Intraday Return Predictability, Informed Limit Orders, and Algorithmic Trading

Job market paper

Darya Yuferova*

November 2015

Abstract

I study the strategic choice of informed traders for market vs. limit orders by analyzing the informational content of the limit order book. In particular, I examine intraday return predictability from market and limit orders for all NYSE stocks over 2002-2010, distinguishing between two sources of predictability: inventory management and information. In contrast to the traditional view in the literature, I find that informed limit (not market) orders are the dominant source of intraday return predictability. The findings further indicate that the advent of algorithmic trading is associated with more informed trading, especially through market orders. Overall, my evidence emphasizes the role of limit orders in informed trading, which has implications for theory, investors, and widely used measures of informed trading.

*Rotterdam School of Management, Erasmus University; e-mail address: dyuferova@rsm.nl; address: T08-56, Burgemeester Oudlaan 50, 3062 PA, Rotterdam, The Netherlands. I am grateful to Dion Bongaerts, Mathijs Cosemans, Sarah Draus, Thierry Foucault, Wenqian Huang, Lingtian Kong, Albert Menkveld, Marco Pagano, Christine Parlour, Loriana Pelizzon, Dominik Rösch, Stephen Rush, Asani Sarkar, Elvira Sojli, Mark van Achter, Mathijs van Dijk, Wolf Wagner, Jun Uno, Marius Zoican, participants of the FMA 2015 Doctoral Consortium, participants of the PhD course on "Market Liquidity" in Brussels, and seminar participants at Erasmus University, NYU Stern, and Tinbergen Insitute for helpful comments. I gratefully acknowledge financial support from the Vereniging Trustfonds Erasmus Universiteit Rotterdam. I am also grateful for the hospitality of NYU Stern, where some work on this paper was carried out. This work was carried out on the National e-infrastructure with the support of SURF Foundation. I thank OneMarket Data for the use of their OneTick software.

1. Introduction

The limit order book is the dominant market design in equity exchanges around the world.[1] The prevalence of limit order book markets calls for a detailed understanding of how such markets function. In particular, understanding the price discovery process on these markets required a detailed study of the trader's choice between submissions of market and limit orders. The conventional wisdom in the microstructure literature used to be that informed traders use only market orders, while uninformed traders use both market and limit orders (for theoretical work see Glosten and Milgrom, 1985; Kyle, 1985; Glosten, 1994; Seppi, 1997). Only recent studies explicitly consider the choice of informed traders for market or limit orders.[2] Informed traders can submit a market order and experience immediate execution at the expense of the bid-ask spread (consume liquidity). Alternatively, informed traders can submit a limit order and thus bear the risk of non-execution, as well as the risk of being picked-off, but earn the bid-ask spread (provide liquidity).

The importance of the informed trader's choice between market and limit orders is emphasized by a heated public debate about whether one group of market participants poses negative externalities to another group of market participants due to informational asymmetries. This informational advantage is especially pronounced for traders with superior technologies for the collection and processing of information. Another feature that enhances informational inequality in the market is the ability to continuously monitor and respond to market conditions. Both characteristics are distinct characteristics of high-frequency traders

[1]According to Swan and Westerholm (2006), 48% of the largest equity markets are organized as pure limit order book markets (e.g., Australian Stock Exchange, Toronto Stock Exchange, Tokyo Stock Exchange), 39% are organized as limit order books with designated market makers (e.g., New York Stock Exchange, Borsa Italiana), and the remaining 12% are organized as hybrid dealer markets (e.g., NASDAQ, Sao Paulo Stock Exchange) as of the beginning of 2000.

[2]For theoretical studies on the choice of uninformed traders between market and limit orders, see Cohen, Maier, Schwartz, and Whitcomb (1981), Chakravarty and Holden (1995), Handa and Schwartz (1996), Parlour (1998), Foucault (1999), Foucault, Kadan, and Kandel (2005), Goettler, Parlour, and Rajan (2005), and Roşu (2009); for theoretical studies on the choice of informed traders between market and limit orders see, Liu and Kaniel (2006), Goettler, Parlour, and Rajan (2009), and Roşu (2015); for empirical studies on the choice between market and limit orders on equity markets see, Bae, Jang, and Park (2003), Anand, Chakravarty, and Martell (2005), Bloomfield, O'Hara, and Saar (2005), and Baruch, Panayides, and Venkataraman (2015); for empirical studies on the choice between market and limit orders on foreign exchange markets see, Menkhoff, Osler, and Schmeling (2010), Kozhan and Salmon (2012), and Kozhan, Moore, and Payne (2014).

(a subset of algorithmic traders). Consistently, several papers identify algorithmic traders' strategies that are disadvantageous for retail investors.[3] Previous research has focused on informed algorithmic trading via market orders with only one exception.[4] In sum, understanding *how* informed trading takes place and *what role* algorithmic traders play in this process are important questions to explore in modern market microstructure.

In this paper, I address these questions by studying intraday return predictability. Naturally, orders submitted by informed traders contain information about future price movements. If an informed trader actively uses market orders, an imbalance between buyer- and seller-initiated volume may be informative about future price movements. If an informed trader actively uses limit orders, the limit order book may contain information that is not yet incorporated into the price. Therefore, strategies employed by informed traders may induce intraday return predictability from market and limit order flows alike.

My main contribution to the literature is twofold. First, I contribute to the literature on intraday return predictability. I distinguish between two sources of intraday return predictability (inventory management and private information). My findings indicate that the main source of the intraday return predictability is private information embedded in limit orders. Furthermore, I show that this result holds for a wide cross-section of stocks and through a prolonged time period.[5] Second, my paper contributes to the ongoing debate on the role of algorithmic traders (especially it subset, high-frequency traders) in informed trading activity (see Biais and Foucault (2014) for review on high-frequency trading activity and market quality). My evidence suggests that an increased degree of algorithmic trading activity leads to an increased usage of both informed limit and informed market orders (with

[3]See for theoretical work, e.g., Foucault, Hombert, and Roşu, 2015; Biais, Foucault, and Moinas, 2015; Foucault, Kozhan, and Tham, 2015; Jovanovic and Menkveld, 2015; see for empirical work, e.g., McInish and Upson, 2012; Hirschey, 2013; Brogaard, Hendershott, and Riordan, 2014; Foucault, Kozhan, and Tham, 2015.

[4]Brogaard, Hendershott, and Riordan (2015) examine informed trading via both market and limit orders by high-frequency traders for the sample of 15 Canadian stocks from October 2012 to June 2013.

[5]For papers studying intraday return predictability from the limit order book in equity markets see Irvine, Benston, and Kandel (2000), Kavajecz and Odders-White (2004), Harris and Panchapagesan (2005), Cao, Hansch, and Wang (2009), Cont, Kukanov, and Stoikov (2013), and Cenesizoglu, Dionne, and Zhou (2014). However, none of these papers uses such comprehensive data as used in this paper.

the main effect concentrated in market orders). Informed limit orders still remain the main source of the intraday return predictability even after increased degree of algorithmic trading activity.

The analysis is organized in two stages. First, I analyze intraday return predictability from market and limit order flows and separate the effect of informed trading from the effect of inventory management. Second, I analyze the impact of algorithmic trading on the choice between market and limit orders made by an informed trader. In particular, I exploit a quasi-natural experiment to establish a causal inference between algorithmic trading and intraday return predictability from market and limit order flows. I also test recent theories of the choice between informed trading through market versus limit orders by exploiting their predictions regarding differences between low and high volatility stocks.

Using tick-by-tick trade data and data on the first 10 best levels of the consolidated limit order book for the NYSE from the Thomson Reuters Tick History (TRTH) database, I construct a time series of mid-quote returns, market order imbalance, and snapshots of the first 10 best levels of the U.S. consolidated limit order book at the one-minute frequency at the individual stock level. The sample covers all NYSE-listed common stocks for the years 2002-2010. TRTH data used in this paper are very comprehensive. In particular, for the stocks under consideration, I have information for 1.36 billion trades and 8.54 billion limit order book updates.

Intraday return predictability from limit order book data can arise from two sources. First, inventory management (Hypothesis 1) may induce intraday return predictability by generating price pressure as a result of limited risk-bearing capacity of risk-averse liquidity providers (e.g., Stoll, 1978; Menkveld, 2013; Hendershott and Menkveld, 2014). Second, private information (Hypothesis 2) may also induce intraday return predictability (see Liu and Kaniel, 2006; Goettler, Parlour, and Rajan, 2009; Roşu, 2015). The latter source of return predictability is the main focus of this paper. I approach the problem of isolating private information source of intraday return predictability from two angles. First, inventory management should result in temporary price effects, while private information should result in permanent price effects. Therefore, controlling for lagged returns in predictive regressions allows me to separate inventory management effects from the effects of private information.

Second, I run a VAR model and decompose market and limit order flows into two components: inventory-related (fitted values) and information-related (surprises) components. The use of surprises as a proxy for informed market and limit order flows is motivated by the fact that both limit and market order flows are persistent (e.g., Hasbrouck, 1991; Biais, Hillion, and Spatt, 1995; Ellul, Holden, Jain, and Jennings, 2003; Chordia, Roll, and Subrahmanyam, 2005) and that this persistence is attributable to reasons other than information (e.g., Degryse, de Jong, and van Kervel, 2013). Huang and Stoll (1997), Madhavan, Richardson, and Roomans (1997), and Sadka (2006) also use surprises in market order imbalance to isolate the adverse selection component of the bid-ask spread.

Combining these two approaches, I run the predictive regressions with lagged surprises in returns, lagged surprises in market order imbalance, and lagged surprises in depth concentration at the inner and outer levels of the ask and bid sides of the limit order book. In this specification any remaining inventory management effects should be captured by the coefficient of lagged surprises in returns. I use both market order flow and limit order book variables in the predictive regressions to capture the trader's choice between market and limit orders. Inclusion of market order imbalance is also motivated by Chordia, Roll, and Subrahmanyam (2005, 2008), who show that market order imbalance is predictive of future price movements.

The findings of the first part of the analysis indicate that the main source of intraday return predictability is private information (inventory management (lagged returns) accounts only for 30% of total predictive power as measured by the average incremental adjusted R^2 from the predictive regressions). In addition, the results indicate that informed trading through the limit order book accounts for 50% of return predictability that is 30% greater than a fraction of return predictability induced by informed trading through market orders.

