders and fleeting orders should have higher fill-rates when compared to limit orders that are priced less aggressively in the limit order book. To test this hypothesis, we regress fill rates on four limit order classification indicator variables. We model this four different ways, where in each specification we omit a different order classification variable. The coefficients of the remaining indicator variables will then be relative to the omitted indicator variable. If one of the coefficients of an order classification indicator variable is insignificant, then it can be determined that it is similar to the omitted variable. This setup is similar to that of the previous hypothesis, which results were displayed in Table 5.

The results for these tests are presented in Table 6. Since the hypothesis addresses limit orders only, we do not include marketable orders in this specification, and we include all limit order classifications, which include limit orders that are fleeting, limit orders that improve the BBO (*Aggressive order)*, limit orders that match the BBO (*Matching Order),* and limit orders that are behind the BBO (*Passive Order)*. We calculate fill rate as the number of shares that execute for an order class, divided by the total number of shares submitted in that order class. In column 1 we omit fleeting orders. As expressed in the intercept, fleeting orders have a fill rate of 3.95%. *Aggressive* limit orders have a fill rate that is 10.76 percent higher, *matching* orders have a fill rate that is 2.06% higher than matching orders, and *passive* orders have a fill rate that is 4.16% lower than fleeting orders. All differences are statistically different. We omit aggressive orders in column 2, matching orders in column 3, and passive orders in column 4. In all specifications, the results suggest that each limit order classification has a significantly significant fill rate. These results do not support hypothesis 3, which states that fleeting orders and aggressive orders have similar fill rates. We additionally test this hypothesis by looking at order size, which is presented in columns

5 through 8 of Table 6. The average fleeting order size is approximately 150 shares, aggressive limit orders are 26 shares larger, matching orders are 18 shares smaller, and passive orders are 14 shares larger. All differences are statistically different, again which does not support our third hypothesis that aggressive limit orders and fleeting order characteristics are similar.

MARKET BEHAVIOR AND ORDER CHARACTERISTICS

The second subsection looks at how market behavior will impact order submission strategies. Our fourth hypothesis deals with the submission of limit orders, and states that traders submit limit orders when volatility is high, depth is low, and spread is wide. Parlour (1998) suggests that traders submit limit orders when volatility is high, depth is low, and the spread is wide. To test this hypothesis, we split each stock-day observation into fifteen minute periods. We then rank each fifteen minute period into one of five quintiles based on the liquidity ranking for that period. We perform the rankings three for three different liquidity variables; spread, depth, and volatility. Quintile 1 represents a fifteen minute period that experiences high depth as evidenced by low quoted spreads, a low CRT 1000, and low volatility during the trading day, while quintile five represents period of low liquidity, evidenced by high spread, high CRT 1000, and high volatility. All rankings are performed for each stock day. We test the hypothesis by identifying the number of orders submitted during periods of low liquidity against periods of high liquidity.

We regress the number of limit orders on five indicator variables representing the five quintiles of liquidity, as well as control variables. The first quintile, representing high liquidity, is omitted. By omitting quintile 1 we can compare the remaining four quantiles against the quintile with the highest liquidity. In all models we employ panel regression methods and include firm fixed effects. We display the results for this test in Table 7. Column 1 displays the results when partitioning by spread. In the periods that experience the lowest spread, there are approximately 3,064 limit orders submitted in the fifteen minute period. The fifteen minute period with the highest spread during a stock day has an additional 744 limit orders submitted, for a total of 3,808 limit orders submitted for the average stock, average day, during periods of high spread. These results are in agreement with the Parlour (1998). When we partition by depth, measured by CRT1000, the fifteen minute period with the highest depth has approximately 3,272 limit orders submitted for the average stock average day, while the periods with the lowest depth have 3,813 limit orders submitted. When we support by volatility, the fifteen minute period with the lowest volatility has approximately 3,313 limit orders submitted for the average stock average day, while the fifteen minute periods with the highest volatility have 4,092 limit orders submitted. Together, all the results from Table 7 support hypothesis 4, which is that limit orders are submitted more during periods of low depth.

It is possible that there is a degree of endogeneity when testing limit order submissions and periods of depth. Measuring order submissions during the same period that liquidity is measured makes it uncertain whether the new orders being submitted are responding to market conditions, or whether the market conditions reflect the order behavior. As an additional measure of robustness, we repeat the analysis by replacing the current period quintile dummy variables with dummy variables that represents the liquidity rankings of the prior one minute period. This specification addresses whether more orders are submitted depending on the market conditions of the prior one minute period, which addresses the issue of causality. We report these tests in the appendix. These results show that following a one minute period of high spread, approximately 222 new limit orders are submitted. During periods of low spread, there are approximately 235 orders submitted. The difference is significant at the 1% level. During periods of high depth, measured by CRT1000, there are approximately 218 limit orders submitted, and during periods of low depth, there are approximately 234 limit orders submitted, again significant at the 1% level. The final column of the appendix Table shows that following a period of low volatility, there are 214 limit orders submitted, however following periods of high volatility there are approximately 302 limit orders submitted.

Foucault, Kadan, and Kandel (2005), and Rosu (2009) predict that market conditions impact the prevalence of more aggressive orders. Following the predictions of these theoretical studies, our fifth hypothesis posits that when liquidity is high (indicated by low volatility, low spread, and high depth), traders will submit more aggressive limit orders, more marketable orders, and more fleeting orders. Following the methods for testing the fourth hypothesis, we separate stock days into fifteen minute periods, ranked by liquidity. The rankings are done within a stock, and not across stocks. We perform three separate rankings, including by spread, by depth, and by volatility. We regress the number of orders on each of the quintile indicator variables. Quintile 1 represents fifteen minute periods of high liquidity, while quintile 5 represents periods of high liquidity. These results are displayed in Table 8. Columns 1 through 3 regress aggressive orders on each of the three periods, where column 1 is ranked by spread, column 2 is ranked by depth, and column 3 is ranked by volatility. For the average stock day, the fifteen minute periods with the lowest spreads receive approximately 132 aggressive limit orders that improve the BBO. During the period of low liquidity, there are approximately 199 aggressive limit orders submitted. Approximately 140 aggressive limit orders are submitted during periods of high depth, and 199 limit orders are submitted during periods of low depth. From column 3, there are approximately 157 price improving limit orders submitted during periods of low volatility, and 223 aggressive limit orders submitted during periods of high volatility. We perform additional tests with marketable orders in columns 4 through 6, and fleeting limit orders in columns 7 through 9. During periods of low spread there are approximately 50 marketable orders submitted and 1,366 fleeting limit orders submitted. During periods of high spread, there are 53 marketable orders submitted and 1,878 fleeting limit orders submitted. We find similar results when ranking by depth and volatility. In general, the results suggest that when liquidity is high, traders submit less marketable orders, less aggressive orders, and less fleeting orders compared to when liquidity is low. We therefore reject the fifth hypothesis.

These results are also sensitive to possible endogeneity concerns, since it is uncertain whether the orders are being submitted in response to current market conditions, or whether the current market conditions reflect the orders being submitted. We perform an additional robustness test, similar to the previous robustness test for hypothesis 4. In this test we regress current period order submissions on indicator variables for the one minute period prior to when the current orders being submitted. By regressing on the prior period quintile variables, we are able to separate the direction of the market response, since the orders in the current one minute period are responding to the liquidity in the one minute period prior. In columns 1 through 3 of the appendix Table 8, we find that there are approximately 13 to 14 aggressive limit orders submitted during the one minute periods following high depth, and there are approximately 17-20 aggressive limit orders submitted following periods of low depth. Columns 4-6 show that when ranking on spread and depth, there are more limit orders submitted during periods of low high depth, and columns 7-9 show that more fleeting orders are submitted during periods of high depth. The robustness tests in appendix table 8 generally support the results of Table 8, which find little support that aggressive orders, marketable orders, and fleeting orders are prevalent when volatility is low and depth is high. We therefore reject our fifth hypothesis.

The sixth and final hypothesis we test addresses whether traders are more impatient towards the end of the trading day. In the model of Foucault, Kadan and Kandel (2005), traders are aware of the time to execution, and towards the end of the trading day they will submit more aggressive orders to assume any positions that were not completed during the trading day. Impatient traders would be evidenced by more aggressively priced limit orders and more marketable orders in general. We test this hypothesis by looking at the proportions of aggressive orders and marketable orders. The proportion of aggressive limit orders is computed as the number of spread improving limit orders submitted within a fifteen minute period divided by the total number of limit orders submitted within the same fifteen minute period. We calculate the proportion of marketable orders by summing all marketable orders in a fifteen minute period and dividing by the total number of orders submitted in the same period (all orders being all marketable and all limit orders). Figure 2 displays the proportion of aggressive orders and the proportion of marketable orders throughout the trading day. Consistently throughout the trading day aggressive limit orders compose approximately 10 percent of total limit orders submitted. At the end of the trading day this proportion jumps to approximately 45%. Marketable orders compose 3-5% through most of the trading day, but jump to approximately 10% at the end of the trading day. These results suggest that traders become aggressive at the end of the trading day.

In addition, we regress the proportional order rates on indicator variables representing different time periods throughout the trading day, as well as control variables. The time of day indicator variables include *Open* (9:30-10:00), *Morning* (10:00-12:00), *Midday* (12:00-13:00), *Afternoon* (13:00-15:30), and *close* (15:30-16:00). To test for time differences we omit *Open* in in columns 1 and 3. The coefficients of the remaining variables can be compared to the open time period, which allows us to identify changes in the proportion of orders. In columns 2 and 4 we omit the midday variable, where the coefficients of the remaining indicator variables can be compared to the omitted midday variable. We report these tests in Table 9. During the opening period, 10 percent of limit orders are aggressively priced, while in the afternoon the proportion of aggressive limit orders increases to 20 percent. The proportion of orders that are marketable orders in the opening is 1 percent, and then rises by 4 percent at the end of the trading day. The results from Table 9 support the model of Foucault, Kadan and Kandel (2005), where we find a higher proportion of both aggressive limit orders, and marketable orders at the end of the trading day compared to the beginning of the trading day. These results support hypothesis 6.

V. CONCLUSION

In this study we investigate the characteristics of orders and trades. Traders place orders into one of two broad classes: limit orders, which are given priority following guidelines established by exchanges, or marketable orders, which execute at the prevailing prices set by limit orders. A trade-print is reported when a marketable order executes against an existing limit order. Since trade prints are a simply a mechanical process in which market participants do not directly choose the characteristics of the resulting trade, the characteristics of trade prints must stem from one of the two orders from which the trade originated. The first focus of our paper is to this end. We investigate which type of order primarily drives the characteristics of trades. Our results suggest that limit orders primarily drive trade print size, while the trade print volatility is driven by marketable orders.

The second contribution of our study identifies how market conditions impact the prevalence and behavior of the different order classes. Our results suggest that when liquidity is low, traders will submit more limit orders, and when liquidity is high, the fill rates of aggressive and marketable orders increase. Finally, our results do find that trader are more aggressive at the end of the trading day, evidenced by more marketable orders and aggressively priced limit orders.

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APPENDIX

APPENDIX 1: DEFINITIONS OF TRADE PRINTS AND ORDER CLASSIFICATIONS

Table 1: Definitions of trade prints and order classifications

Definition and description of Order and Trade Types	
Trade Print	Trade prints occur when a marketable order executes against a limit order that is standing on the limit order book.
Marketable Order	Marketable orders are calculated by summing all trades that occur for the same stock, at the same price, in the same nanosecond.
Limit Order	All non-marketable order that are added to the limit order book. These orders may later execute, be updated, or be deleted.
Executed Limit Order	These orders are the subset of limit orders that will end up being executed during the trading day.
Fleeting Order	These orders are a subset of limit orders, which are added to the limit order book and subsequently executed or deleted within 2 seconds.
Aggressive order	These orders are a subset of limit orders, and are submitted within the current best bid and offer.
Price-Matching order	These orders are a subset of limit orders, and are submitted at the current best prices (best bid for buy orders, best offer for sell orders).
Passive order	These orders are a subset of limit orders, which are submitted behind the current best prices (best bid for buy orders, best offer for sell orders).