The findings contradict the traditional view that only market orders are used for informed trading. Furthermore, the findings suggest that informed trading via market orders is of less importance than informed trading via limit orders.

In the second part of the analysis, I investigate how the presence of algorithmic traders affects the order choices made by informed traders. This is a non-trivial task as algorithmic traders endogenously determine the extent of their participation in each stock at each point in time. I follow the approach of Hendershott, Jones, and Menkveld (2011) and use the NYSE Hybrid Market introduction — a permanent technological change in market design[6] — as an instrumental variable to help determine the causal effects of algorithmic trading activity on intraday return predictability from informed market and limit order flows. The rollout to the Hybrid Market was implemented in a staggered way, which helps clean identification. I follow Hendershott, Jones, and Menkveld (2011) and Boehmer, Fong, and Wu (2015) and use the daily number of best bid-offer quote updates relative to the daily trading volume (in $10,000) as a proxy for algorithmic trading activity on each stock-day.

I develop two competing hypotheses of the effects of algorithmic trading on informed traders' choices: the efficient technology hypothesis (Hypothesis 3) and the competition hypothesis (Hypothesis 4). On the one hand, the technological advantage of algorithmic traders makes limit orders more attractive to them as they are able to reduce pick-off risks better than the other market participants (the efficient technology hypothesis). On the other hand, competition between algorithmic traders for (trading on) the same information makes market orders more attractive to them as they guarantee immediate execution (the competition hypothesis).

The results show that algorithmic trading activity leads to increased informational content in both market and limit orders. However, an increase in the predictive power associated with limit order book variables (the efficient technology hypothesis) is smaller than the increase in predictive power associated with market order imbalance (the competition hypothesis). Although the evidence is consistent with both hypotheses, the effects of the competition hypothesis seem to dominate the effects of the efficient technology hypothesis. In other

[6]NYSE Hybrid Market introduction allowed market orders to "walk" through the limit order book automatically and thus, increased automation and speed (Hendershott and Moulton, 2011).

words, increased algorithmic trading activity is associated with a relative shift from liquidity provision (limit orders) to liquidity consumption (market orders) by informed traders.

Overall, my paper provides evidence that informed traders tend to act more often as liquidity providers (use limit orders), than liquidity demanders (use market orders). However, with an increased presence of algorithmic traders, the amount of informed liquidity provision increases less than the amount of informed liquidity consumption. One important implication of my analysis concerns measures of asymmetric information and/or informed trading (e.g., PIN measure by Easley, Kiefer, O'Hara, and Paperman (1996); adverse selection component of bid-ask spread by Glosten and Harris (1988) and Huang and Stoll (1997)), which have been used widely in studies on market microstructure, asset pricing, and corporate finance.[7] These measures are exclusively based on market orders, and thus neglect the lion's share of informed trading on the equity markets — informed trading via limit orders.

2. Hypotheses

In this section, I develop the hypotheses for the tests of the choice between limit and market orders by informed traders based on the evidence from intraday return predictability. In section 2.1, I develop two hypotheses regarding the sources of intraday return predictability: the inventory management hypothesis and the private information hypothesis. In section 2.2, I describe the hypotheses regarding the effect of algorithmic trading activity on the strategies employed by informed traders (the efficient technology hypothesis and the competition hypothesis). The effect of the realized volatility is described in section 2.3.

2.1. Sources of intraday return predictability

Intraday return predictability from the limit order book can arise from two (not mutually exclusive) sources: inventory management and private information. Under the inventory management hypothesis, depth concentration at the inner levels of the limit order book indicates that a liquidity provider wants to unload inventory. This situation creates a temporary

[7] E.g., Easley, Hvidkjaer, and O'Hara (2002), Vega (2006), Chen, Goldstein, and Jiang (2007), Korajczyk and Sadka (2008), Bharath, Pasquariello, and Wu (2009), and Easley, de Prado, and O'Hara (2012).

price impact that is reverted as soon as the inventory position of the liquidity provider is liquidated (e.g., Stoll, 1978; Ho and Stoll, 1981; Menkveld, 2013; Hendershott and Menkveld, 2014). Indeed, a liquidity provider will be hesitant to immediately replenish the ask side of the limit order book as a large market buy order walks through the limit order book, because she would prefer to liquidate excessive inventory first. It is optimal for her to post aggressive limit orders on the bid side of the book, while on the ask side she will post a limit order deep in the limit order book. In this way, she encourages other market participants to sell her their stocks while discouraging them from buying from her. Therefore, I formulate the *inventory management hypothesis* as follows:

H1 (the inventory management hypothesis): Depth concentration at the inner levels of the ask (bid) sides of the limit order book is associated with decrease (increase) in future stock returns, with depth concentration at the outer levels having virtually no effect on future stock returns.

Under the traditional approach to the adverse selection problem in equity markets only inventory management should drive intraday return predictability from the limit order book. This approach is built under the assumption of informed traders only using market orders (e.g., Glosten and Milgrom, 1985; Kyle, 1985; Glosten, 1994; Seppi, 1997), which may be an inadequate approximation of reality. Later studies build upon this initial work and allow both informed and uninformed traders to choose between the order types (Liu and Kaniel, 2006; Goettler, Parlour, and Rajan, 2009; Roşu, 2015).

Based on theoretical predictions from Goettler, Parlour, and Rajan (2009), an informed trader, who receives good news about a stock, has three different options to exploit this information. First, the trader can submit a buy market order. Second, the trader can submit a limit buy order at the inner level of the bid side of the limit order book; this limits execution probability, but saves transaction costs. Third, the trader can also submit a limit sell order at the outer levels of the ask side of the limit order book in combination with one of the two above mentioned orders to lock-in the benefit from the price difference. The opposite is true for the bad news scenario.

In reality, an informed trader's choice between market and limit orders depends on the strength of the signal received, the lifespan of the information, the ratio of informed to uninformed traders, etc. In the case of a weak and very short-lived signal, the trader is likely to use market orders. In the case of very strong signal that has a relatively long lifespan, the trader is likely to use limit orders at the inner and outer levels of the limit order book. In the case of the average signal with a short lifespan (which I believe is the dominant type of signal), the trader is likely to use a mixture of market and limit orders (see Table 1).

Therefore, I formulate the *private information hypothesis* as follows:

H2 (the private information hypothesis): Depth concentration at the inner levels of the ask side of the limit order book is associated with decrease in future stock returns, while depth concentration at the outer levels of the ask side of the limit order book is associated with increase in future stock returns. The opposite is true for the bid side of the limit order book.

The main purpose of this paper is to test the private information hypothesis and investigate the effect of algorithmic traders on the informed trader's choice between market and limit orders discussed in the next subsection.

2.2. Effect of algorithmic trading activity

During the past decade, a new group of market participants — algorithmic traders — has emerged and evolved into a dominant player responsible for the majority of trading volume. Algorithmic trading "is thought to be responsible for as much as 73 percent of trading volume in the United States in 2009" (Hendershott, Jones, and Menkveld, 2011, p. 1). Therefore, it is a natural question to ask what role algorithmic traders are playing in informed trading process and to what extent their presence affects the informed trader's choice between market and limit orders.

Possessing private information is equivalent to having capacity to absorb and analyze publicly available information (including information from the past order flow) faster than other market participants (Foucault, Hombert, and Roşu, 2015; Foucault, Kozhan, and Tham, 2015; Menkveld and Zoican, 2015). Efficient information processing technology is a distinct feature of algorithmic traders, hence they are more likely to be informed than other market participants. However, ex ante it is not clear whether algorithmic traders would prefer to use market or limit orders to profit from their informational advantage.

On the one hand, limit orders are attractive for traders who can accurately predict execution probabilities, continuously monitor the market, and quickly adapt to market conditions. Algorithmic traders possess all of these characteristics. Thus, they may be inclined to use limit orders for informed trading.

On the other hand, competition among informed traders will lead to a faster price discovery and a shorter lifespan for the information obtained by the informed trader. Algorithmic traders compete for the same information by processing the same news releases or by analyzing past order flow patterns as fast as possible. In a competitive market, a trader must be the first in line to trade on information in order to profit from it. Given that only market orders can guarantee immediate execution, algorithmic traders may be inclined to use market orders for informed trading. Therefore, I formulate two competing hypotheses for the strategies employed by informed algorithmic traders:

H3 (the efficient technology hypothesis): The predictive power of informed market orders is lower for stocks subject to high algorithmic trading activity than for stocks subject to low algorithmic trading activity. On the other hand, the predictive power of informed limit orders is higher for stocks subject to high algorithmic trading activity than for stocks subject to low algorithmic trading activity.

H4 (the competition hypothesis): The predictive power of informed market orders is higher for stocks subject to high algorithmic trading activity than for stocks subject to low algorithmic trading activity. On the other hand, the predictive power of informed limit orders is lower for stocks subject to high algorithmic trading activity than for stocks subject to low algorithmic trading activity.

2.3. Effect of realized volatility

According to Goettler, Parlour, and Rajan (2009), informed traders may prefer market orders to limit orders at the inner levels of the limit order book for high volatility stocks and limit orders at the inner levels of the limit order book to market orders for low volatility stocks.

The intuition is as follows. Posting a limit order is like writing an option (e.g., Copeland and Galai, 1983; Jarnecic and McInish, 1997; Harris and Panchapagesan, 2005). It is known that the sensitivity of the option price to the changes in the volatility of the underlying asset, i.e., vega (ν), is positive. In other words, the option price increases when the volatility of the underlying asset increases. In this way, the option writer gets compensated for the increased risk of option execution. Thus, the increased volatility of the stock will make limit orders riskier and hence, less profitable. In addition, market orders become more profitable due to picking off the stale limit orders posted by slow (and most likely uninformed) traders. And last but not least, in a highly volatile environment it is harder to distinguish between informed and uninformed market orders and hence, hiding informed trading is easier.

Given that on an intraday horizon, realized volatility based on the mid-quote returns is a good proxy for fundamental volatility, I formulate the *realized volatility hypothesis* as follows:

H5 (the realized volatility hypothesis): The predictive power of informed market orders is greater for high volatility stocks than for low volatility stocks. On the other hand,the predictive power of informed limit orders concentrated at the inner levels of the limit order book is greater for low volatility stocks than for high volatility stocks.