APPENDIX 2: DAILY SUMMARY STATISTICS

Table 2: Daily Summary Statistics

This table presents stock-day summary statistics for the securities in our sample. Panel A reports the daily summary statistics of the firm, while Panel B reports the characteristics of orders and trades, averaged at the daily level. The order classes include marketable orders, limit orders, as well subsets of limit orders which includes limit orders that execute, limit orders that are fleeting (added and deleted/executed within 2 seconds). Data is gathered from the NASDAQ Historical TotalView ITCH database, and covers the three months from August to October 2014.

	No.	Mean	Median	St. Dev.	Min	Max
Panel A: Firm level daily summary statistics						
Price	41,664	45.71	30.79	66.37	5.14	1,899.64
Market	41,664	5,666,771	1,068,623	26,593,012	54,764	618,546,679
Range	41,664	0.92	0.60	1.38	0.02	75.08
Panel B: Order and Trade Characteristics						
Trades	41,664	2,356	983	5,249	34	281,231
Marketable	41,664	987	484	1,893	6	113,698
Executed Limit	41,664	1,464	595	3,395	7	184,963
Limit Orders	41,664	33,150	14,403	67,541	294	2,905,789
Fleeting Orders	41,664	18,632	6,188	49,271	16	2,585,543
Trade Size	41,664	96.34	85.92	48.30	9.70	1,938.95
Market Order	41,664	168.40	117.96	196.73	17.50	4,259.46
Executed Order	41,664	118.81	101.21	69.29	19.66	2,215.45
Limit Order Size	41,664	145.66	110.60	276.65	31.84	12,950.47
Fleeting Order	41,664	146.33	106.67	366.98	30.15	16,796.91
Trade Volume	41,664	227,112	66,184	721,806	765	42,391,021
Limit Order	41,664	7,089,756	1,700,838	43,333,047	62,794	2,096,399,369
Fleeting Order	41,664	4,359,592	684,304	33,243,210	1947	1,601,934,053
Trade Std.	41,664	0.01	0.01	0.01	0.00	0.50
Market Order	41,664	0.01	0.01	0.01	0.00	0.51
Executed Order	41,662	0.02	0.01	0.04	0.00	2.25
Limit Order Std.	41,664	19.86	0.20	105.64	0.02	6,641.26
Fleeting Order	41,664	15.43	0.09	129.76	0.00	6,148.48

APPENDIX 3: ORDER AND TRADE CHARACTERISTICS AND CORRELATIONS

Table 3: Order and Trade characteristics and correlations

This table reports the characteristics of trades and orders. Trade prints occur when a marketable and limit order intersect. The orders analyzed include marketable and limit orders. Limit orders are further partitioned into limit orders that execute, limit orders that are aggressive (submitted within the BBO), limit orders that are matching (submitted at the BBO), and orders that are passive (submitted inferior to the BBO). Panel A reports the mean order to trade ratio for each of the order classes, as well as the mean size and mean price volatility of each of the order and trade classes. Panel B displays the size correlations of the order classes, and Panel C covers the correlations of price standard deviations of the order classes. Data is gathered from the NASDAQ Historical TotalView ITCH database, and covers the three months from August to October 2014.

Panel A: Mean order and trade characteristics

	Trade prints	Marketable Orders	Executed Limit Orders	All Limit Orders	Aggressive Orders
Order-Trade Ratio	n/a	0.4931	0.4980	7.2977	0.9863
Size	96.37	168.40	118.89	145.51	173.19
Volatility	0.0095	0.0109	0.0193	19.6087	0.0364

Panel B: Size correlations							
	Trade prints	Marketable Orders	Limit Orders	Executed Limit Orders	Aggressive	Matching	Passive
Trade Prints							
Marketable	.8705*						
Limit	.4105*	.3015*					
Executed Limit	.9158*	.7403*	.3809*				
Aggressive	.5637*	.5554*	.8320*	.5007*			
Matching	.3805*	.2355*	.9371*	.3438*	.8716*		
Passive	.3252*	.2079*	.9719*	.3082*	.7492*	.8733*	

Panel C: Standard deviation correlations							
	Trade prints	Marketable Orders	Limit Orders	Executed Limit Orders	Aggressive	Matching	Passive
Trade Prints							
Marketable	.9969*						
Limit	.0572*	.0574*					
Executed Limit	.9218*	.9151*	.0661*				
Aggressive	.5326*	.5743*	.0304*	.4819*			
Matching	.1309*	.1335*	.0047	.1105*	.1901*		
Passive	.0388*	.0399*	.9713*	.0472*	.0237*	.0043	

*Statistically different at 1% level

APPENDIX 4: DETERMINANTS OF TRADE CHARACTERISTICS

Table 4: Determinants of Trade Characteristics

This table presents the estimates for cross sectional panel regressions. The dependent variables include two characteristics of trades, size and volatility. In models [1] through [4] the independent variables include the size of marketable orders, limit orders, executed limit orders, aggressive limit orders, price matching limit orders, and passive limit orders, as well as four control variables. In models [5] through [8] the independent variables include the price standard deviation of marketable orders, limit orders, executed limit orders, aggressive limit orders, price matching limit orders, and passive limit orders, as well as four control variables. The control variables include market capitalization, the daily closing price, daily trading volume, and the daily range as a proxy for stock volatility.

Dependent Variable	Trade Size	Trade Size	Trade Size	Trade Size	Trade Price Std. Dev	Trade Price Std. Dev	Trade Price Std. Dev	Trade Price Std. Dev
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Intercept	58.1232***	37.9621***	59.0712***	38.5321***	-0.0007***	-0.0005***	-0.0007***	-0.0005***
	(14.454)	(12.721)	(13.684)	(14.235)	(-3.902)	(-4.490)	(-3.916)	(-4.499)
Marketable	0.2199***	0.1412***	0.2194***	0.1434***	0.9004***	0.8831***	0.9005***	0.8831***
	(8.790)	(10.435)	(8.271)	(11.042)	(90.769)	(63.929)	(90.624)	(63.856)
Limit Order	0.0222	0.0043			0.0000***	0.0000**		
	(1.468)	(1.277)			(2.939)	(2.558)		
Executed Limit Order		0.3144***		0.3168***		0.0151***		0.0151***
		(14.810)		(14.532)		(3.625)		(3.627)
Aggressive			0.0026	-0.0061			-0.0001	-0.0000
			(0.221)	(-1.362)			(-0.601)	(-0.284)
Matching Order			0.0122**	0.0102***			0.0000	0.0000
			(2.010)	(4.410)			(1.177)	(1.249)
Passive Order			0.0026	-0.0052			0.0000*	0.0000*
			(0.387)	(-1.128)			(1.948)	(1.740)
Market Cap	-0.0000**	-0.0000**	-0.0000**	-0.0000**	-0.0000	-0.0000	-0.0000	-0.0000
	(-2.159)	(-2.365)	(-2.138)	(-2.056)	(-1.602)	(-1.127)	(-1.602)	(-1.126)
Price	-0.0491	-0.0813**	-0.0502	-0.0833**	0.0000	-0.0000	0.0000	-0.0000
	(-1.229)	(-2.375)	(-1.244)	(-2.421)	(0.631)	(-0.023)	(0.633)	(-0.023)
Daily Volume	0.0000**	0.0000	0.0000**	0.0000	0.0000***	0.0000***	0.0000***	0.0000***
	(2.537)	(1.077)	(2.470)	(0.792)	(4.231)	(4.174)	(4.226)	(4.170)
Range	1.1856***	0.6896***	1.1882***	0.6856***	0.0004***	0.0002***	0.0004***	0.0002***
	(3.367)	(3.280)	(3.372)	(3.291)	(10.937)	(7.873)	(10.917)	(7.896)

Table 4 continued

Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,089	1,089	1,089	1,089	1,089	1,089	1,089	1,089
Observations	162,356	162,356	162,356	162,356	162,354	162,354	162,354	162,354
R-Squared	0.4825	0.7256	0.4815	0.7272	0.4258	0.5486	0.4304	0.5520

*** Statistically different at 1% level

** Statistically different at 5% level

*Statistically different at 10% level

APPENDIX 5: CHARACTERISTICS OF AGGRESSIVE ORDERS

Table 5: Characteristics of aggressive orders

This table investigates how different order classifications compare to each other. The dependent variable is the order characteristic, while the main independent variables are indicator variables to identify the order classification. To test the hypothesis fleeting orders, executed orders, and market orders have similar characteristics, we run the regression while omitting an order class, enabling a comparison of order characteristics against the omitted order class.

Dependent Variable	Order Size	Order Size	Order Size	Order Size	Price Std. Dev	Price Std. Dev	Price Std. Dev	Price Std. Dev
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Intercept	169.39***	119.81***	147.24***	174.11***	-0.79	-0.79	14.57***	-0.77
	(29.929)	(19.512)	(16.738)	(23.140)	(-0.683)	(-0.676)	(10.411)	(-0.661)
Market Order		49.51***	22.08**	-4.79		-0.01***	-15.37***	-0.03***
		(11.490)	(2.076)	(-0.528)		(-13.021)	(-14.035)	(-31.068)
Executed Limit	-49.51***		-27.44***	-54.30***	0.01***		-15.36***	-0.02***
Order Indicator	(-11.490)		(-2.690)	(-5.296)	(13.021)		(-14.028)	(-20.822)
Fleeting	-22.07**	27.43***		-26.87***	15.37***	15.36***		15.35***
Order Indicator	(-2.076)	(2.690)		(-3.978)	(14.035)	(14.028)		(14.013)
Aggressive Limit	4.78	54.30***	26.87***		0.02***	0.02***	-15.35***	
Order Indicator	(0.528)	(5.296)	(3.978)		(31.068)	(20.822)	(-14.013)	
Market Cap	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.676)	(0.676)	(0.676)	(0.676)	(0.469)	(0.469)	(0.469)	(0.469)
Price	-0.18	-0.18	-0.19	-0.19	-0.03	-0.03	-0.03	-0.03
	(-1.507)	(-1.507)	(-1.507)	(-1.507)	(-1.093)	(-1.093)	(-1.093)	(-1.093)
Daily Volume	0.00**	0.00**	0.00**	0.00**	0.00	0.00	0.00	0.00
	(2.130)	(2.130)	(2.130)	(2.130)	(1.568)	(1.568)	(1.568)	(1.568)
Range	0.91**	0.90**	0.91**	0.91**	1.89***	1.89***	1.89***	1.89***
	(2.209)	(2.209)	(2.209)	(2.209)	(2.599)	(2.599)	(2.599)	(2.599)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,089	1,089	1,089	1,089	1,089	1,089	1,089	1,089
Observations	162,356	162,356	162,356	162,356	162,354	162,354	162,354	162,354
R-Squared	0.0120	0.0120	0.0120	0.0120	0.0112	0.0112	0.0112	0.0112

*** Statistically different at 1% level

** Statistically different at 5% level

*Statistically different at 10% level

APPENDIX 6: FILL RATES AND ORDER SIZES OF LIMIT ORDERS

Table 6: Fill rates and order sizes of limit orders

This table investigates the similarities of fleeting aggressive orders, marketable orders, and passive orders. We test the differences in fill rates and the differences in order size of these order classes. The dependent variable is the fill rates of limit orders in columns 1 through 4, and is the order size in columns 5 through 8. To test the hypothesis of limit order fill rates, we run each regression while omitting a single order class, enabling a comparison of order characteristics against the omitted order class.

Dependent Variable	Fill Rate	Fill Rate	Fill Rate	Fill Rate	Order Size	Order Size	Order Size	Order Size
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Intercept	0.03***	0.14***	0.06***	-0.00	150.66***	177.52***	131.90***	165.21***
	(9.289)	(31.840)	(14.241)	(-0.504)	(19.785)	(27.081)	(24.642)	(19.393)
Fleeting Order		-0.11***	-0.02***	0.04***		-26.86***	18.75***	-14.55***
		(-39.209)	(-37.894)	(65.293)		(-3.978)	(4.061)	(-4.877)
Aggressive Order	0.11***		0.08***	0.14***	26.86***		45.62***	12.31*
	(39.209)		(32.677)	(55.506)	(3.978)		(9.140)	(1.676)
Matching Order	0.02***	-0.09***		0.06***	-18.75***	-45.62***		-33.30***
	(37.894)	(-32.677)		(82.383)	(-4.061)	(-9.140)		(-5.821)
Passive Order	-0.04***	-0.15***	-0.06***		14.55***	-12.30*	33.30***	
	(-65.293)	(-55.506)	(-82.383)		(4.877)	(-1.676)	(5.821)	
Market Cap	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(1.499)	(1.499)	(1.499)	(1.499)	(0.669)	(0.669)	(0.669)	(0.669)
Price	0.00	0.01	0.00	0.00	-0.24	-0.24	-0.24	-0.24
	(0.984)	(0.984)	(0.984)	(0.984)	(-1.462)	(-1.462)	(-1.462)	(-1.462)
Daily Volume	0.00***	0.00***	0.00***	0.00***	0.00	0.00	0.00	0.00
	(3.106)	(3.106)	(3.106)	(3.106)	(1.090)	(1.090)	(1.090)	(1.090)
Range	0.00***	0.00***	0.00***	0.00***	0.81**	0.81**	0.81**	0.81**
	(5.920)	(5.920)	(5.920)	(5.920)	(2.105)	(2.105)	(2.105)	(2.105)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,089	1,089	1,089	1,089	1,089	1,089	1,089	1,089
Observations	162,334	162,334	162,334	162,334	162,356	162,356	162,356	162,356
R-Squared	0.5360	0.5360	0.5360	0.5360	0.0120	0.0120	0.0120	0.0120

*** Statistically different at 1% level

** Statistically different at 5% level

*Statistically different at 10% level

APPENDIX 7: PREVALENCE OF LIMIT ORDERS DURING FIFTEEN MINUTE PERIODS OF HIGH DEPTH AND LOW VOLATILITY

Table 7: Prevalence of limit orders during periods of high depth and low volatility

The dependent variable is the number of orders submitted for a given fifteen minute period, where the first three columns look at aggressive orders submitted, the second three look at the number of marketable orders submitted, and the final three columns look at the number of fleeting orders submitted. The trading day for a stock is split into fifteen minute periods, where each of the periods are partitioned into liquidity quintiles, where low values are placed in *Rank 1*, and high values are placed in *Rank 5*.

Dependent Variable	# Limit Orders	# Limit Orders	# Limit Orders
Ranking Variable	Quoted Spread	CRT 1000 (Depth)	Trade Price Volatility
	[1]	[2]	[3]
Intercept	3,064.5898***	3,272.87***	3,313.3303***
	(7.275)	(7.86)	(8.258)
$Q1_t$ (High Liquidity)			
$Q2_t$	184.36***	100.84***	40.64***
	(11.59)	(9.07)	(6.61)
$Q3_t$	334.07***	215.35***	207.61***
	(14.00)	(10.98)	(22.89)
$Q4_t$	522.40***	367.82***	473.06***
	(15.97)	(12.63)	(16.40)
$Q5_t$ (Low Liquidity)	744.69***	541.23***	779.55***
	(16.41)	(14.9)	(16.54)
Market Capitalization	-0.00**	-0.00**	-0.00**
	(-2.36)	(-2.36)	(-2.36)
Price	-10.94	-10.94	-10.71
	(-1.32)	(-1.32)	(-1.30)
Volume	0.00***	0.00***	0.00***
	(5.13)	(5.13)	(5.12)
Range	157.23***	157.23***	153.46***
	(2.84)	(2.84)	(2.82)
Fixed Effects	Yes	Yes	Yes
N	1,089	1,089	1,089
Observations	1,087,350	1,087,350	1,087,350
R-squared	0.1710	0.1683	0.1783

*** Statistically different at 1% level

** Statistically different at 5% level

*Statistically different at 10% level

Panel B			
Dependent Variable	# Limit Orders	# Limit Orders	# Limit Orders
Ranking Variable	Quoted Spread	CRT 1000 (Depth)	Trade Price Volatility
	[1]	[2]	[3]
Intercept	222.47***	218.77***	214.44***
	(7.506)	(7.402)	(7.545)
$Q1_{t-1}$ (High Liquidity)			
$Q2_{t-1}$	-3.85***	1.75**	8.37***
	(-3.613)	(2.015)	(7.876)
$Q3_{t-1}$	6.76***	6.63***	24.83***
	(11.399)	(5.065)	(18.394)
$Q4_{t-1}$	12.05***	11.68***	42.95***
	(14.690)	(7.597)	(18.716)
$Q5_{t-1}$ (Low Liquidity)	12.23***	16.25***	88.71***
	(7.666)	(8.785)	(13.966)
Market Capitalization	-0.00**	-0.00**	-0.00**
	(-2.399)	(-2.399)	(-2.393)
Price	-0.75	-0.75	-0.73
	(-1.322)	(-1.322)	(-1.287)
Volume	0.00***	0.00***	0.00***
	(5.135)	(5.135)	(5.064)
Range	10.92***	10.92***	9.75***
	(2.839)	(2.839)	(2.705)
Fixed Effects	Yes	Yes	Yes
N	1,089	1,089	1,089
Observations	15,358,037	15,358,037	15,358,037
R-squared	0.09	0.09	0.11

APPENDIX 8: THE PREVALENCE OF AGGRESSIVE, FLEETING, AND MAKRETABLE ORDERS DURING FIFTEEN MINUTE PERIODS OF HIGH DEPTH AND LOW VOLATILITY

Table 8: The prevalence of aggressive, fleeting, and marketable orders during periods of high depth and low volatility

The dependent variable is the number of orders submitted for a given fifteen minute period, where the first three columns look at aggressive orders submitted, the second three look at the number of marketable orders submitted, and the final three columns look at the number of fleeting orders submitted. The trading day for a stock is split into fifteen minute periods, where each of the periods are partitioned into liquidity quintiles, where low values are placed in *Rank 1*, and high values are placed in *Rank 5*.

Dependent	Aggressive Orders	Aggressive Orders	Aggressive Orders	Market Orders	Market Orders	Market Orders	Fleeting Orders	Fleeting Orders	Fleeting Orders
Ranking	Spread	Depth	Volatility	Spread	Depth	Volatility	Spread	Depth	Volatility
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Intercept	132.6***	140.7***	157.8***	49.9***	47.6***	36.4***	1,366.7***	1,529.8***	1,592.0***
	(7.168)	(7.604)	(8.566)	(4.699)	(4.422)	(3.363)	(4.910)	(5.594)	(6.065)
$Q2_t$	10.97***	11.76***	6.37***	-0.74	-1.10***	3.52***	120.03***	65.86***	10.50**
	(23.67)	(26.43)	(17.74)	(-1.62)	(-3.42)	(24.55)	(10.36)	(8.46)	(2.50)
$Q3_t$	21.44***	20.59***	16.68***	0.55	-0.22	7.02***	215.84***	138.54***	105.69***
	(29.22)	(29.63)	(31.71)	(0.90)	(-0.47)	(38.24)	(11.97)	(9.66)	(17.68)
$Q4_t$	36.18***	32.10***	32.75***	2.07**	1.40*	13.45***	339.47***	236.85***	265.16***
	(28.48)	(25.74)	(29.05)	(2.20)	(1.86)	(21.36)	(13.23)	(10.65)	(13.02)
$Q5_t$	67.14***	59.75***	66.72***	3.35**	5.80***	24.36***	512.13***	352.00***	454.48***
	(29.07)	(28.18)	(27.27)	(2.51)	(5.10)	(17.51)	(13.61)	(12.32)	(13.98)
Market Cap	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00**	-0.00**	-0.00**
	(-0.57)	(-0.57)	(-0.58)	(-0.45)	(-0.45)	(-0.45)	(-2.42)	(-2.42)	(-2.42)
Price	-0.69*	-0.69*	-0.67*	-0.14	-0.14	-0.14	-3.40	-3.40	-3.27
	(-1.68)	(-1.68)	(-1.64)	(-0.63)	(-0.63)	(-0.62)	(-0.63)	(-0.63)	(-0.61)
Volume	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(3.11)	(3.11)	(3.11)	(4.99)	(4.99)	(4.99)	(4.56)	(4.56)	(4.55)
Range	22.94***	22.94***	22.64***	9.53***	9.54***	9.47***	73.31**	73.31**	71.20**
	(3.82)	(3.82)	(3.83)	(3.93)	(3.93)	(3.93)	(2.31)	(2.31)	(2.27)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,089	1,089	1,089	1,089	1,089	1,089	1,089	1,089	1,089
R-squared	0.14	0.14	0.16	0.24	0.24	0.25	0.17	0.17	0.17

Panel B									
Dependent Variable	Aggressive Orders	Aggressive Orders	Aggressive Orders	Market Orders	Market Orders	Market Orders	Fleeting Orders	Fleeting Orders	Fleeting Orders
Ranking Variable	Spread	Depth	Volatility	Spread	Depth	Volatility	Spread	Depth	Volatility
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Intercept	14.09***	13.21***	14.54***	8.25***	8.91***	6.91***	121.24***	118.96***	117.49***
	(8.595)	(8.108)	(8.919)	(5.770)	(6.242)	(4.840)	(6.222)	(6.135)	(6.347)
$Q2_{t-1}$	-0.28***	0.51***	0.54***	0.44***	-0.75***	0.23***	-2.13***	1.32**	3.27***
	(-5.770)	(11.683)	(6.162)	(11.715)	(-20.747)	(3.586)	(-2.966)	(2.260)	(4.146)
$Q3_{t-1}$	0.42***	0.97***	1.43***	-0.05***	-0.88***	0.56***	4.09***	4.27***	11.88***
	(15.339)	(14.946)	(13.305)	(-2.739)	(-17.372)	(7.756)	(9.812)	(4.660)	(11.599)
$Q4_{t-1}$	0.97***	1.54***	2.60***	-0.11***	-0.96***	1.04***	7.58***	7.49***	23.31***
	(16.711)	(14.998)	(22.980)	(-2.714)	(-12.472)	(27.667)	(11.843)	(6.627)	(14.305)
$Q5_{t-1}$	2.11***	3.01***	6.31***	-0.35***	-0.99***	2.64***	8.15***	10.63***	53.10***
	(19.274)	(18.691)	(22.883)	(-3.680)	(-7.935)	(12.807)	(7.076)	(7.424)	(11.365)
Market Cap	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00**	-0.00**	-0.00**
	(-0.550)	(-0.550)	(-0.542)	(-0.402)	(-0.402)	(-0.391)	(-2.443)	(-2.444)	(-2.440)
Price	-0.05	-0.05	-0.05	-0.01	-0.01	-0.01	-0.24	-0.24	-0.22
	(-1.570)	(-1.569)	(-1.525)	(-0.652)	(-0.649)	(-0.645)	(-0.639)	(-0.638)	(-0.605)
Volume	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(3.031)	(3.031)	(3.000)	(4.840)	(4.840)	(4.807)	(4.563)	(4.563)	(4.513)
Range	1.51***	1.51***	1.44***	0.69***	0.69***	0.66***	5.09**	5.09**	4.44**
	(3.551)	(3.551)	(3.521)	(3.361)	(3.360)	(3.334)	(2.307)	(2.307)	(2.128)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,089	1,089	1,089	1,089	1,089	1,089	1,089	1,089	1,089
R-squared	0.05	0.05	0.06	0.12	0.12	0.13	0.09	0.09	0.10

*** Statistically different at 1% level

** Statistically different at 5% level

*Statistically different at 10% level

APPENDIX 9: ORDER AGGRESSIVENESS BY TIME OF DAY

Table 9: Order aggressiveness by time of day

This table identifies if order become more aggressiveness at the end of the trading day. The first two columns look at the proportion of aggressive orders, which is calculated as the number of limit orders submitted within the BBO divided by the total number of limit orders submitted. The second two columns report the estimates for regressing the proportion of market orders, which is calculated as the number of market orders submitted divided by the total number of orders submitted (limit orders + marketable orders). The main independent variables are time of day identifiers, with the variable of interest being the indicator variable *close*.