3. Data, Variables, and Summary Statistics

In this section, I describe the data, variables, and summary statistics. I obtain intraday consolidated data on trades and the 10 best levels of the limit order book for the U.S. market from the Thomson Reuters Tick History (TRTH) database. The TRTH database is provided by the Securities Industry Research Centre of Asia-Pacific (SIRCA). Data on trades and best bid-offer quotes are available since 1996. Data on the limit order book levels are available only from 2002 as the NYSE opened its limit order book to the public on January 24, 2002. The limit order book data provided by TRTH does not include order level information (e.g., no order submission, revision, or cancellation details), only the 10 best price levels and the depth on bid and ask sides of the book that is visible to the public. The data comes from the consolidated tape. In other words, the best bid-offer reported in the data is the best bid-offer for any exchange in the U.S. The same applies to the other levels of the limit order book.

TRTH data are organized by Reuters Instrumental Codes (RICs), which are identical to TICKERs provided by the Center for Research in Security Prices (CRSP). Merging data from CRSP and TRTH allows me to identify common shares that indicate the NYSE as their primary exchange and to use company specific-information (e.g., market capitalization, turnover, etc.). This study is limited to NYSE-listed stocks only as intraday return predictability from limit order book information as well as the behavior of the informed traders could be very sensitive to market design. Hence, it seems inappropriate to put, for example, the NASDAQ (hybrid dealer market) and NYSE (limit order book with designated market makers) data together.

The available data for the limit order book cover the period from 2002 to 2010. The joint size of the trade and limit order book data reaches 2.5 terabytes. In order to make the analysis feasible, I compute one-minute mid-quote returns and market order imbalances, and take snapshots of the limit order book at the end of each one-minute interval. I filter the data to discard faulty data entries and data entries outside continuous trading session (see the Appendix for details).

3.1. Variable descriptions

In this section, I describe the variables used to study the choice of informed traders between market and limit orders by means of intraday return predictability from the limit order book. In particular, I look at the return predictability one-minute ahead. Therefore, I need intraday data on returns, market order imbalances ($MOIB$), and limit order book data (LOB) at one-minute frequency. For all the variables, I discard overnight observations.

I follow Chordia, Roll, and Subrahmanyam (2008) and compute one-minute log-returns (Ret) based on the prevailing mid-quotes (average of the bid and ask prices) at the end of the one-minute interval, rather than the transaction prices or mid-quotes matched with the last transaction price. In this way I avoid the bid-ask bounce and ensure that the returns for every stock are indeed computed over a one-minute interval. I implicitly assume that there are no stale best bid-offer quotes in the sample, thus I consider a quote to be valid until a new quote arrives or until a new trading day starts.

To calculate a one-minute $MOIB$, I match trades with quotes and sign trades using the Lee and Ready (1991) algorithm. TRTH data are stamped to the millisecond, therefore the Lee and Ready (1991) algorithm is quite accurate. In particular, a trade is considered to be buyer-initiated (seller-initiated) if it is closer to the ask price (bid price) of the prevailing quote. For each one-minute interval, I aggregate the trading volume in USD for buyer- and seller-initiated trades separately at the stock level. Thereafter, I subtract seller-initiated dollar volume from buyer-initiated dollar volume to obtain $MOIB$.

There are multiple ways to describe the limit order book. Most of the papers that study intraday return predictability either focus on different levels of the limit order book or on the corresponding ratios of these levels between the ask and bid sides of the limit order book. For instance, Wuyts (2008), Cao, Hansch, and Wang (2009), and Cenesizoglu, Dionne, and Zhou (2014) use slopes and depth at different levels of the limit order book to summarize its shape. However, due to variation in the shape of the limit order book as well as in the number of available levels of the limit order book (in my sample the daily average number of levels can be as low as just six levels), I believe that definition of inner and outer levels by means of a relative threshold is more suitable than definition by means of the number of levels in the limit order book (e.g., levels from 2 to 5 are inner levels and levels from 6 to 10 are outer levels).

Examples of a relative approach to limit order book description are Cao, Hansch, and Wang (2009), who also use volume-weighted average price for different order sizes to describe the limit order book, and Kavajecz and Odders-White (2004), who use a so-called "near-depth" measure, which is a proportion of the depth close to the best bid-offer level relative to the cumulative depth within a certain price range.

For the purpose of testing the private information hypothesis, I focus on the ratios within the ask and bid sides separately, rather than across the ask and bid sides of the limit order book. I use a modification of the "near-depth" measure introduced by Kavajecz and Odders-White (2004). First, I compute a snapshot of the ask and bid sides of the limit order book at the end of each one-minute interval. Then, I define the inner depth concentration as cumulative depth lying between the mid-quote and one-third of the total distance between the 10th available limit price and the mid-quote relative to the total cumulative depth of the ask and bid side of the limit order book separately ($Ask\ Inner$ and $Bid\ Inner$). I define the outer depth concentration as cumulative depth lying between one-third and two-thirds of the total distance between the 10th available limit price and the mid-quote relative to the total cumulative depth of the ask and bid side of the limit order book separately ($Ask\ Outer$ and $Bid\ Outer$). Please refer to Table 2 for the summary of variables' descriptions.

My relative approach allows me to define inner and outer levels of the limit order book even if not all 10 levels are present for a particular stock at a particular time. Hence, I can define in unified fashion the levels that are close to the best bid-offer level, as well as the levels that are far away from the best bid-offer level across stocks and through time.

3.2. Summary statistics

Table 3 presents summary statistics for the one-minute mid-quote returns (*Ret*), dollar market order imbalance ($MOIB$), and depth concentration at the inner levels ($Bid\ Inner$ and $Ask\ Inner$) and outer levels ($Bid\ Outer$ and $Ask\ Outer$) of the ask and bid sides of the limit order book (LOB), and cutoff points between the inner and outer levels of the limit order book measured relative to the mid-quote ($Bid\ Cutoff$ and $Ask\ Cutoff$) at the end of each one-minute interval for the whole period (from January 2002 to December 2010) and two sub-periods (from January 2002 to June 2006 and from July 2006 to December 2010). I start with winsorizing all variables at the 1% and 99% levels on a stock-day basis. Then, I compute averages of the one-minute observations for mid-quote returns (*Ret*), dollar market order imbalance ($MOIB$), and depth concentration at the inner and outer levels of the ask and bid sides of the limit order book per stock-day. Afterwards, I winsorize stock-day averages of the variables at the 1% and 99% levels based on the whole sample period or sub-periods and compute summary statistics.

The mean of the daily average one-minute mid-quote returns is -0.003 basis points for the whole sample period (see Panel A of Table 3). The average negative return is due to the inclusion of the recent financial crisis period in the sample. Indeed, in the first half of the sample period the average returns are 0.014 basis points, while in the second half of the period the average returns are -0.02 basis points. The mean of the daily average one-minute dollar market order imbalance is $4,133.34. This indicates that on average there is more buying than selling pressure in the market. However, this buying pressure is much more moderate at $840.15 – when I focus on the second half of the sample period due to the inclusion of the recent financial crisis.

Panel A of Table 3 also shows the depth concentration at the inner and outer levels separately of the ask and bid side of the limit order book for the whole sample period. The average proportion of the cumulative depth at the inner levels of the limit order book is 31.49% and 32.19% of the ask and bid side of the limit order book, respectively. The average proportion of the cumulative depth at the outer levels of the limit order book is 31.36% and 31.20% of the ask and bid sides of the limit order book, respectively. Although the average depth concentration is very similar for the inner and outer levels for both ask and bid sides of the limit order book, depth concentration at the inner levels exhibits higher variation than depth concentration at the outer levels both in terms of within and between standard deviations. Notably, the ask and bid sides of the limit order book exhibit similar characteristics in terms of the depth concentration at the inner and outer levels.

Panel A of Table 3 also reports the cutoff points between inner and outer levels of the ask and bid sides of the limit order book measured as a percentage deviation from the mid-quote. For the whole sample period, the cutoff point (one-third of the total distance between the 10th available limit price and the mid-quote) is 1.47% and -1.43% of the ask and bid sides of the limit order book, respectively.

Sub-period analysis (see Panels B and C of Table 3) reveals that although on average through the whole sample period depth concentration at the inner and outer levels for both sides of the limit order book is similar, depth concentration at the inner levels tends to decrease over time, while depth concentration at the outer levels tends to increase over time.

In particular, in the first half of the sample period, depth concentration at the inner levels of the ask (bid) side of the limit order book is 42.66% (45.31%). In the second half of the sample period, depth concentration at the inner levels of the ask (bid) side of the limit order book is 21.53% (20.47%). In the first half of the sample period, depth concentration at the outer levels of the limit order book of the ask (bid) side of the limit order book is 25.49% (24.69%), while in the second half of the sample period it reaches 36.59% (37.03%).

This trend in the limit order book composition is also reflected in the cutoff points between the inner and outer levels of the limit order book. In particular, in the first half of the sample period, price levels of the limit order book are more dispersed than in the second half of the sample period. Hence, for the first half of the sample period I define inner depth as depth concentrated at price levels that do not differ from the mid-quote more than 2.34% (2.45%) of the ask (bid) side of the limit order book, respectively. The cutoff points for the second half of the period are 0.68% (0.51%) for the ask (bid) side of the limit order book, respectively.

This decreasing (increasing) trend in depth concentration at the inner (outer) levels of the limit order book can be also observed in Panel A of Figure 1. Panel B of Figure 1 shows the trend in cutoff points between the inner and outer levels of the limit order book.

The composition changes in the limit order book may be attributable to the different structural changes of the NYSE during the sample period such as autoquote introduction in 2003 (Hendershott, Jones, and Menkveld, 2011), NYSE Hybrid introduction in 2006-2007 (Hendershott and Moulton, 2011), Reg NMS implementation in 2007, and replacement of the specialist by designated market makers at the end of 2008.

4. Methodology

In this section, I describe the methodology used in the paper in order to investigate whether market and/or limit orders are used for informed trading. In particular, I empirically distinguish between two sources of intraday return predictability: inventory management (Hypothesis 1) and private information (Hypothesis 2). Given that the main goal of this paper is to investigate the informed trader's choice between market and limit orders, the latter source of the intraday return predictability is the one I focus on.

I run stock-day predictive regressions at one-minute frequency using one-minute mid-quote returns as the dependent variable. As explanatory variables I use lagged returns, lagged market order imbalance ($MOIB$), and lagged depth concentration at the inner and outer levels of the ask and bid sides of the limit order book. I include $MOIB$ in the model as I want to show that the LOB variables contain useful information for intraday return predictability beyond $MOIB$. Controlling for lagged returns allows me to differentiate between temporary effect (inventory management) and permanent effect (private information). The regression equation is given by:

$$\begin{aligned} Ret_t = \alpha + \beta_1 Ret_{t-1} + \beta_2 MOIB_{t-1} + \beta_3 Bid\ Inner_{t-1} + \beta_4 Ask\ Inner_{t-1} + \\ + \beta_5 Bid\ Outer_{t-1} + \beta_6 Ask\ Outer_{t-1} + \epsilon_t \end{aligned} \tag{1}$$

where Ret_t is the mid-quote return during the t-th one-minute interval, $MOIB_{t-1}$ is the dollar market order imbalance during the $(t-1)$-th one-minute interval, LOB_{t-1}: $Bid\ Inner_{t-1}$, $Ask\ Inner_{t-1}$, $Bid\ Outer_{t-1}$, $Ask\ Outer_{t-1}$ are the depth concentrations at the inner and outer levels of the ask and bid sides of the limit order book at the end of the $(t-1)$-th one-minute interval.

As a next step, I identify the private information component of the market and limit order flows and enhance the above mentioned methodology. Hasbrouck (1991) and Chordia, Roll, and Subrahmanyam (2005) show that $MOIB$ is positively autocorrelated. Moreover, Biais, Hillion, and Spatt (1995) and Ellul, Holden, Jain, and Jennings (2003) show that order flow is also persistent for limit orders. Biais, Hillion, and Spatt (1995) argue that there are three possible reasons for the order flow persistence: order splitting, imitation of other traders' behavior, and reaction to the public information in a sequential manner (e.g., due to the differences in trading speed). Degryse, de Jong, and van Kervel (2013) show that order flow persistence is caused by reasons other than private information. Previous empirical studies (e.g., Huang and Stoll, 1997; Madhavan, Richardson, and Roomans, 1997; Sadka, 2006) use unexpected changes in the market order flow in order to isolate information-related component. I extend this approach one step further and apply it to market and limit order flows. I argue that it is an appropriate extension as both market and limit order flows are persistent. Therefore, I use unexpected changes in the order flow for both market and limit orders as a proxy for the private information component of the order flow.

I obtain the surprises in returns, $MOIB$, and LOB variables by estimating stock-day $VAR(k)$ regression (number of lags, k, can take values from 1 to 5 and is selected by AIC criteria) and keeping the residual values:

$$X_t = \alpha + \sum_{l=1}^{l=k} \beta X_{t-l} + \epsilon_t \tag{2}$$

where X_t is a vector that includes Ret_t, $MOIB_t$, $Bid\ Inner_t$, $Ask\ Inner_t$, $Bid\ Outer_t$, and $Ask\ Outer_t$ measured at the t-th one-minute interval; ϵ_t is vector of residuals that includes the Ret_t^U, $MOIB_t^U$, $Bid\ Inner_t^U$, $Ask\ Inner_t^U$, $Bid\ Outer_t^U$, and $Ask\ Outer_t^U$.

In the remainder of the paper, the superscript U indicates a residual value from $VAR(k)$ rather than the variable itself. Misspecification of the $VAR(k)$ model may lead to some inventory effects ending up in the surprises. In order to address this issue, I include lagged surprises in returns as explanatory variable in the predictive regressions to capture return reversal, which is a distinct feature of the inventory management hypothesis. I run predictive regressions per stock-day with lagged surprises in returns, lagged surprises in $MOIB$, and lagged surprises in depth concentration at the inner and outer levels of the ask and bid sides of the limit order book as explanatory variables:

$$\begin{aligned} Ret_t = \alpha + \beta_1 Ret_{t-1}^U + \beta_2 MOIB_{t-1}^U + \beta_3 Bid\ Inner_{t-1}^U + \beta_4 Ask\ Inner_{t-1}^U + \\ + \beta_5 Bid\ Outer_{t-1}^U + \beta_6 Ask\ Outer_{t-1}^U + \epsilon_t \end{aligned} \tag{3}$$

5. Empirical Results

In this section, I provide empirical evidence for the informed trader's choice between market and limit orders by analyzing intraday return predictability from market and limit order flows (section 5.1). Then, I discuss the role of algorithmic trading activity in the choice made by informed trader (section 5.2). In section 5.3, I provide supplementary analysis of the effects of realized volatility on the informed trader's choice.

5.1. Intraday return predictability

I start with examining whether limit order book variables are useful in predicting intraday returns without explicitly decomposing order flow into inventory- and information-related components. Table 4 presents estimation results of equation (1): predictive stock-day regressions of one-minute mid-quote returns on one-minute lagged mid-quote returns, one-minute lagged market order imbalance, and one-minute lagged depth concentration at the inner and outer levels of the ask and bid sides of the limit order book.

Panel A of Table 4 reports average coefficients together with average Newey-West t-statistics, as well as the proportion of the regressions that have significant individual t-statistics.[8] Ret_{t-1} is negatively related to the future returns. Such return reversals are in line with the inventory management hypothesis (Hypothesis 1). $MOIB_{t-1}$ is positively related to future stock returns (in line with, e.g., Chordia, Roll, and Subrahmanyam, 2005, 2008). In particular, the $MOIB_{t-1}$ coefficient is 4.65 and is positive and significant in 26.43% of the stock-day regressions. These results hold for the whole sample period as well as for the sub-periods.[9] The increase of one within standard deviation in $MOIB_{t-1}$ is associated with a 0.72 basis points increase in the future returns, which is equivalent to an increase of 1.24 within standard deviation for returns.

In line with the inventory management (Hypothesis 1) and informed limit orders (Hypothesis 2) hypotheses, depth concentration at the inner levels of the bid (ask) sides of the limit order book, $Bid\ Inner_{t-1}$ ($Ask\ Inner_{t-1}$) is positively (negatively) related to the future price movements. For the whole sample period, one within standard deviation increase

[8] To compute average Newey-West t-statistics, I do the following steps (following Rösch, Subrahmanyam, and van Dijk, 2015). First, I use a time series of the estimated coefficients for each stock to compute Newey-West t-statistics (Newey and West, 1987). Second, I average the cross-section of the Newey-West t-statistics to determine the average Newey-West t-statistics estimate.

[9] As a comparison, Rösch, Subrahmanyam, and van Dijk (2015) document that coefficient of $MOIB_{t-1}$ is 3.79 and is positive and significant in 30.07% of the predictive regressions using only lagged dollar market order imbalance over 1996-2010 for NYSE common stocks.

in *Bid Inner*$_{t-1}$ (*Ask Inner*$_{t-1}$) corresponds to an increase of future returns by 0.35 basis points (decrease of future returns by -0.35 basis points), which is equivalent to an increase of 0.61 within standard deviation for returns (decrease of 0.61 within standard deviation for returns).

However, the fact that *Bid Outer*$_{t-1}$ (*Ask Outer*$_{t-1}$) is negatively (positively) related to future price movements in the second half of the period cannot be explained under the inventory management hypothesis (Hypothesis 1), while it is true under the private information hypothesis (Hypothesis 2). Notably, the sign of *Bid Outer*$_{t-1}$ (*Ask Outer*$_{t-1}$) changes from insignificantly positive (negative) in the first half of the sample period to significantly negative (positive) in the second half of the sample period. In other words, informational content at the outer levels of the limit order book is lower in the first half of the sample period compared to the second half of the sample period. These results are also in line with increasing depth concentration at the outer levels of the limit order book and decreasing depth concentration at the inner levels of the limit order book over the sample period. For the whole sample period, one within standard deviation increase in *Bid Outer*$_{t-1}$ (*Ask Outer*$_{t-1}$) corresponds to decrease of future returns by -0.017 basis points (increase of future returns by 0.012 basis points), which is equivalent to decrease of 0.03 within standard deviation for returns (increase of 0.02 within standard deviation for returns).

Remarkably, the effects of the ask and bid sides of the limit order book are similar in terms of the absolute size of the coefficients. However, the median of daily correlation coefficients between *Bid Inner*$_{t-1}$ and *Ask Inner*$_{t-1}$ (*Bid Outer*$_{t-1}$ and *Ask Outer*$_{t-1}$) is quite low – at only 6.24% (2.21%). Put differently, the depth concentration of the ask and bid sides of the limit order book tend to vary largely independently from each other, thus their effects on future returns should not offset each other.

At the same time, Panel A of Table 4 shows a clear discrepancy in the absolute size of the coefficients between depth concentration at the inner and outer levels: 1.89 (-2.02) to -0.16 (0.11) of the bid (ask) side during the whole sample period, respectively.[10] This discrepancy

[10]A natural concern is that the inner and outer levels of the limit order book are negatively correlated by

could be due to the fact that outer levels are not likely to be used for inventory management. In addition, outer levels are used for informed trading if and only if an informed trader receives a relatively strong signal, which is unlikely to happen regularly on the market.

In order to measure the relative importance of market and limit order variables, I look at the R^2 decomposition of the predictive regressions. Panel B of Table 4 shows that the average adjusted R^2 of the predictive regressions is equal to 1.64% for the whole sample period. Adjusted R^2 attributable to $MOIB_{t-1}$ is 0.34% in absolute terms, which accounts for 20.66% of the total explanatory power. As a comparison, Chordia, Roll, and Subrahmanyam (2008) document an adjusted R^2 of 0.51% for predictive regressions using only lagged dollar market order imbalance for the 1993-2002 period, which is of the same order of magnitude as my estimate. Lagged return accounts for 32.38% of the total predictive power, while 46.96% of the total predictive power comes from the limit order book variables (with 27.79% attributable to the depth concentration at the inner levels of the limit order book and 19.17% attributable to the depth concentration at the outer levels of the limit order book).