Dependent Variable	Aggressive Order Proportion	Aggressive Order Proportion	Market Order Proportion	Market Order Proportion
	[1]	[2]	[3]	[4]
Intercept	0.10***	0.09***	0.01***	0.02***
	(15.969)	(15.009)	(6.612)	(9.545)
Opening		0.01***		-0.01***
		(5.585)		(-22.301)
Morning	-0.01***	-0.00***	0.01***	-0.00***
	(-13.794)	(-11.268)	(22.995)	(-10.554)
Midday	-0.01***		0.01***	
	(-5.585)		(22.301)	
Afternoon	-0.01***	-0.00***	0.01***	0.00***
	(-6.200)	(-3.533)	(34.657)	(30.156)
Close	0.10***	0.11***	0.04***	0.03***
	(81.161)	(90.330)	(72.768)	(71.254)
Market Capitalization	-0.00	-0.00	0.00	0.00
	(-0.871)	(-0.871)	(1.503)	(1.503)
Price	0.00	0.00	0.00***	0.00***
	(1.554)	(1.554)	(2.795)	(2.795)
Volume	0.00**	0.00**	0.00***	0.00***
	(2.058)	(2.058)	(3.146)	(3.146)
Range	0.00***	0.00***	0.00***	0.00***
	(4.040)	(4.040)	(6.149)	(6.149)
Fixed Effects	Yes	Yes	Yes	Yes
N	1,089	1,089	1,089	1,089
Observations	1,072,755	1,072,755	1,028,214	1,028,214
R-squared	0.13	0.13	0.13	0.13

*** Statistically different at 1% level

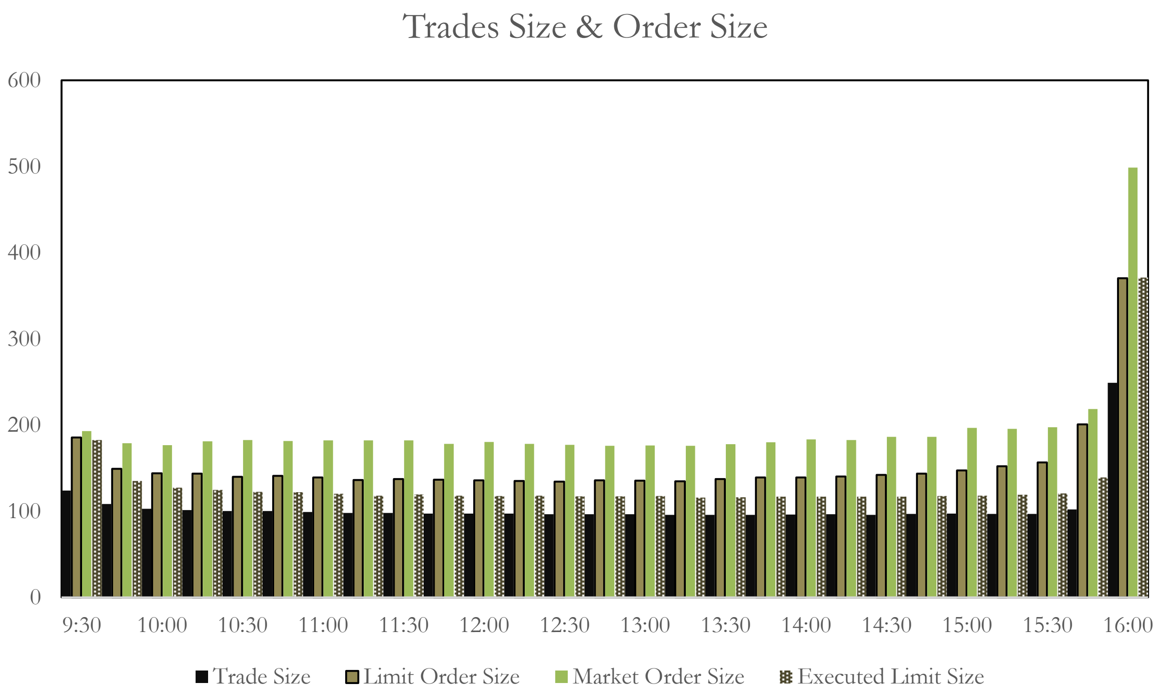
** Statistically different at 5% level

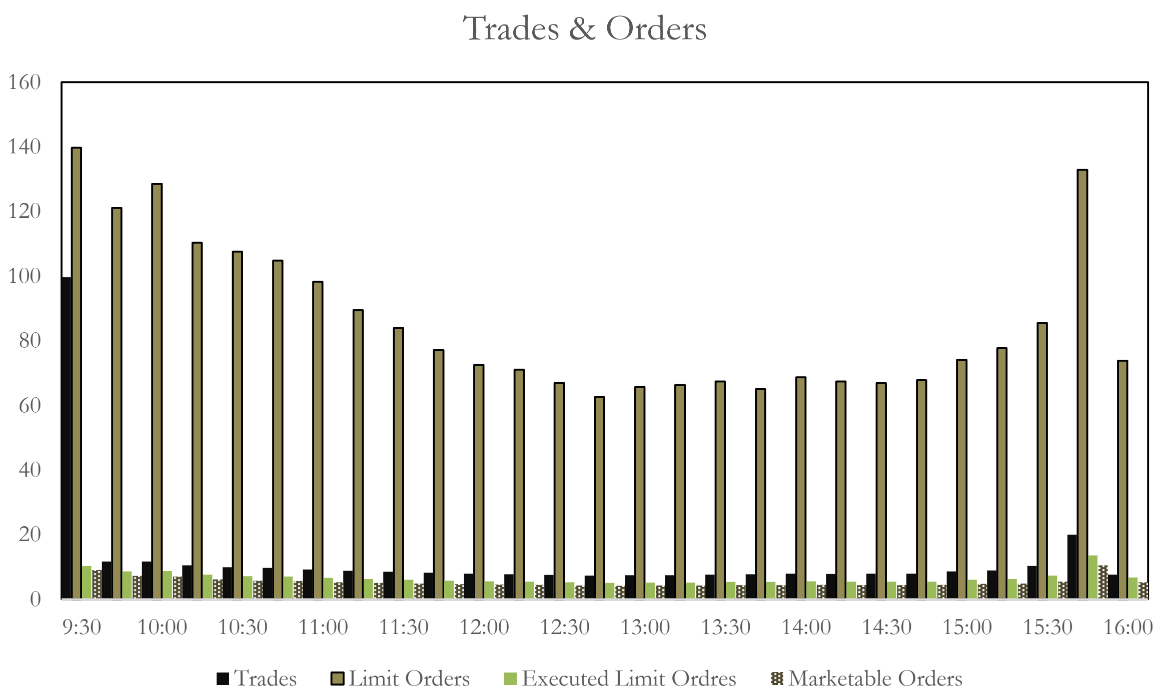
*Statistically different at 10% level

APPENDIX 10: INTRADAY ORDER AND TRADE CHARACTERISTICS

Figure 1: Intraday order and trade characteristics

This figure reports the number of orders and trades averaged to the minute, for the average stock day in our sample. Panel A reports intraday order and trade print frequencies, while panel B reports intraday patterns of order sizes and trade print sizes.

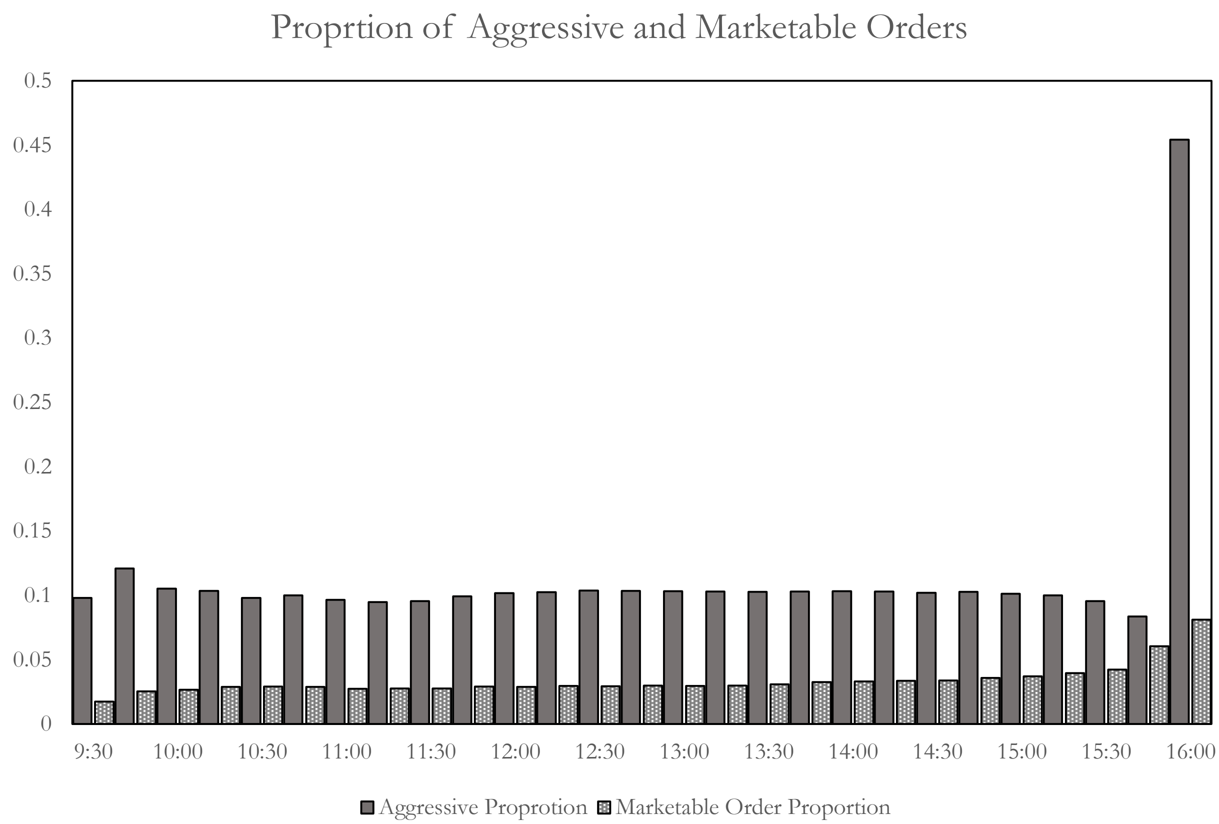




APPENDIX 11: ORDER AGGRESSIVENESS THROUGHOUT THE TRADING DAY

Figure 2: Order aggressiveness throughout the trading day

This Figure presents intraday patterns for the proportion of aggressive limit orders and marketable orders. The proportion of aggressive orders is calculated as the number of price improving limit orders expressed as a ratio over all limit orders, while the proportion of marketable orders is calculated as the number of marketable orders divided by all orders received. Statistics are computed for the average one minute period for the average stock in our sample.



PART 3: BREAKDOWNS IN FINANCIAL MARKETS: FLASH CRASHES AND LIQUIDITY CRISES

I. INTRODUCTION

Financial markets facilitate trading by providing a venue for buyers and sellers to exchange securities. A liquid market contains a sufficient number of shares available to buyers and sellers, and the security's price is considered fair and accurate (O'Hara 2003). Liquid markets promote investor confidence (Chordia, Roll, and Subrahmanyam (2001)), while illiquid markets impede trading and price discovery. Markets may experience liquidity crises when depth evaporates, and the asset price is driven from its true value, causing a suspension in the price dissemination process and often causing investors to lose confidence (Greenwald and Stein (1991)). Liquidity crises may be the result of fundamental events (such as economic changes and market news) or non-fundamental events (like the May 2010 flash crash, and the April 2013 Associated Press Twitter hack). In the case of fundamental events, a tangible shock to the market disrupts trading. Liquidity is suppressed while the information is processed. When the shock secedes, the information is incorporated into the price of the security and regular trading resumes. In the case of non-fundamental events, a shock disrupts trading, but no essential news is transmitted. During the crash, liquidity is suppressed and minimal trading occurs. When it is discovered that no fundamental event transpired, markets rebound and liquidity returns to the market (Gabaix, Gopikrishnan, Plerou and Stanley (2006); Bernardo and Welch (2004)). Short, non-fundamental liquidity crises are frequently referred to as flash crashes. Liquidity crises vary in duration. During the crash of October 1987, illiquidity and suppressed prices spanned multiple trading days (Carlson

(2007)). The May 2010 flash crash, in contrast, only lasted 36 minutes and experienced illiquidity caused by thin depth and suppressed prices (Kirilenko, Kyle, Samadi, Tuzun (2014)).