My results are also consistent with Cao, Hansch, and Wang (2009), who document an increase in adjusted R^2 after inclusion of additional levels of the limit order book with a monotonic decrease of the added value for each additional level. My results are however at odds with Cont, Kukanov, and Stoikov (2013), who argue that only imbalances at the BBO level drive intraday return predictability. Despite the fact that Cao, Hansch, and Wang (2009) and Cont, Kukanov, and Stoikov (2013) also investigate intraday return predictability from the limit order book, the data used in their studies is quite limited. Specifically, Cao, Hansch, and Wang (2009) use one month of data on 100 stocks traded on the Australian Stock Exchange, while Cont, Kukanov, and Stoikov (2013) use one month of data on 50 stocks from S&P 500 constituents. Overall, my results allow me to draw more generalizable conclusions regarding intraday return predictability and observed time series and cross-sectional patterns.

construction. If there is an extremely high correlation between depth concentration at the inner and outer levels of the limit order book, I can run into a multicollinearity problem. However, across all stock-days, these correlation coefficients never fall below -70%, and the median value is around -46% for both ask and bid sides of the limit order book.

The sub-period analysis yields the following results. Total predictive power of the regressions decreases slightly from 1.71% in the first half of the sample period to 1.58% in the second half. This decrease is attributable to the limit order book (adjusted R^2 decreases from 0.85% to 0.71%). The predictive power of the $MOIB$ increases slightly from 0.33% to 0.35%. This evidence is consistent with the fact that intraday return predictability from the limit order book is a persistent phenomenon during 2002-2010 for all NYSE-listed common stocks.

Next, I enrich the analysis discussed above in order to emphasize the importance of private information source of intraday return predictability. To determine the pure effect of private information on intraday return predictability from market and limit order flows, I follow the previous literature (e.g., Huang and Stoll, 1997; Madhavan, Richardson, and Roomans, 1997; Sadka, 2006) and use surprises in market and limit order flows to define the informational component of the order flows. I calculate surprises as residual values of the $VAR(k)$ regression on a stock-day basis with the number of lags determined by AIC criteria (see equation 2). I then repeat the above-mentioned analysis with these surprises used as explanatory variables (see equation 3). I use superscript U to refer to surprises in the variables.

Table 5 presents the average estimation results of this analysis. The results in Table 5 are similar to the results in Table 4, with the only exception of the depth concentration at the outer levels of the ask side of the limit order book, which is no longer significant during the second half of the period. Nevertheless, all the signs during the whole sample period and the second half of the sample period are consistent with the private information hypothesis (Hypothesis 2).

Based on the whole sample period, adjusted R^2 attributable to the $MOIB^U$ is 0.31% in absolute terms (20.92% in relative terms), while the adjusted R^2 attributable to surprises in LOB variables is 0.71% in absolute terms (47.21% in relative terms). The inner levels of the limit order book contribute 27.65% and outer levels contribute 19.56% of this predictive power.

All in all, this suggests that private information is the main source of the intraday return predictability: roughly 20% of this predictability is attributable to the informed market orders, roughly 50% is attributable to the informed limit orders. Remaining 30% are stemming from inventory management concerns (lagged returns).

Furthermore, the evidence is consistent with the majority of informed trading taking place via limit orders contrary to the traditional view of informed trading taking place via market orders only.

5.2. Algorithmic trading and informed trader's choice

To this end, I provide evidence consistent with limit orders being actively used for informed trading. Furthermore, my findings suggest that informed limit orders are a prevalent source of intraday return predictability. I now examine the role of algorithmic trading activity in the choice made by the informed trader.

In particular, I identify the effects of algorithmic trading activity on intraday return predictability from the limit order book. The results of this section add to the ongoing debate on whether algorithmic traders improve or decrease market quality. Identifying the causal effects of the algorithmic trading activity is not a trivial task as the degree of algorithmic trading activity in each stock on each day is an endogenous choice made by the algorithmic trader. Therefore, I adopt an instrumental variable approach following Hendershott, Jones, and Menkveld (2011) to identify the causal effects of the algorithmic trading on limit order book informational content.

Since January 2002 when the NYSE opened its limit order book to public, there were two major technological advances in NYSE equity market design that impacted algorithmic trading activity: Autoquote in 2003 (Hendershott, Jones, and Menkveld, 2011) and NYSE Hybrid Market in 2006-2007 (Hendershott and Moulton, 2011). After the NYSE Hybrid Market introduction, orders were allowed to "walk" through the limit order book automatically, before this technological change market orders were executed automatically at the best bid-offer level only. I use the NYSE Hybrid Market introduction as an instrument for algorithmic trading activity that allows me to investigate the role of algorithmic traders in informed trading activity.

I obtain data on the NYSE Hybrid Phase 3 rollout, which was when the actual increase in the degree of automated execution and speed took place (Hendershott and Moulton, 2011) from Terrence Hendershott's website. This rollout was implemented in a staggered way from October 2006 until January 2007 (see Figure 2), which allows for a clean identification. My analysis is focused on the period around Hybrid introduction from June 2006 to May 2007. All stocks in the sample have CRSP data available during the whole period under consideration. I discard stocks with average monthly price bigger than \$1,000 and smaller than \$5. I winsorize all the variables at the 1% and 99% levels.

I consider the following proxy for algorithmic trading activity in the spirit of Hendershott, Jones, and Menkveld (2011) and Boehmer, Fong, and Wu (2012): AT, a daily number of best bid-offer quote updates relative to daily trading volume (in \$10,000).[11]

I follow Hendershott, Jones, and Menkveld (2011) and estimate the following IV panel regression with stock and day fixed effects (implicit difference-in-difference approach) and double-clustering of the standard errors (Petersen, 2009):

$$Y_{i,t} = \alpha_i + \gamma_t + AT_{i,t} + MCAP_{i,m-1} + 1/PRC_{i,m-1} + Turnover_{i,m-1} + Volatility_{i,m-1} + \epsilon_{i,t} \quad (4)$$

where $Y_{i,t}$ is either coefficients estimates from equation (3), or incremental adjusted R^2 from equation (3) for stock i on day t, and α_i and γ_t are stock and day fixed effects. $AT_{i,t}$ is a proxy for algorithmic trading activity for stock i on day t . In addition, I control for daily log of market capitalization in billions ($MCAP_{i,m-1}$), inverse of price ($1/P_{i,m-1}$), annualized turnover ($Turnover_{i,m-1}$), and square root of high minus low range ($Volatility_{i,m-1}$) averaged over the previous month, $m-1$. As a set of instruments, I use all explanatory variables with

[11]The results are robust for using a different proxy for algorithmic trading activity: a daily number of limit order book updates relative to daily trading volume (in \$10,000). On the one hand, by construction this is a better proxy for algorithmic trading activity in the limit order book. On the other hand, my limit order book data is limited as it takes into account only first 10 levels of the limit order book (aggregated depth at first 10 price levels). In addition, I do not have order level data (submission, revision, cancellation). Therefore, the change in this measure due to NYSE Hybrid Market introduction is bounded from above due to data limitations. Results with this proxy are available from the author upon a request.

$AT_{i,t}$ replaced by $Hybrid_{i,t}$, a dummy variable that equals one if the stock i on day t is rolled-out to the NYSE Hybrid Market and 0 otherwise. In other words, I estimate equation (4) by means of 2SLS with an exclusion restriction on the Hybrid Market introduction dummy.

Unreported results of the first stage regression show that AT increases significantly with NYSE Hybrid Market introduction (an increase of 1.12 best bid-offer updates per $10,000 of daily trading volume). The null hypothesis that instrument does not enter first-stage regression is strongly rejected.

The results for the second stage regression for AT are presented in Table 6. In particular, I estimate the effect of algorithmic trading on the coefficients (Panel A) and incremental adjusted R^2 (Panel B) from predictive regressions of one-minute mid-quote returns on lagged surprises in returns, $MOIB$, and LOB variables (see equation 3). I test the efficient technology hypothesis (Hypothesis 3) against the competition hypothesis (Hypothesis 4).

Panel A of Table 6 shows that in line with the competition hypothesis, the coefficients of lagged $MOIB^U$ significantly increase in an absolute sense with an increase in algorithmic trading activity. However, there is also an increase in the $Bid\ Inner^U$ and $Ask\ Inner^U$ coefficients in line with the efficient technology hypothesis. This is consistent with slow traders, who are likely to be uninformed, moving away from the inner to outer levels, while fast and potentially informed traders continue operating at the inner levels of the bid and ask sides of the limit order book. The coefficients of the lagged returns also increase in an absolute sense, consistent with the fact that high-frequency traders (subset of algorithmic traders) are known to end their day with a flat inventory position. Therefore, inventory management concerns should generate a stronger return reversal in the presence of algorithmic traders.

Panel B of Table 6 reports the effect of algorithmic trading on the incremental adjusted R^2 from equation (3). Algorithmic trading participation increases the predictive power of all variables, although the increase in predictive power of the depth concentration at the outer levels of the bid and ask sides of the limit order book is marginal. In particular, a one standard deviation increase in AT leads to an increase of 8.2 basis points in the adjusted R^2 attributable to lagged surprises returns, a 5.3 basis points increase in the adjusted R^2

attributable to $MOIB^U$, a 2.6 (2.7) basis points increase in the adjusted R^2 attributable to $Bid\ Inner^U$ ($Ask\ Inner^U$), and a 0.7 (0.6) basis points increase in the adjusted R^2 attributable to $Bid\ Outer^U$ ($Ask\ Outer^U$).[12] Put differently, I find evidence consistent with both the efficient technology (predictive power of limit orders increases) and the competition (predictive power of market orders increases) hypotheses. However, the effects of the competition hypothesis may dominate those of the efficient technology hypothesis.

Note that intraday return predictability (total as well as incremental) increases with the size and turnover, and decreases with the inverse of price and volatility. Size and turnover could be viewed as a proxies for stocks' liquidity. Lower transaction costs allow traders to benefit even from small pieces of information, on which they would not trade otherwise, which in turn increases the predictive power of limit and primarily market orders.

Overall, I contribute to the debate on whether algorithmic traders adversely select other market participants. I provide evidence that the increased degree of algorithmic trading participation is associated with an increase in the informational content of not only market orders, but also limit orders at the inner levels of the limit order book (with outer levels being only marginally affected). In other words, an increase in algorithmic trading activity leads to an increase in informed trading via both market (demanding liquidity) and limit orders (providing liquidity), with a relative shift from informed liquidity provision to informed liquidity consumption.