Our focus in this paper is intraday liquidity crises and flash crashes. Using nanosecond exchange data for the NASDAQ exchange, we detect short-term flash crashes that have direct impacts on market quality, which go undetected using datasets with less precise timestamps. The events in our study are shocks to the market that disrupt trading, but contain no fundamental information. Theoretical studies suggest non-fundamental crashes may be due to liquidity concerns (Bernardo and Welch (2004)), or heavy trading when the market is experiencing waning depth (Gabaix, Gopikrishnan, Plerou, and Stanley (2006)). Flash crashes interrupt the trading process and degrade investor confidence. We study the impact that flash crashes and liquidity crises have on financial markets. Specifically, we address crash frequency, crash triggers, and the resulting market quality once markets resume normal trading.

Flash crashes and liquidity crises are related to trading halts and market crashes, and as a result we draw from those streams of literature. The first stream of literature studies market crashes (Bhattacharya and Spiegel (1998); Grossman (1992); Gabaix, Gopikrishnan, Plerou, and Stanley (2006)). The crashes in these studies may be fundamental in nature, or non-fundamental. Although the events in our study are short-term intraday events, there is overlap in the theoretical causes of a crash. Flash crashes also draw from the stream of literature regarding trading halts, where trading halts are periods when the price discovery process is hindered (Lee, Ready, and Seguin (1994); Goldstein and Kavajecz (2004); Greenwald and Stein (1991)). There are two reasons flash crashes relate to trading halts. First, as evidenced by the May 2010 flash crash, liquidity crises can trigger trading halts and circuit breakers (Kirilenko, Kyle, Samadi, Tuzun (2014)). Therefore, we are careful in our analysis to control for instances of trading halts that occur simultaneously with flash crashes. Second, liquidity crises are interruptions to the price discovery process. In this sense, market crashes can also be viewed as trading halts in that they disrupt efficiency, liquidity, and price discovery.

How frequent are flash crashes? To what extent was the May 2010 flash crash an isolated event? Bhattacharya and Spiegel (1998) find that approximately every day from 1974-1988, four stocks on the NYSE have a market failure that results in a trading suspension. Gao and Mizrach (2013) find that market quality breakdowns are common in equity markets. In their sample, 1993-2011, there are approximately 44 breakdowns each day in the TAQ database, with the post Reg NMS period having fewer breakdowns than the pre Reg NMS period. Golub, Keane, and Poon (2012) find that Reg NMS and intermarket sweep orders (ISOs) contribute to mini-flash crashes. From these studies it is clear that mini-flash crashes are common in financial markets, and that the May 2010 flash crash was not an isolated event. Our study compliments the existing work by identifying crashes in a nanosecond framework. In fast and automated markets, computers respond to market conditions at incredible speeds. Studies at lower latencies may miss potential crashes. In addition, our methodology does not rely on the automated quote feed to determine crashes, since we use order level data to calculate crashes that would be revealed to traders in real-time. Our paper also studies the depth implications of flash crashes. As O'Hara (2014) has pointed out, studies regarding high speed markets should look at other measures of liquidity beyond spread and top of book depth. We find that flash crashes are frequent events. In our sample period of three months, over 40% of the securities experienced at least one crash.

What triggers flash crashes? The flash crash of May 2010 is partially attributed to a large trade that was initiated during a period of high volatility and thin depth (CFTC-SEC (2010)), which is consistent with the theory of Gabaix, Gopikrishnan, Plerou, and Stanley (2006). There are two components of liquidity crises: price deviations and low depth. Price deviations are instances of the price discovery process being impeded due to large swings away from a security's fundamental price. Low depth is associated with a market not being able to facilitate trading since there is an insufficient number of shares from traders supplying liquidity for traders demanding liquidity. These two components are related, where causality may flow in either direction. A sudden decrease in a security's price may lead traders to withdraw shares from the market due to increased uncertainty and volatility, resulting in a severe decrease in depth. Alternatively, the flash crash may be liquidity caused. If depth for a security is thin, a large marketable order may remove all available liquidity causing wide swings in prices depending on the structure of depth on the limit order book. We analyze both scenarios in this study. Our results provide evidence that crashes are due to thin depth, and high trading on one side of the limit order book. We find little evidence that short selling constraints cause flash crashes.

Do flash crashes have a lingering impact on market quality? Our analysis also investigates the post-breakdown effects of flash crashes. Flash crashes are a disruption in the information flow of asset prices, and are similar to trading halts. Drawing inferences from the trading halt literature, markets may react to a crash in one of two ways. Once news is disseminated to traders that no fundamental event has occurred, and the crash is non-fundamental in nature, normal trading resumes and market quality stabilizes (Greenwald and Stein (1991)). It is also possible, however, that after the event transpires, market participants may be reluctant to enter a volatile market. Post-breakdown market quality will remain high due to increased uncertainty (Lee, Ready, and Seguin (1994); Christie, Corwin, and Harris (2002)). Using a difference-in-difference approach, we find flash crashes in our sample have little impact on spread, but do have a negative impact on the depth of the security.

Related to the flash crash effects on market quality, do breakdowns have a contagion effect? Jiang, McInish, and Upson (2009) find that trading halts have an impact on related securities that do not experience a trading halt. Related securities experience an increase in spread and price impact. Their results are in support of informed trading theories by Tookes (2008). The CFTC-SEC (2010) joint report finds that the flash crash of May 2010 spread from the futures market to the equities market. We also investigate the contagion effects of mini-flash crashes. We find that the depth of related securities that do not experience a flash crash are negatively impacted.

II. BACKGROUND AND HYPOTHESES

Exchanges and markets facilitate trading, where the principal function of the market is to provide price discovery and liquidity (O'Hara (2003)). The recent May 6, 2010 Flash crash is a highly publicized example of liquidity crisis in both aspects, liquidity was thin and the price discovery process was hindered. The CFTC-SEC joint report (2010) attributes a large, E-mini (S&P 500 futures) trade at approximately 2:32 p.m. EST to triggering the flash crash. This trade was placed during a period of waning depth as a hedge against an equity position already established. Following the trade, computer algorithms exacerbated the volatility and magnitude of the crash, and spread the crash into other financial markets like the equities market. Nearly 13 minutes after the beginning of the flash crash, the Chicago Mercantile Exchange (CME) implemented a five second trading halt. Following the halt, prices stabilized, and by 3:08 p.m. the prices returned to their pre-crash levels. We look to see if the events of the May 2010 flash crash apply to all flash crashes. We specifically look at the triggers of flash crashes, and the lasting impact of flash crashes.

WHAT TRIGGERS LIQUIDITY CRISES?

Theoretical studies on market crashes highlight a number of potential triggers of market failures. We apply these theories to flash crashes. Market failures are associated with a decrease in available depth to trade, and a large fluctuation in the price of a security. In Gabaix, Gopikrishnan, Plerou and Stanley (2006), large spikes in return and volatility may be due to a large trade by an institutional investor during a period if thin liquidity. Even though the large trade does not carry any news, the conditions of the market lead to a severe fluctuation in prices. The events of the flash crash are consistent with this hypothesis. Liquidity crises may occur when the depth on the limit order book is thin, and large market orders consume available depth. We are careful in our analysis to determine causality. In our data we are able to detect market orders, and whether liquidity dries-up before an incoming order, or whether large orders consume available liquidity. We thus expect flash crashes in our sample to occur due to large traders during periods of thin depth.

Hypothesis 1: Liquidity crashes occur following large trades

Hypothesis 2: Liquidity crashes occur during times when depth is thin

Flash crashes may also be caused by investor fears and herding behavior. In a modern market, herding may not necessarily be traders reacting to each other, rather, herding may be algorithms responding to changes in market conditions. In the model by Bernardo and Welch (2004), investors rush to buy or sell an asset due to the fear of a future liquidity shock, even though current liquidity is adequate. This rush to trade will trigger price pressure and a cascade of buy or sell trades, which in turn creates the market failure. In this model, investor fear of illiquidity is the cause of illiquidity. The implication for our study is that intense pressure on one side of the limit order book will consume all available liquidity, driving the price of the asset down. Intense selling pressure will cause a large price decrease, and intense buying pressure will cause a price increase. Hong and Stein (2003) develop a model in which market crashes are due to short selling constraints. If investors are constrained from short selling, then their negative information will not be incorporated into stock prices until stock prices begin to drop.

Hypothesis 3: Liquidity crashes occur due intense pressure on the limit order book

Hypothesis 4: Liquidity crashes occur due to short-selling constraints

HOW DO FLASH CRASHES IMPACT LIQUIDITY?

Flash crashes interrupt the price discovery mechanism of markets. This interruption may continue to affect market quality once normal trading resumes. Flash crashes are breaks in trading, and in this aspect they are similar to trading halts. The trading halt literature finds that following an interruption in trading, market quality is impacted. Lee, Ready, and Seguin (1994) find that volume and volatility are high following halts. A related study by Christie, Corwin, and Harris (2002) show that there is substantial volume and volatility lingering after the trading halt has passed. These results relate to flash crashes. Although normal trading may resume following a quick drop and rebound in prices, uncertainty regarding future prices and volatility may remain.

Hypothesis 5: Liquidity crises have a negative impact on post-crash market quality

DO FLASH CRASHES HAVE A CONTAGION EFFECT?

In Hong and Stein's (2003) model, they define crashes to be market-wide events that contain a considerable amount of cross-sectional correlation. In their model, short selling is constrained and negative information is only released during sharp downturns. Securities will build up negative information until a large trading event is triggered, and all negative information is released. The sharp decrease in one security's price will trigger the built up negative information in another security's price. Hong and Stein predict that contagion will be high during market down turns. This leads us to our final hypothesis.

Hypothesis 6: Negative flash crashes contain significant contagion

III. DATA AND METHODS

In this study we primarily use order level data for the NASDAQ exchange. Each of the exchange datasets contain messages for orders added, deleted, updated, and executed. We draw on theories by Gabaix, Gopikrishnan, Plerou and Stanley (2006) and Bernardo and Wlech (2004) for much of the analysis in our paper, which have theoretical predictions based on the depth of the limit order book. Therefore, an accurate study of intraday flash crashes cannot look at top of book liquidity alone, and must look at the structure of the limit order book to identify true liquidity crises. We therefore construct the limit order book for all four of the exchanges in our data. The limit order book is created by inserting add order messages into a dynamic dataset. The dataset sorts on price and time to find the single order at the top of the book with price-time priority, which yields a best bid and best offer for that security. We are also able to capture depth at the best bid and best offer, as well as depth in the remainder of the limit order book. The dynamic limit order book dataset will appropriately adjust for incoming delete, execute, and update messages. When a new message is incorporated into the dataset, a new output for best bid, best offer, depth at the top of the book, and depth beyond the top of the book is recorded. We gather additional stock information like daily closing prices, volume, and share outstanding from the Center for Research and Securities Prices (CRSP).

The sample spans the three trading months from August 2014 through October 2014. Since the data in our study comes from the NASDAQ exchange, we only consider NASDAQ listed securities. We apply additional filters to remove securities that do not trade at least 1,000 shares each day of the sample. Securities that do not have a closing price above five dollars for each day of the sample are also removed. These filters reduce our sample from approximately 2,700 stocks down to 1,186 NASDAQ listed securities. When calculating depth measures we do not include stub quotes. We filter stub quotes as orders below one dollar (Since all the securities in our sample have closing prices above five dollars), and orders that are greater than $50,000.

Gabaix, Gopikrishnan, Plerou and Stanley (2006) predict that market crashes occur during periods of thin liquidity and following large market orders. We therefore need a measure of a thin markets, and a method to detect large market orders. Since a thin market is determined by the shape and structure of the limit order book, we use two depth measures, the depth-weighted average price (DWAP) and the cost of a round trip trade (CRT), to identify when a security is experiencing thin depth. The depth-weighted average price is the average price of the limit order book, weighted by depth in the limit order book. We follow Johnson and Upson (2015) and express DWAP as

$$DWAP = \frac{\sum_{i=1}^{I} P_i D_i}{\sum_{i=1}^{I} D_i}, \tag{1}$$

where the price and depth of tick i are expressed as P_i and D_i. We compute the DWAP for both the bid and offer side of the limit order book. Taking the difference of the DWAP bid and the DWAP ask yields the $\text{DWAP}_{\text{SPREAD}}$.

The CRT measure of limit order book thickness identifies how expensive it is for a trader to buy and sell q number of shares. The intuition being that if depth is concentrated at the top of the book, the investor can expect trading costs close to the quoted spread. If a trader wishes to buy and sell q shares of a security, and q is less than depth at the top of the book, then the ex-ante per share trade price should be the quoted spread. If q is greater than the top of the book, the ex-ante per share trade price will be greater than the quoted spread. The cost of a round trip trade is formally identified in Domowitz, Hansch, and Wang (2005). Using similar notation as Domowitz et al., we define the CRT as

$$CRT = \left[\sum_{j=1}^{k-1} D_{j,ask}\, P_{j,ask} + \left(q - \sum_{j=1}^{k-1} D_{j,ask}\right) P_{k,ask}\right] - \left[\sum_{j=1}^{k'-1} D_{j,bid} P_{j,bid} + \left(q - \sum_{j=1}^{k'-1} D_{j,bid}\right) P_{k,bid}\right], \tag{2}$$

which we extend to be expressed on a per share basis. We define the CRT_{SPREAD} as

$$CRT_{SPREAD} = \frac{CRT}{q}. \tag{4}$$

This measure is interpreted equivalently as $Thin_{DWAP}$. High measures indicate that the limit order book is relatively thin, and low measures represent thick limit order books. Using both the DWAP and CRT measures we can identify when the market is experiencing thinning liquidity.

To identify when large orders are executed, we calculate market orders using a method similar to Johnson, McInish, and Upson (2015). To compute the size of a marketable order we sum the size of all trades for a given stock during the same nanosecond. Johnson, McInish, and Upson. find that this method of calculating marketable orders is highly accurate.

Hong and Stein (2003) make predictions that market crashes are more likely during periods of restricted short-selling. The data in our study identify Rule 201 short selling periods, and is similar to the data used in Davis, Jurich, Roseman, Watson (2015). Rule 201 is triggered when the price of a security moves away from its previous day's closing national best bid (NBB) by ten percent. Rule 201 prohibits short sales at prices below the last price. Our sample uses order level data that identifies when short sell restrictions occur. A short sell restriction occurs on the day a price drops, and remains in effect for the remainder of the current day and the entirety of the day following the initial price drop. We are able to see to the nanosecond when short selling is restricted. In our sample of 1,186 NASDAQ securities, 247 have a Rule 201 short selling restriction at least once during the sample period.

IDENTIFYING CRASHES AND SUMMARY STATISTICS

Our method of identifying temporary flash crashes is as follows. We first identify jumps in the BBO as changes greater than 3% from the previous BBO. Our choice of three percent is to avoid events that would truncate our sample. For example, Level 1 circuit breakers are triggered at 7%, and Short sell restrictions are triggered at 10% deviations. Although Clearly Erroneous Executions may occur at 3% for highly priced stocks, the impact should be minimal on our study.

Every time an order is added, executed, or deleted from the limit order book we compute the change in the BBO by comparing against the most recent BBO (which may be only nanoseconds prior). Identifying flash crashes in this manner allows us to identify the specific order and reason (deleted depth or large execution) the jump occurred, as well as the nanosecond in which it occurred. This methodology is different than Bhattacharya and Spiegel (1998) who identify market failures as trading suspensions, but is similar to Gao and Mizrach (2013) who identify crashes as changes in the BBO. The difference between our methodology and Gao and Mizrach is our use of order-level data rather than TAQ quote data. With order level data we can determine the cause of the crash, rather than just when the crash occurred. We also differ in methodology from Golub, Keane, and Poon (2012), who identify mini-flash crashes as ten consecutive downticks (or upticks) before an uptick (or downtick) occurs. In our sample of three trading months from August 2014 through October 2014 there are 13,460 separate jumps that are greater than three percent.

Our analysis is concerned about flash crashes, which would require that the jumps are only temporary price changes, which therefore must revert to the pre-jump price. We define a flash crash as two separate jumps, one jump away from the current price, followed by a price-reverting jump. For buy orders the jump away would be a negative decrease, and the returning jump would be positive, while the opposite is true for sell orders. If a flash crash indeed occurs, then the sum of the two jumps (one away and one reverting) should be approximately zero. To identify flash crashes in our sample, we sum all price jumps for each stock on each day of the sample. If the sum of all jumps does not approach zero then it is removed from the sample. This eliminates permanent jumps that never revert to the pre-jump price. In Panel I of Figure 1, we report an example of a jump that does not revert to the pre-jump price. Permanent jumps are not included in the sample.

We apply one final filter to ensure that the jumps in our sample are indeed flash crashes. The definition for a flash crash is an event where liquidity decreases. Some of the jumps in the data are temporary improvements in the spread, where the best bid increase (or best offer decreases) temporarily increases before reverting. We remove all temporary jumps that improve the BBO, since we are concerned with jumps away from the BBO. In Panel B of Figure 2 we report two examples of temporary jumps. Panel II shows a temporary jump that improves the spread, which are not included in the sample, and Panel III shows a temporary jump that does not improve the spread, which we classify as a flash crash, and is subsequently included in the final sample. We are left with a sample of 949 flash crashes. Although our filters may not capture every flash crash that occurs, we manually inspect each crash to ensure that each jump in our sample can be identified as a flash crash.

Table 1 reports the summary statistics of the securities in our sample. Panel A reports the summary statistics for the total 1,186 securities in our sample that meet the filtering criteria, while panel B reports the statistics of the 412 securities that experience a flash crash during our sample period. The average stock in our sample trades at $37.26, compared to the trade price of $26.85 for securities that experience a flash crash. The average market capitalization for NASDAQ securities in our sample is nearly $5.7 billion, while the market capitalization of NASDAQ securities that experience flash crash is much lower at $777 million. Flash crash securities trade nearly half as often as the average NASDAQ security in our sample (382 vs 626), totaling one fifth of the volume (201,824 vs 1,120,198). The order volume is much lower, where the average NASDAQ security receives over 34,000 orders, while the average flash-crash security is receives much less order flow with less than 10,000 orders each day.

IV. RESULTS

In this section we answer three questions regarding flash crashes. How frequent are flash crashes? Prior work that studies crashes in a pre-HFT period suggest that multiple breakdowns occur every day. What is the cause of flash crashes? Theory suggests that large orders during periods of thin depth cause crashes, as well as short selling constraints may trigger a crash. And finally, what is the post-crash impact on market quality? Theory suggests that breakdowns are an interruption in the price discovery process, which impacts post-crash liquidity negatively, and that there is a contagion effect.

HOW FREQUENT ARE FLASH CRASHES?

We report flash crash event summary statistics in Table 2. There are 949 crashes in our sample, of which 614 are on the bid side of the limit order book. Bid crashes are associated with a sudden price drop, followed by a sudden increase. The remaining 335 are ask-side crashes, which are sudden price increases, subsequently followed by a reverting price drop. The majority of crashes are between 3-5%. In our sample, only 20 are greater than 5% away from the pre-crash BBO. Of the 1186 securities in our sample, 412 experience at least one crash in the three trading months from August 2014 through October 2014, leaving 774 stocks that never experience a crash. Panel B reports the statistics of the crashes. On average, a stock experiences 0.0362 flash crashes each day, or one crash every 27 days. The average crash occurs at 9:35 in the morning, and occurs for 10 seconds. During the crash there are 1.86 trades and 9 orders submitted. Before and after the crash, the spread is approximately 63 cents, but during the crash the spread is 164 cents.

WHAT CAUSES FLASH CRASHES?

What causes flash crashes? Our first hypothesis states that flash crashes occur following large trades, and the second hypothesis states that flash crashes occur when depth is thin. In the model of Gabaix, Gopikrishnan, Plerou, and Stanley (2006), crashes are due to large trades entering a market that is experiencing thin depth. This large trade will consume the available liquidity, which in turn triggers a crash. We test this theory by looking at the number of crashes that are due to trades and deleted orders. From Panel A of Table 3, the majority of crashes are triggered by an order being deleted. Only 60 of the 949 crashes are triggered due to a trade executing. Further, the average trade size of the marketable order that initiates the crash is 190.85 shares. This signifies that it is not a large marketable order executing against thin depth, rather it is a normal size trades that initiated the crash. We reject Hypothesis 1 since the majority of the crashes are not due to trades.

To test whether thinning depth is a major contribution of the crash, we look at the average spread and depth during the 60 second period prior to the crash. In Panel A of Table 4 we present liquidity measures for the 60 seconds prior to, and including the crash period. We use a control sample as a comparison, which includes the five trading days prior to the crash, for the same stock that experienced the crash. The control period is time of day matched to the nanosecond to alleviate any time of day driven results in market quality. We report the control sample in Panel B. The differences between the crash period and control period are reported in Panel C. For the stock experiencing a crash, the average spread is approximately 42 cents 60 seconds prior to the crash, and for the control period the spread is 48 cents prior to the faux crash period. This difference is insignificant. In the 10 seconds prior to the crash, the crash period spread is 51 cents, while the faux crash is 46 cents, which is also insignificantly different. Looking at spread alone does not indicate a crash. However, spread is only one of the aspects of market quality. Equally important is the amount of depth available to trade on the limit order book. To measure depth, we use the cost a trader will pay to simultaneously buy and sell 1000 shares, the *CRT1000*, to measure how much depth is available. If depth is weighted towards the top of the book then the *CRT1000* will be close to the quoted spread, however if there is little depth available, then the *CRT1000* will be larger than the quoted spread. A larger value of this variable indicates less depth, since it costs more to trade. During the crash period the cost to simultaneously buy and sell 1000 shares would cost 185 cents, compared to 132 cents during the crash period. In the 10 seconds prior to the crash, the *CRT1000* is 184 cents which is significantly higher than the faux crash which is 120 cents. As an additional check to understand the behavior during the 60 seconds prior to the crash, we look at the number of orders submitted and executed. We find trading activity is insignificantly different between the crash period and faux period, however there are slightly less orders submitted during the crash period compared against the faux period. The results presented in Table 4 do provide some evidence supporting the theory of Gabaix, Gopikrishnan, Plerou, and Stanley. Although we do not find that trade executions trigger the flash crash, we indeed find that during the 60 seconds prior to the flash crash there is significantly less depth on the limit order book. The results of thin depth prior to the flash crash support hypothesis 2.

Bernardo and Welch (2004) develop a model where buying and selling pressure will trigger market breakdowns. We apply this to flash crashes by looking to see if high trading activity for a security increases the likelihood of a stock experiencing a crash. Our third hypothesis states that flash crashes are due to pressure on the limit order book. Additionally, Hong and Stein (2003) predict that short selling restrictions will also trigger flash crashes. Our fourth hypothesis stems from this model, which is that crashes occur due to short-selling constraints. We test these hypotheses in a multivariate logit setting, where the dependent variable is an indicator variable equal to one if a security experiences a flash crash during a 10 second period. The sample for the model includes the crash day of the security along with the 5 trading days prior to the crash. The period also includes the 60 seconds prior to the crash, the time of the crash, and the 60 seconds following the crash, which is time of day matched for the control dates. We partition the sample into 10 second periods, and identify the 10 second period that experiences a crash with an indicator variable equal to 1. We regress the following model for the crash that occurs for stock *i* at time *t*:

$$\begin{aligned} Crash_{i,t} = {} & \alpha + \beta_1 Trades_{i,t-1} + \beta_2 Orders_{i,t-1} + \beta_3 Quoted_{i,t-1} + \beta_4 CRT1000_{i,t-1} \\ & + \beta_5 price_{i,t} + \beta_6 Volatility_{i,t-1} + \beta_7 range_{i,t} + \beta_8 marketcap_{i,t} \\ & + \beta_9 restricted_{i,t} + \lambda_i + \lambda_t + \varepsilon_{i,t} \end{aligned} \tag{1}$$

where crash is an indicator variable equal to one if a crash occurs during the ten second period at time *t*. We include trading and market quality statistics which includes *Trades*, the number of trades submitted during the period, *Orders*, the number of orders submitted during the period, *Quoted*, the quoted spread during the period, and *CRT1000*, which is the depth during the period. We include several control variables, including *Price*, the closing price for the security, *Volatility*, which is measured as the midpoint volatility, *Range*, which is the daily high price minus the daily low price, and captures the general volatility of the stock, *marketcap*, which is the securities market capitalization, and *restricted*, which is an indicator variable equal to one if the security is currently under a Rule 201 short sale restriction.