5.3. Realized volatility and informed trader's choice

I test the realized volatility hypothesis based on the theoretical predictions from Goettler, Parlour, and Rajan (2009), who argue that informed traders tend to use market orders for high volatility stocks and limit orders for low volatility stocks (Hypothesis 5). These effects should be mainly observed for the orders posted at the inner levels of the limit order book as these orders are more likely to be hit.

[12] Recall from section 5.1 that an average adjusted R^2 for the whole sample period is 1.50%.

I estimate predictive regressions of one-minute mid-quote returns (see equation 3) with one-minute lagged surprises in returns, one-minute lagged surprises in market order imbalance, and lagged surprises in depth concentration at the inner and outer levels of the ask and bid sides of the limit order book as explanatory variables on a stock-day basis. Then, I sort the stocks into four portfolios based on one-day lagged realized volatility (realized volatility is computed from one-minute mid-quote returns during the day).

Ex ante, I expect a monotonic increase in the absolute coefficient of the surprises in market order imbalance and adjusted R^2 from the low volatility portfolio to the high volatility portfolio, while I expect the opposite for the surprises in depth concentration at the inner levels of the ask and bid sides of the limit order book. Table 7 reports the estimation results for the average coefficients and the average Newey-West t-statistics (Panel A) and adjusted R^2 decomposition (Panel B) for the whole sample period only.

Table 7 Panel A shows a monotonic increase for the coefficient of $MOIB^U$ from 1.18 to 11.63 while moving from the low realized volatility portfolio to the high realized volatility portfolio. In other words, coefficient of $MOIB^U$ is 9.86 times greater for high volatility stocks than for low volatility stocks. The coefficients of $Bid\ Inner^U$($Ask\ Inner^U$) also increase monotonically in absolute sense from the low volatility portfolio to the high volatility portfolio from 1.64 (-1.71) to 3.78 (-3.81), but this increase is very moderate compared to $MOIB^U$. The coefficients of $Bid\ Outer^U$($Ask\ Outer\ ^U$) are not significant.[13]

Table 7 Panel B shows adjusted R^2 decomposition for each of the explanatory variables for the four realized volatility portfolios. There is a monotonic increase in the adjusted R^2 attributable to $MOIB^U$ while moving from the low realized volatility portfolio to the high realized volatility portfolio from 0.29% to 0.38% in absolute terms (19.42% to 22.88% in relative terms). However, there is a slightly U-shaped pattern for the adjusted R^2 attributable to LOB variables in absolute terms and a monotonically decreasing pattern in relative terms (48.51% to 44.97%). The rest of predictive power comes from surprises in lagged returns.

[13]The results are robust for the sub-period analysis.

All in all, I provide evidence that informed traders may prefer market orders to limit orders at the inner levels of the limit order book for high volatility stocks and limit orders at the inner levels of the limit order book to market orders for low volatility stocks. In other words, informed traders are more likely to consume liquidity for high volatility stocks and to supply liquidity for low volatility stocks.

6. Conclusion

The recent public debates regarding algorithmic traders (and their subset — high-frequency traders) adversely selecting retail investors highlighted the importance of understanding how the informed trading is taking place and how it was affected by the emergence of algorithmic trading. Motivated by this, I investigate the intraday return predictability from informed market orders and informed limit orders to answer the questions of whether informed traders choose to act as liquidity suppliers or liquidity demanders and what are the determinants of their choice. In particular, I study one-minute mid-quote return predictability from the lagged informed market order flow (measured by surprises in market order imbalances) and lagged informed limit orders (measured by surprises in depth concentration at the inner and outer levels of the ask and bid sides of the limit order book).

To the best of my knowledge, I am the first to address this question with such a comprehensive data set, which includes one-minute observations for all NYSE-listed common stocks for the 2002-2010 period. I show that informed limit orders are predictive of intraday returns beyond the informed market orders. Moreover, the majority of informed trading occurs via limit orders (as measured by incremental adjusted R^2 from predictive regressions). This result holds for the whole period under consideration as well as for the sub-period analysis.

I also examine the effect of algorithmic trading activity on informed trader's choice between market and limit orders. Overall, there is a relative shift from informed liquidity provision (limit orders) to informed liquidity consumption (market orders) while moving from stocks with a low presence of algorithmic traders to stocks with a high presence of algorithmic traders.

In conclusion, informed traders actively use both market orders (consume liquidity) and limit orders (provide liquidity) with the largest chunk of the informed trading happening via limit orders. This fact should not be neglected while analyzing the adverse selection effects on financial markets.

Appendix. Sample Selection and Data Screens

A1. Sample selection

In this paper, I use two databases to construct my sample: TRTH and CRSP. From the TRTH database, I obtain trade data, best bid-offer data, and limit order book data for the U.S. consolidated limit order book for NYSE-listed securities. I use Reuters Instrumental Codes (RICs), which are identical to TICKERs, to obtain data on common stocks and primary exchange code from CRSP database (PRIMEXCH=N, and SHRCD=10 or 11, EXCHCD =1 or 31). Thus, I focus on all NYSE-listed common stocks that have NYSE as their primary exchange from 2002 untill 2010. These filters leave me with 2,047 unique TICKERs in total.

A2. Data Screens

I filter the data following Rösch, Subrahmanyam, and van Dijk (2015). First, I discard trades, quotes, and limit order book data that are not part of the continuous trading session. Continuous trading session hours for NYSE are 9:30-16:00 ET and they remain unchanged during the sample period.

Second, I discard block trades, i.e., trades with a trade size greater than 10,000 shares, as these trades are likely to receive a special treatment.

Third, I discard data entries that are likely to be faulty. Faulty entries include entries with negative or zero prices or quotes, entries with negative bid-ask spread, entries with proportional bid-ask spread bigger than 25%, entries that have trade price, bid price, or ask price which deviates from the 10 surrounding ticks by more than 10%.

In addition, I require that at least five levels of the limit order book are available in the end of each one-minute interval. For a stock-day to enter my sample, at least 100 valid one-minute intervals with at least one trade are required.

References

Anand, A., S. Chakravarty, and T. Martell (2005). Empirical evidence on the evolution of liquidity: Choice of market versus limit orders by informed and uninformed traders. *Journal of Financial Markets 8*(3), 288–308.

Bae, K.-H., H. Jang, and K. S. Park (2003). Traders' choice between limit and market orders: evidence from NYSE stocks. *Journal of Financial Markets 6*(4), 517–538.

Baruch, S., M. Panayides, and K. Venkataraman (2015). Informed trading and price discovery before corporate events. *Working paper*.

Bharath, S. T., P. Pasquariello, and G. Wu (2009). Does asymmetric information drive capital structure decisions? *Review of Financial Studies 22*(8), 3211–3243.

Biais, B. and T. Foucault (2014). HFT and market quality. *Bankers, Markets and Investors 128*, 5–19.

Biais, B., T. Foucault, and S. Moinas (2015). Equilibrium fast trading. *Journal of Financial Economics 116*(2), 292–313.

Biais, B., P. Hillion, and C. Spatt (1995). An empirical analysis of the limit order book and the order flow in the Paris Bourse. *Journal of Finance 50*(5), 1655–1689.

Bloomfield, R., M. O'Hara, and G. Saar (2005). The "make or take" decision in an electronic market: Evidence on the evolution of liquidity. *Journal of Financial Economics 75*(1), 165–199.

Boehmer, E., K. Fong, and J. Wu (2015). International evidence on algorithmic trading. *Working paper*.

Boehmer, E., K. Y. Fong, and J. Wu (2012). Algorithmic trading and changes in firms' equity capital. *Working paper*.

Brogaard, J., T. Hendershott, and R. Riordan (2014). High-frequency trading and price discovery. *Review of Financial Studies 27*(8), 2267–2306.

Brogaard, J., T. Hendershott, and R. Riordan (2015). Price discovery without trading: Evidence from limit orders. *Working paper*.

Cao, C., O. Hansch, and X. Wang (2009). The information content of an open limit-order book. *Journal of Futures Markets 29*(1), 16–41.

Cenesizoglu, T., G. Dionne, and X. Zhou (2014). Effects of the limit order book on price dynamics. *Working paper*.

Chakravarty, S. and C. W. Holden (1995). An integrated model of market and limit orders. *Journal of Financial Intermediation 4*(3), 213–241.

Chen, Q., I. Goldstein, and W. Jiang (2007). Price informativeness and investment sensitivity to stock price. *Review of Financial Studies 20*(3), 619–650.

Chordia, T., R. Roll, and A. Subrahmanyam (2005). Evidence on the speed of convergence to market efficiency. *Journal of Financial Economics 76*(2), 271–292.

Chordia, T., R. Roll, and A. Subrahmanyam (2008). Liquidity and market efficiency. *Journal of Financial Economics 87*(2), 249–268.

Cohen, K. J., S. F. Maier, R. A. Schwartz, and D. K. Whitcomb (1981). Transaction costs, order placement strategy, and existence of the bid-ask spread. *Journal of Political Economy*, 287–305.

Cont, R., A. Kukanov, and S. Stoikov (2013). The price impact of order book events. *Journal of Financial Econometrics 12*(1), 47–88.

Copeland, T. E. and D. Galai (1983). Information effects on the bid-ask spread. *Journal of Finance 38*(5), 1457–1469.

Degryse, H., F. de Jong, and V. van Kervel (2013). Does order splitting signal uninformed order flow? *Working paper*.

Easley, D., M. M. L. de Prado, and M. O'Hara (2012). Flow toxicity and liquidity in a high-frequency world. *Review of Financial Studies 25*(5), 1457–1493.

Easley, D., S. Hvidkjaer, and M. O'Hara (2002). Is information risk a determinant of asset returns? *Journal of Finance 57*(5), 2185–2221.

Easley, D., N. M. Kiefer, M. O'Hara, and J. B. Paperman (1996). Liquidity, information, and infrequently traded stocks. *Journal of Finance 51*(4), 1405–1436.

Ellul, A., C. W. Holden, P. Jain, and R. Jennings (2003). Determinants of order choice on the New York Stock Exchange. *Working paper*.

Foucault, T. (1999). Order flow composition and trading costs in a dynamic limit order market. *Journal of Financial markets 2*(2), 99–134.

Foucault, T., J. Hombert, and I. Roşu (2015). News trading and speed. *Journal of Finance, forthcoming*.

Foucault, T., O. Kadan, and E. Kandel (2005). Limit order book as a market for liquidity. *Review of Financial Studies 18*(4), 1171–1217.

Foucault, T., R. Kozhan, and W. W. Tham (2015). Toxic arbitrage. *Working paper*.

Glosten, L. R. (1994). Is the electronic open limit order book inevitable? *Journal of Finance 49*(4), 1127–1161.

Glosten, L. R. and L. E. Harris (1988). Estimating the components of the bid/ask spread. *Journal of Financial Economics 21*(1), 123–142.

Glosten, L. R. and P. R. Milgrom (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics 14*(1), 71–100.

Goettler, R. L., C. A. Parlour, and U. Rajan (2005). Equilibrium in a dynamic limit order market. *Journal of Finance 60*(5), 2149–2192.

Goettler, R. L., C. A. Parlour, and U. Rajan (2009). Informed traders and limit order markets. *Journal of Financial Economics 93*(1), 67–87.

Handa, P. and R. A. Schwartz (1996). Limit order trading. *Journal of Finance 51*(5), 1835–1861.

Harris, L. E. and V. Panchapagesan (2005). The information content of the limit order book: evidence from NYSE specialist trading decisions. *Journal of Financial Markets 8*(1), 25–67.

Hasbrouck, J. (1991). Measuring the information content of stock trades. *Journal of Finance 46*(1), 179–207.

Hendershott, T., C. M. Jones, and A. J. Menkveld (2011). Does algorithmic trading improve liquidity? *Journal of Finance 66*(1), 1–33.

Hendershott, T. and A. J. Menkveld (2014). Price pressures. *Journal of Financial Economics 114*(3), 405–423.

Hendershott, T. and P. C. Moulton (2011). Automation, speed, and stock market quality: The NYSE's hybrid. *Journal of Financial Markets 14*(4), 568–604.

Hirschey, N. (2013). Do high-frequency traders anticipate buying and selling pressure? *Working paper*.

Ho, T. and H. R. Stoll (1981). Optimal dealer pricing under transactions and return uncertainty. *Journal of Financial Economics 9*(1), 47–73.

Huang, R. D. and H. R. Stoll (1997). The components of the bid-ask spread: A general approach. *Review of Financial Studies 10*(4), 995–1034.

Irvine, P. J., G. J. Benston, and E. Kandel (2000). Liquidity beyond the inside spread: Measuring and using information in the limit order book. *Working paper*.

Jarnecic, E. and T. H. McInish (1997). An empirical investigation of the option value of the limit order book on the Australian Stock Exchange. *Working paper*.

Jovanovic, B. and A. J. Menkveld (2015). Middlemen in limit-order markets. *Working paper*.

Kavajecz, K. A. and E. R. Odders-White (2004). Technical analysis and liquidity provision. *Review of Financial Studies 17*(4), 1043–1071.

Korajczyk, R. A. and R. Sadka (2008). Pricing the commonality across alternative measures of liquidity. *Journal of Financial Economics 87*(1), 45–72.

Kozhan, R., M. Moore, and R. Payne (2014). Market order flows, limit order flows and exchange rate dynamics. *Working paper*.

Kozhan, R. and M. Salmon (2012). The information content of a limit order book: The case of an fx market. *Journal of Financial Markets 15*(1), 1–28.

Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica 53*(6), 1315–1335.

Lee, C. and M. J. Ready (1991). Inferring trade direction from intraday data. *Journal of Finance 46*(2), 733–746.

Liu, H. and R. Kaniel (2006). So what orders do informed traders use? *Journal of Business 79*(4), 1867–1913.

Madhavan, A., M. Richardson, and M. Roomans (1997). Why do security prices change? a transaction-level analysis of NYSE stocks. *Review of Financial Studies 10*(4), 1035–1064.

McInish, T. H. and J. Upson (2012). Strategic liquidity supply in a market with fast and slow traders. *Working paper*.

Menkhoff, L., C. L. Osler, and M. Schmeling (2010). Limit-order submission strategies under asymmetric information. *Journal of Banking and Finance 34*(11), 2665–2677.

Menkveld, A. J. (2013). High frequency trading and the new market makers. *Journal of Financial Markets 16*(4), 712–740.

Menkveld, A. J. and M. A. Zoican (2015). Need for speed? exchange latency and liquidity. *Working paper*.

Newey, W. K. and K. D. West (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelationconsistent covariance matrix. *Econometrica 55*(3), 703–708.

Parlour, C. A. (1998). Price dynamics in limit order markets. *Review of Financial Studies 11*(4), 789–816.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies 22*(1), 435–480.

Roşu, I. (2009). A dynamic model of the limit order book. *Review of Financial Studies 22*(11), 4601–4641.

Roşu, I. (2015). Liquidity and information in order driven markets. *Working paper*.

Rösch, D. M., A. Subrahmanyam, and M. A. van Dijk (2015). An empirical analysis of co-movement in market efficiency measures. *Working paper*.

Sadka, R. (2006). Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk. *Journal of Financial Economics 80*(2), 309–349.

Seppi, D. J. (1997). Liquidity provision with limit orders and a strategic specialist. *Review of Financial Studies 10*(1), 103–150.

Stoll, H. R. (1978). The supply of dealer services in securities markets. *Journal of Finance 33*(4), 1133–1151.

Swan, P. L. and P. J. Westerholm (2006). Market architecture and global exchange efficiency: One design need not fit all stock sizes. *Working paper*.

Vega, C. (2006). Stock price reaction to public and private information. *Journal of Financial Economics 82*(1), 103–133.

Wuyts, G. (2008). The impact of liquidity shocks through the limit order book. *Working paper*.

Table 1: Expected signs of the coefficients for two sources of intraday return predictability

This table shows the expected behavior of informed trader conditional on the type of news received (Panel A) as well as variables and corresponding expected signs of the coefficients under private information and inventory management hypotheses in the following predictive regression of one-minute mid-quote return with lagged return, lagged market order imbalance ($MOIB$), and lagged depth concentration at the inner and outer levels of the ask and bid sides of the limit order book (LOB: $Bid\ Inner$, $Bid\ Outer$, $Ask\ Inner$, $Ask\ Outer$) as explanatory variables (Panel B):

$$Ret_t = \alpha + \beta_1 Ret_{t-1} + \beta_2 MOIB_{t-1} + \beta_3 Bid\ Inner_{t-1} + \beta_4 Ask\ Inner_{t-1} +$$

$$+ \beta_5 Bid\ Outer_{t-1} + \beta_6 Ask\ Outer_{t-1} + \epsilon_t \ (1)$$

Panel A: Expected behavior of informed trader

Order type		Good news	Bad news
Market	Buy	×	
	Sell		×
Limit Bid	Inner levels	×	
	Outer levels		×
Limit Ask	Inner levels		×
	Outer levels	×	

Panel B: Expected signs under inventory management and private information hypothesis

Variable	Inventory Management	Private Information
Ret_{t-1}	NEG	NA
$MOIB_{t-1}$	POS	POS
$Bid\ Inner_{t-1}$	POS	POS
$Bid\ Outer_{t-1}$	NA	NEG
$Ask\ Inner_{t-1}$	NEG	NEG
$Ask\ Outer_{t-1}$	NA	POS

Table 2: Variables descriptions

This table shows the description of the variables used in the paper. Panel A shows variables for the first part of the analysis regarding intraday return predictability from market and limit order flows. Panel B shows variables for the second part of the analysis regarding the effect of algorithmic trading on the choice made by informed trader.

Panel A: Intraday return predictability

Variable	Description
Ret	One-minute log-returns based on the prevailing mid-quotes (average of the bid and ask prices) at the end of the one-minute interval at individual stock level.
$MOIB$	One-minute market order imbalance (buy volume minus sell volume) at individual stock level.
$Bid\ Inner$ ($Ask\ Inner$)	Based on a snapshot of the bid (ask) side of the limit order book at the end of each one-minute interval, I define the inner depth concentration as cumulative depth lying between mid-quote and one-third of the total distance between 10th available limit price and mid-quote relative to the total cumulative depth of the bid (ask) side of the limit order book.
$Bid\ Outer$ ($Ask\ Outer$)	Based on a snapshot of the bid (ask) side of the limit order book at the end of each one-minute interval, I define the outer depth concentration as cumulative depth lying between one-third and two-thirds of the total distance between 10th available limit price and mid-quote relative to the total cumulative depth of the bid (ask) side of the limit order book.

Panel B: Effect of algorithmic trading activity

Variable	Description
AT	The daily number of best bid-offer quote updates relative to the daily trading volume (in $10,000) on stock-day basis.
$MCAP$	Monthly average of the daily log of market capitalization in billions at individual stock level.
$1/PRC$	Inverse of monthly average of the daily closing price at individual stock level.
$Turnover$	Monthly average of the daily annualized turnover at individual stock level.
$Volatility$	Square root of monthly average of the daily high minus low range at individual stock level.

Table 3: Descriptive statistics

This table shows summary statistics of one-minute mid-quote returns, market order imbalance ($MOIB$), and depth concentration at the inner and outer levels of the ask and bid sides of the limit order book for the NYSE-listed common stocks during 2002-2010. Returns are reported in basis points, market order imbalance is reported in USD, depth concentration at the inner and outer levels is reported in percentage, cutoff points between inner and outer levels are reported in percentage relative to the mid-quote. For detailed description of the variables please refer to Table 2. To compute summary statistics, I follow the following procedure. First, I winsorize one-minute observations per stock-day at the 1% and 99% levels. Second, the average of the one-minute observations per stock-day is calculated for each variable. Third, I winsorize daily observations at the 1% and 99% levels for the whole sample period. Then, the summary statistics across all stock-days are computed for each variable. All the results are reported for the whole sample period (Panel A: Jan-2002 untill Dec-2010) and for the two sub-sample periods (Panel B: Jan-2002 untill Jun-2006 and Panel C: Jul-2006 untill Dec-2010). To be included in the sample, a stock should have NYSE as its primary exchange. Data on common stocks and primary exchange code are obtained from CRSP database (PRIMEXCH=N, and SHRCD=10 or 11, EXCHCD =1 or 31). Data on consolidated trades, quotes, and 10 best levels of the limit order book are provided by TRTH.