We present the results for this test in Table 5. In models 1 and 2 we keep orders and trades aggregated, while in mdels 3 and 4 we separate orders and trades into whether they are on the same side of the crash or the opposite side of the crash. Following the model of Bernardo and Welch, and our third hypothesis, we would expect trading activity to have a significant impact on the probability of a flash crash. We find that when orders and trades are aggregated, there is little evidence that orders and trades increases the likelihood of a flash crash. However, when we partition orders and trades into whether they occur on the same side or the opposite side of the crash we find that that an increase in trades on the same side of the limit order book is a strong predictor of the likelihood of a flash crash, which supports hypothesis 3.

Our control variables also add to the discussion. We find that when the spread is wide, the probability of a flash crash is low, however when depth is low (indicated by a high value of *CRT1000*), the probability of a flash crash increases. Lower priced stocks also have an increased probability of a flash crash. These results support the model of Bernardo and Welch. The final variable included in Table 5, *Restricted*, is an indicator variable equal to one if the period is under a Rule 201 short selling restriction. In both specifications this model is insignificant, which suggests that short sale bans do not impact the likelihood of a flash crash, providing little support for the model of Hong and Stein. We reject hypothesis 4.

WHAT IS THE EFFECT OF FLASH CRASHES?

The final concern regarding flash crashes is whether there are detrimental effects as a result of the flash crash. We identify the effects in two ways. We first test hypothesis 5, which looks at the market quality of the security that experienced the flash crash. The second way to identify the effects of a flash crash is to test hypothesis 6, which states that there is a contagion effect of flash crashes. According to our hypothesis, which follows Hong and Stein's (2003) model, a flash crash in one security will have a negative impact on market quality of related securities.

To investigate the effects of market quality following the crash, we compare market quality measures for the 60 seconds following the crash against the 60 seconds prior to the crash. Since many of our crashes occur early in the trading day, there are likely time of day driven results. To eliminate these results we then conduct a difference in difference test, where our control sample is the market quality for the 5 days prior to the crash day, for the same stock during the exact same time period as the flash crash. Conducting a difference in difference test in this manner should eliminate any results that are driven by changing market quality conditions.

We present the results for this test in Table 6. The first test looks at the quoted spread, where one minute prior to the flash crash the quoted spread is 42 cents, and following the crash the spread is 39 cents. When we average the before and after period, we find that the one minute after period has a spread that is 11 cents narrower than before the spread. We then compare this 11 cent difference against the control sample, where the control sample spread is narrowed by 3 cents. The difference between the control sample and crash sample is insignificant, which suggests that there is no difference in spread before and after the crash. We investigate depth by looking at the cost of a round trip trade of 1000 shares. One minute before the crash, a trader would pay approximately 185 cents to buy and sell 1000 shares simultaneously, however after the crash depth improves and a trader would pay 121 cents. The control sample is much narrower, where the *CRT1000* is 132 cents before and 99 cents after. When we look at the difference-in-difference, we find that on crash days the depth is abnormally low, indicated by a higher *CRT1000*. As an additional insight into trading activity, we look at orders and trades in Panels C and D respectively. We find that following the flash crash, there is an abnormally high amount of orders being submitted, however there is no difference in trading activity. The results from Table 6 provide some support for Hypothesis 5. Although the spread remains narrow following the crash, the amount of depth available to traders is significantly lower, indicating degradation in at least one aspect of market quality.

To test our final hypothesis, we identify how a flash crash impacts the market quality of related securities. The theoretical model of Hong and Stein (2003) predicts that crashes are market-wide events. When negative information is released during a crash in one security, related securities will also be affected. To test whether there is a contagion affect, we construct a one-to-many matched sample by identifying securities within the same 3-digit SIC code that have a market capitalization within 10% of the security that experienced a flash crash. The summary statistics of the matched sample are reported Table 7. Our matched sample includes 211 securities, of which the average closing price is \$120.51. Both the average and median daily trading volume is lower in the matched sample although there are more trades and orders on average in the matched sample.

To test market quality we regress market quality measures on ten second time indicator variables for the minute following the crash. The dependent variables are measures for the control sample, and include the spread, CRT1000, Number of orders submitted, and number of trades executed. The entire period of the test includes the 60 seconds prior to and following the crash. We regress a model of the following form:

$$
\begin{aligned}
MktQuality_{i,t} \\
&= \alpha + \gamma_1 Crash_{i,t} + \sum_{j=2}^{7} \gamma_j \, TenSeconds_j + \beta_1 price_{i,t} \\
&+ \beta_2 Volatility_{i,t-1} + \beta_3 range_{i,t} + \beta_4 marketcap_{i,t} + \beta_5 restricted_{i,t} \\
&+ \lambda_i + \lambda_t + \varepsilon_{i,t}
\end{aligned}
\tag{2}
$$

where the indicator variables of interest include an indicator variable equal to one if a 10 second period has a flash crash, zero otherwise, and six indicator variables equal to one for each ten second period for the minute following the flash crash. We include control variables as well as firm and time of day fixed effects. The results for this test are presented in Table 8. We find that during the crash period, there is very little effect on matched control samples. However, each of the indicator variables following presents interesting results. Following the crash the spread narrows and depth increases. The number of orders and number of trades immediately increase. It appears that, in general, there is very little to suggest that there is a significant negative impact on market quality, rather it appears that market quality remains unharmed, providing little support for the contagion theory from Hong and Stein (2003). Since we find no evidence of a change in market quality, we reject hypothesis 6.

V. CONCLUSION

Financial markets facilitate trading by providing a venue for buyers and sellers to exchange securities. A liquid market provides a venue for liquidity, and also allows for price discovery. A flash crash is a period where both price discovery and liquidity are impeded. During flash crashes, the price of a security temporarily jumps away from the current price, only to shortly revert back to pre-crash levels.

This paper studies intraday flash crashes using nanosecond exchange data for the NASDAQ exchange. Our paper provides meaningful insight into these flash crashes, in that we answer three direct questions. How frequent are flash crashes? What causes flash crashes? And what is the market impact of flash crashes? We find that flash crashes are rather frequent events, where approximately 40% of the securities in our sample experience at least once flash crash. In our sample of 1,186 securities, there are a total of 949 crashes. Approximately two thirds of the crashes in our sample occur on the bid side of the limit order book, and one third are on the ask side.

What causes flash crashes? Flash crashes are almost always triggered by a liquidity supplying order at the BBO being deleted, which will widen the bid-ask spread by greater than 3%. Only 6% of the crashes in ours study are triggered by executions consuming all available depth. Our findings support the theoretical models, which suggest that crashes occur as a result of non-fundamental events and liquidity concerns (Bernardo and Welch (2004)) and thin depth

(Gabaix, Gopikrishnan, Plerou, and Stanley (2006)). We do not find any evidence that flash crashes occur during short sell restrictions, as predicted.

What are implications of flash crashes? The trading halt literature suggests that interruptions in the trading process may degrade investor confidence. In this sense, a flash crash is a disruption in trading flow. We investigate this by looking at idiosyncratic market quality, as well as by looking at any contagion affects in related securities. When looking at market quality for securities that experience a flash crash, we find that depth is significantly decreased. However, in related securities of the same 3 digit SIC code, and a similar market capitalization, there is virtually no negative impact on market quality.

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APPENDIX

APPENDIX 1: SUMMARY STATISTICS OF SECURITIES EXPERINCING A FLASH CRASH

Table 1: Summary Statistics of securities experiencing a flash crashes

This table presents summary statistics for our sample of securities. Panel A presents statistics of the entire sample of securities that meet our filtering criteria described in the data section. Panel B presents statistics summary statistics for the securities that experience a flash crash. Data comprises order level data for the three trading months from August 2014 through October 2014 on the NASDAQ exchange.

Panel A: Summary statistics of average NASDAQ listed stocks				
	Mean	Median	Min	Max
Price	37.26	25.76	5.00	1,309.42
Market Capitalization (000s)	5,666,771	1,068,623	54,764	618,546,679
Daily Volume	1,120,198	303,593	12,489	233,883,264
Daily Trades	626	266	13	71,735
Daily Orders	34,849	12,919	953	1,145,409
Panel B: Summary statistics of NASDAQ listed stocks experiencing a crash				
Price	26.85	23.06	5.00	144.38
Market Capitalization (000s)	771,210	602,394	27,886	5,701,465
Daily Volume	201,824	123,544	17,395	4,245,643
Daily Trades	382	285	49	5,660
Daily Orders	9,814	7,582	881	103,784

APPENDIX 2: SUMMARY STATISTICS OF FLASH CRASHES

Table 2: Summary Statistics of Flash Crashes

This table presents summary statistics for the flash crashes that occur in our sample. Panel A reports the frequency and major causes of the crashes, while panel B reports on the statistics before and during the crash. Data comprises order level data for the three trading months from August 2014 through October 2014 on the NASDAQ exchange.

Panel A: Frequency				
Crashes	949			
Bid Crashes	614			
Ask Crashes	335			
3-5%	927			
5-7%	20			
>7%	0			
Stocks in Sample	1186			
Stocks w/crash during sample	412			
Panel B: Intraday crash summary statistics				
	Mean	Median	Min	Max
Crashes per stock-day	0.0362	0	0	49
Trades During Crash	1.86	1.00	1.00	14.00
Orders During Crash	9.09	1.00	1.00	334.00
Spread Before Crash ($)	0.63	0.46	0.01	5.34
Spread During Crash ($)	1.64	1.36	0.02	7.93
Spread After Crash ($)	0.64	0.45	0.00	6.00
Duration of Crash (seconds)	10.02	0.03	0.00	1919.48
Time of Crash	9:35:00	9:30:18	9:30:01	15:55:34

APPENDIX 3: TRIGGERS OF FLASH CRASHES

Table 3: Triggers of flash crashes

This table reports the market event that triggers flash crashes. Panel A reports the number of crashes that are due to a limit order being deleted or due to an execution. Panel B reports the average order size of trade triggered crashes. Data comprises order level data for the three trading months from August 2014 through October 2014 on the NASDAQ exchange.

Panel A: Crashes to due cancelled orders and executions	
Total Crashes:	949
Crashes caused by executions:	60
Crashes caused by order deletions:	889

Panel B: Size of traders that trigger crashes				
	Mean	Median	Min	Max
Marketable Order	190.85	100	1	2000
Limit Order	205.61	100	1	2000

APPENDIX 4: LIQUIDITY BEFORE AND DURING THE CRASH

Table 4: The liquidity before and during the crash.

This table reports the liquidity measures before and during the crash. We report the liquidity measures for the stock day that experiences a crash in Panel A. We include a control period, which includes a time of day matched sample for the same stock during the five days prior to the crash date. Panel A reports the liquidity measures leading up to, and including the crash period. Panel B reports the liquidity measures for the control stock. Panel C reports the differences of the crash period against the control period. Data comprises order level data for the three trading months from August 2014 through October 2014 on the NASDAQ exchange.

	Spread	CRT1000	Orders	Executions
Panel A: Crash Period				
t-60, t-50	0.42	1.85	0.58	0.02
t-50, t-40	0.51	1.99	0.55	0.00
t-40, t-30	0.59	1.87	0.61	0.00
t-30, t-20	0.53	1.84	0.56	0.01
t-20, t-10	0.55	1.92	0.56	0.01
t-10, t	0.51	1.84	0.56	0.02
Crash Period	0.64	1.75	0.55	0.03
Panel B: Control Period				
t-60, t-50	0.48	1.32	0.58	0.01
t-50, t-40	0.48	1.34	0.61	0.02
t-40, t-30	0.45	1.27	0.60	0.01
t-30, t-20	0.46	1.25	0.60	0.01
t-20, t-10	0.44	1.28	0.62	0.02
t-10, t	0.46	1.20	0.64	0.02
Faux Crash Period	0.46	1.17	0.66	0.02

Panel C: Differences between control period and crash period

	Diff	T-test	Diff	T-test	Diff	T-test	Diff	T-test
t-60, t-50	-0.06	-0.75	0.53*	1.88	0.00	0.17	0.01	0.88
t-50, t-40	0.04	0.35	0.65**	2.08	-0.06	-1.58	-0.02	-1.28
t-40, t-30	0.14	1.32	0.59**	2.07	0.00	0.14	-0.01	-1.34
t-30, t-20	0.07	0.63	0.59**	2.05	-0.03	-1.10	0.00	-0.31
t-20, t-10	0.11	1.10	0.64**	2.29	-0.06	-1.69	-0.01	-1.01
t-10, t	0.06	0.62	0.64**	2.49	-0.08**	-2.88	0.00	0.21
Faux Crash Period	0.18*	1.86	0.58**	2.20	-0.12***	-3.89	0.01	1.39

APPENDIX 5: TRADE PRESSURE AND FLASH CRASHES

Table 5: Trade pressure and flash crashes

This table reports logit regression estimates for whether a 10 second time period experiences a flash crash. The dependent variable is an indicator equal to one of a 10 second period experiences a flash crash, zero otherwise. The independent variables include the number of trades and orders from the 10 second period prior to the crash. Theory states that crashes are due to intense pressure on the limit order book. We also separate orders and trades into whether they are on the same side or opposite side of the limit order book that the crash occurs. Data comprises order level data for the three trading months from August 2014 through October 2014 on the NASDAQ exchange.

Dependent Variable	Crash Indicator	Crash Indicator	Crash Indicator	Crash Indicator
	[1]	[2]	[3]	[4]
Intercept	-0.69***	-0.61**	-0.97***	-0.82***
	(-3.118)	(-2.087)	(-5.419)	(-2.686)
Trades $_{t-1}$	0.02	0.04		
	(0.353)	(0.604)		
Orders $_{t-1}$	0.00**	0.00***		
	(2.123)	(2.704)		
SameTrades $_{t-1}$			0.29***	0.24**
			(2.582)	(2.037)
OppositeTrades $_{t-1}$			-0.16	-0.17
			(-1.321)	(-1.284)
SameOrders $_{t-1}$			0.00	0.00
			(0.301)	(0.457)
OppositOrders $_{t-1}$			0.01	0.01
			(1.015)	(1.126)
Quoted $_{t-1}$	-1.79***	-1.74***		-1.79***
	(-3.568)	(-3.527)		(-3.532)
Crt1000 $_{t-1}$	0.53***	0.91***		0.85***
	(3.497)	(4.288)		(4.067)
Price $_{t-1}$		-0.07***		-0.05*
		(-2.940)		(-2.076)
Volatility		-0.00		-0.00
		(-0.461)		(-0.262)
Range		0.75**		0.58
		(2.080)		(1.564)
Marketcap		0.00*		0.00
		(1.736)		(0.971)
Restricted		-0.08		-0.54
		(-0.051)		(-0.322)
Fixed Effects	Yes	Yes	Yes	Yes
N	259	259	259	259
Likelihood Ratio Chi-squared	16.38	24.92	17.17	34.87

APPENDIX 6: LINGERING IMPACT OF FLASH CRASHES

Table 6: Lingering impact of flash crashes

This table identifies whether liquidity degrades following flash crashes. The sample includes all stock days that experience a flash crash. Panel A reports the results for liquidity the 60 seconds before and the 60 seconds following a crash. Panel B reports depth measures, panes C and D report the number of orders and trades received on the average 10 second period. Column 13 tests the difference of the 60 seconds after against the 60 seconds before. Data comprises order level data for the three trading months from August 2014 through October 2014 on the NASDAQ exchange.

	t-60	t-50	t-40	t-30	t-20	t-10	t+10	t+20	t+30	t+40	t+50	t+60	After - Before	t-stat
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]
Panel A: Quoted Spread														
Crash	0.42	0.51	0.59	0.53	0.55	0.51	0.43	0.43	0.39	0.42	0.39	0.39	-0.11***	3.04
Control	0.48	0.48	0.45	0.46	0.44	0.46	0.45	0.43	0.43	0.44	0.41	0.42	-0.03	0.94
Difference													-0.08	1.58
Panel B: CRT 1000														
Crash	1.85	1.99	1.87	1.84	1.92	1.84	1.40	1.40	1.38	1.44	1.33	1.21	-0.52***	4.77
Control	1.32	1.34	1.27	1.25	1.28	1.20	1.02	0.97	0.99	0.97	0.92	0.99	-0.30***	3.77
Difference													-0.22*	1.72
Panel C: Orders														
Crash	0.58	0.55	0.61	0.56	0.56	0.56	0.61	0.65	0.65	0.63	0.61	0.62	0.11***	3.04
Control	0.58	0.61	0.60	0.60	0.62	0.64	0.62	0.63	0.63	0.64	0.63	0.62	0.02**	-2.05
Difference													0.09**	2.04
Panel D: Trades														
Crash	0.02	0.00	0.00	0.01	0.01	0.02	0.01	0.00	0.00	0.01	0.00	0.00	-0.01**	2.46
Control	0.01	0.02	0.01	0.01	0.02	0.02	0.03	0.02	0.00	0.02	0.02	0.01	-0.00	0.33
Difference													0.01	1.10

*** Statistically different at 1% level

** Statistically different at 5% level

*Statistically different at 10% level

APPENDIX 7: MATCHED SAMPLE

Table 7: Matched Sample

This table reports the summary statistics of our matched sample. The matched sample is constructed by identifying firms within the same 3-digit SIC code that have a market capitalization within 10% of a firm experiencing a flash crash. Panel A reports the number of stocks in the crash sample and the matched sample, while Panel B reports statistics for the matched sample. Data comprises order level data for the three trading months from August 2014 through October 2014 on the NASDAQ exchange.

Panel A: Number of Matched stocks	
Stocks Experiencing a Crash	247
Stocks in Matched Sample	211

Panel B: Summary statistics of Matched Sample	Mean	Median	Min	Max
Price	120.51	87.54	3.49	2,687.70
Market Capitalization (000s)	766,606	624,664	80,473	3,707,209
Daily Volume	105,775	40,038	942	2,167,433
Daily Trades	722	388	14	10,199
Daily Orders	15,532	8,411	230	514,265

APPENDIX 8: CONTAGION OF FLASH CRASHES IN MATCHED SAMPLE

Table 8: Contagion of Flash Crashes in matched sample

This table reports the impact of flash crashes on a matched sample of controls stocks. The matched sample is constructed by finding stocks in the same 3-digit SIC code, and a market capitalization within 10%. The matched sample period is during the exact same time-frame as the flash crash sample. The dependent variables include the spread, CRT 1000, number of orders, and number of trades for the 10 second periods during the 60 seconds surrounding the flash crash. The main independent variables include crash, a variable equal to 1 if the reference security experiences a flash crash, zero otherwise, and a variable equal to one for the 10 second period following the end of the crash. Control variables include market cap, price, range volume, as well as crash fixed effects, stock fixed effects, and minute fixed effects for each minute of the trading day. Data comprises order level data for the three trading months from August 2014 through October 2014 on the NASDAQ exchange.

Dependent Variable	Spread	CRT 1000	Orders	Trades
Intercept	0.12	-0.14	596.85	9.58
	(0.451)	(-0.299)	(1.214)	(0.962)
Crash Period	-0.01	0.04	-22.82	1.29
	(-0.333)	(0.460)	(-0.380)	(0.843)
Crash Ends – t+10	-0.02*	-0.02	34.11**	1.64***
	(-1.824)	(-1.113)	(2.520)	(2.686)
T+10 – t+20	-0.03**	-0.08***	37.45**	1.05**
	(-2.541)	(-3.378)	(2.364)	(2.221)
T+20 – t+30	-0.04**	-0.10***	8.85	0.53
	(-2.367)	(-3.389)	(0.690)	(1.014)
T+30 – t+40	-0.05***	-0.13***	25.25	0.47
	(-3.351)	(-4.219)	(1.499)	(0.828)
T+40 – t+50	-0.06***	-0.13***	20.36	0.42
	(-2.952)	(-3.753)	(0.941)	(0.793)
T+50 – t+60	-0.04**	-0.11***	45.69*	1.32*
	(-2.278)	(-3.143)	(1.772)	(1.695)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
N	885	885	885	885
R-Squared	0.25	0.32	0.92	0.97

*** Statistically different at 1% level

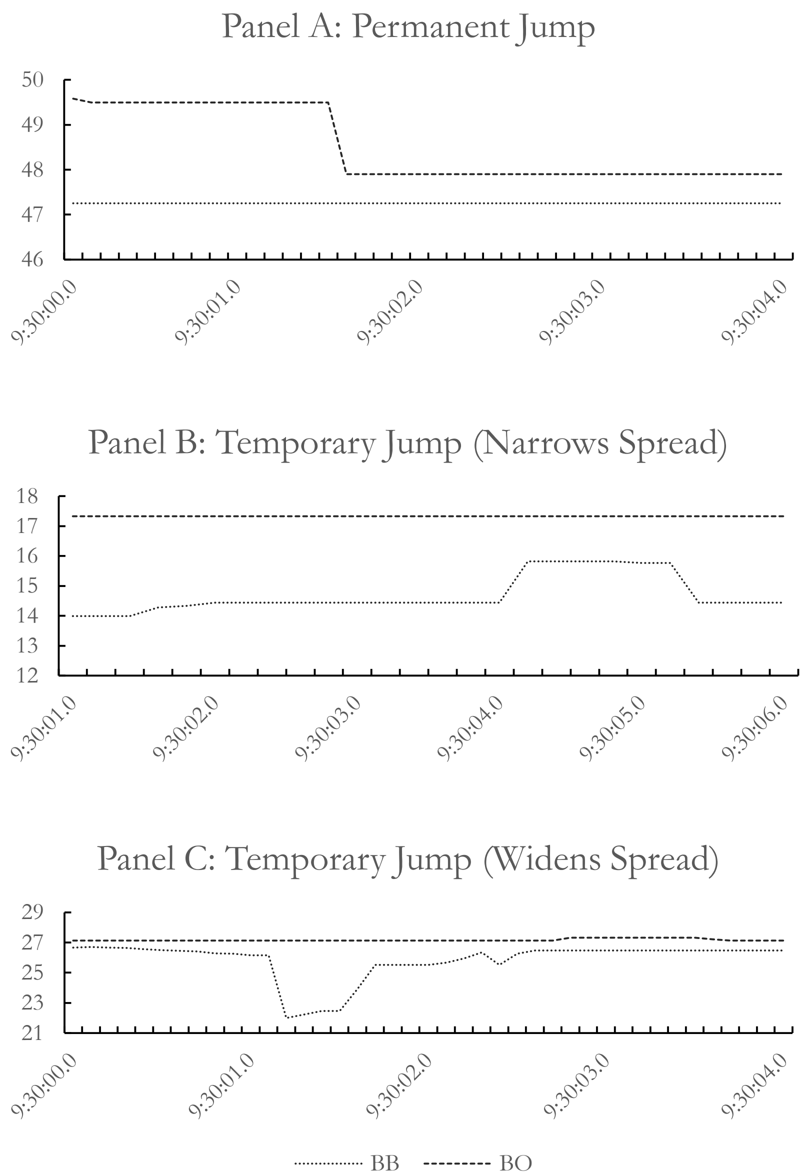
** Statistically different at 5% level

*Statistically different at 10% level

APPENDIX 9: BBO PRICE JUMPS

Figure 1: BBO Price Jumps

This figure presents the three types of pricing jumps encountered in the sample. Permanent price jumps are changes in either the best bid or best offer, which never revert to pre-jump levels, and are removed from our sample. Temporary jumps may occur for two different reasons. First, a temporary jump may narrow the spread before reverting to pre-jump levels. These jumps do not qualify as *flash crashes* and are removed from our sample. The second temporary jump is a change in the BBO that widens the spread temporarily before reverting to the pre-jump level. We classify these jumps as *flash crashes* and are the primary focus of our study. The data for Panels A, B, and C are jumps from Woodward, Inc. (Oct 21, 2014), SciQuest, Inc. (Sep 25, 2014), and Ultratech, Inc. (Sep 8, 2014) respectively.



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