Panel A: Jan-2002 untill Dec-2010

	Ret	$MOIB$	$Bid\ Inner$	$Ask\ Inner$	$Bid\ Outer$	$Ask\ Outer$	$Bid\ Cutoff$	$Ask\ Cutoff$
Mean	-0.003	4,133.34	32.19%	31.49%	31.20%	31.36%	-1.43%	1.47%
St. Dev. Within	0.583	15,484.35	18.74%	17.47%	11.14%	10.92%	2.34%	2.63%
St. Dev. Between	0.160	5,930.18	11.43%	11.05%	6.40%	5.99%	2.27%	2.86%

Panel B: Jan-2002 untill Jun-2006

	Ret	$MOIB$	$Bid\ Inner$	$Ask\ Inner$	$Bid\ Outer$	$Ask\ Outer$	$Bid\ Cutoff$	$Ask\ Cutoff$
Mean	0.014	7,725.14	45.31%	42.66%	24.69%	25.49%	-2.45%	2.34%
St. Dev. Within	0.493	15,263.00	16.15%	15.35%	9.65%	9.45%	2.83%	3.20%
St. Dev. Between	0.181	9,590.36	11.70%	10.60%	6.09%	5.11%	3.01%	3.78%

Panel C: Jul-2006 untill Dec-2010

	Ret	$MOIB$	$Bid\ Inner$	$Ask\ Inner$	$Bid\ Outer$	$Ask\ Outer$	$Bid\ Cutoff$	$Ask\ Cutoff$
Mean	-0.020	840.15	20.47%	21.53%	37.03%	36.59%	-0.51%	0.68%
St. Dev. Within	0.664	14,398.41	10.64%	11.45%	8.69%	9.11%	0.72%	1.28%
St. Dev. Between	0.081	3,200.42	10.04%	10.71%	5.83%	6.28%	0.87%	1.34%

Table 4: Estimation results of the intraday return predictability from $MOIB$ and LOB

This table shows the average estimation results of predictive regressions of one-minute mid-quote returns on lagged returns, lagged market order imbalance ($MOIB$), and lagged depth concentration at the inner and outer levels of the ask and bid sides of the limit order book for NYSE-listed common stocks during the sample period (2002-2010):

$$Ret_t = \alpha + \beta_1 Ret_{t-1} + \beta_2 MOIB_{t-1} + \beta_3 Bid\ Inner_{t-1} + \beta_4 Ask\ Inner_{t-1} + \beta_5 Bid\ Outer_{t-1} + \beta_6 Ask\ Outer_{t-1} + \epsilon_t \quad (1)$$

I run this regression on the stock-day basis. The table reports average coefficients together with average Newey-West t-statistics (Panel A), and adjusted R^2 decomposition (Panel B). Coefficient for order imbalance is scaled by 10^9. All other coefficients are scaled by 10^4. To compute average Newey-West t-statistic, I use a time-series of estimated coefficients for each stock to compute Newey-West t-statistics and average it across stocks. Individual regression t-statistics are used to determine the proportion of regressions that report significant coefficients (either positive or negative). The ordering of the variables used to decompose the adjusted R^2 is identical to the order in which they appear in the table. The last two rows show the total number of stock-day observations and the average number of stocks per day. To be included in the sample, a stock should have NYSE as its primary exchange. Data on common stocks and primary exchange code are obtained from CRSP database (PRIMEXCH=N, and SHRCD=10 or 11, EXCHCD =1 or 31). Data on consolidated trades, quotes, and 10 best levels of the limit order book are provided by TRTH. ***,**,* indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Coefficient estimates (dependent variable: Ret_t)

	Jan-2002 untill Dec-2010			Jan-2002 untill Jun-2006			Jul-2006 untill Dec-2010		
		% of significant and			% of significant and			% of significant and	
	Coef	Positive	Negative	Coef	Positive	Negative	Coef	Positive	Negative
Constant	0.048	8.29%	7.74%	0.111	8.50%	7.50%	-0.006	8.10%	7.96%
	(0.46)			(0.73)			(0.00)		
Ret_{t-1}	-0.011***	14.57%	20.23%	-0.013***	13.31%	20.24%	-0.009***	15.69%	20.21%
	(-4.86)			(-4.86)			(-3.19)		
$MOIB_{t-1}$	4.650***	26.43%	2.48%	3.145***	24.87%	2.46%	6.278***	27.81%	2.50%
	(18.87)			(15.17)			(15.08)		
$Bid\ Inner_{t-1}$	1.894***	16.02%	4.80%	1.714***	16.31%	4.41%	2.055***	15.76%	5.14%
	(9.66)			(9.24)			(7.23)		
$Ask\ Inner_{t-1}$	-2.021***	4.41%	17.65%	-2.113***	3.41%	19.56%	-1.915***	5.30%	15.95%
	(-11.00)			(-12.38)			(-6.95)		
$Bid\ Outer_{t-1}$	-0.155	7.21%	8.09%	0.154	7.92%	7.14%	-0.434**	6.57%	8.93%
	(-0.95)			(0.73)			(-2.15)		
$Ask\ Outer_{t-1}$	0.113	8.08%	7.27%	-0.168	7.20%	7.88%	0.356*	8.87%	6.74%
	(0.74)			(-0.88)			(1.81)		
Adjusted R^2	1.64%			1.71%			1.58%		
# of stock-days	2,740,593			1,291,413			1,448,989		
Average # of stocks	1,228			1,167			1,289		

Table 4: Estimation results of the intraday return predictability from $MOIB$ and LOB (continued)

Panel B: Adjusted R^2 decomposition (dependent variable: Ret_t)

	Jan-2002 untill Dec-2010		Jan-2002 untill Jun-2006		Jul-2006 untill Dec-2010	
	Adjusted R^2		Adjusted R^2		Adjusted R^2	
	Absolute	Relative	Absolute	Relative	Absolute	Relative
$Constant$						
Ret_{t-1}	0.53%	32.38%	0.54%	31.32%	0.53%	33.38%
$MOIB_{t-1}$	0.34%	20.66%	0.33%	19.28%	0.35%	21.98%
$Bid\ Inner_{t-1}$	0.21%	13.05%	0.23%	13.66%	0.20%	12.45%
$Ask\ Inner_{t-1}$	0.24%	14.74%	0.28%	16.08%	0.21%	13.42%
$Bid\ Outer_{t-1}$	0.16%	9.57%	0.17%	9.86%	0.15%	9.34%
$Ask\ Outer_{t-1}$	0.16%	9.60%	0.17%	9.79%	0.15%	9.44%
$Total\ Inner$	0.45%	27.79%	0.51%	29.74%	0.41%	25.87%
$Total\ Outer$	0.32%	19.17%	0.34%	19.65%	0.30%	18.78%
$Total\ LOB$	0.77%	46.96%	0.85%	49.39%	0.71%	44.65%
$Total$	1.64%	100.00%	1.71%	100.00%	1.58%	100.00%
# of stock-days	2,740,593		1,291,413		1,448,989	
Average # of stocks	1,228		1,167		1,289	

Table 5: Estimation results of the intraday return predictability from surprises in $MOIB$ and LOB

This table shows the average estimation results of predictive regressions of one-minute mid-quote returns on lagged surprises in returns, lagged surprises in market order imbalance ($MOIB$), and lagged surprises in depth concentration at the inner and outer levels of the ask and bid sides of the limit order book for NYSE-listed common stocks during the sample period (2002-2010):

$$Ret_t = \alpha + \beta_1 Ret^U_{t-1} + \beta_2 MOIB^U_{t-1} + \beta_3 Bid\ Inner^U_{t-1} + \beta_4 Ask\ Inner^U_{t-1} + \beta_5 Bid\ Outer^U_{t-1} + \beta_6 Ask\ Outer^U_{t-1} + \epsilon_t \quad (3)$$

Surprises are computed as residual values from $VAR(k)$ regression per stock-day, number of lags, k, can take values from 1 to 5 and is selected by AIC criteria (see equation 2). Superscript U indicates that this a residual value from $VAR(k)$. I run this regression on the stock-day basis. The table reports average coefficients together with average Newey-West t-statistics (Panel A), and adjusted R^2 decomposition (Panel B). Coefficient for order imbalance is scaled by 10^9. All other coefficients are scaled by 10^4. To compute average Newey-West t-statistic, I use a time-series of estimated coefficients for each stock to compute Newey-West t-statistics and average it across stocks. Individual regression t-statistics are used to determine the proportion of regressions that report significant coefficients (either positive or negative). The ordering of the variables used to decompose the adjusted R^2 is identical to the order in which they appear in the table. The last two rows show the total number of stock-day observations and the average number of stocks per day. To be included in the sample, a stock should have NYSE as its primary exchange. Data on common stocks and primary exchange code are obtained from CRSP database (PRIMEXCH=N, and SHRCD=10 or 11, EXCHCD =1 or 31). Data on consolidated trades, quotes, and 10 best levels of the limit order book are provided by TRTH. ***,**,* indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Coefficient estimates (dependent variable: Ret_t)

	Jan-2002 untill Dec-2010			Jan-2002 untill Jun-2006			Jul-2006 untill Dec-2010		
		% of significant and			% of significant and			% of significant and	
	Coef	Positive	Negative	Coef	Positive	Negative	Coef	Positive	Negative
$Constant$	-0.002	6.72%	6.19%	0.013	7.14%	6.26%	-0.017	6.35%	6.13%
	(0.10)			(0.73)			(-0.57)		
Ret^U_{t-1}	-0.015***	13.38%	20.56%	-0.020***	11.86%	21.18%	-0.011***	14.74%	20.01%
	(-6.21)			(-6.34)			(-3.74)		
$MOIB^U_{t-1}$	4.774***	25.25%	2.27%	3.213***	23.75%	2.34%	6.459***	26.58%	2.20%
	(18.83)			(14.99)			(15.19)		
$Bid\ Inner^U_{t-1}$	2.520***	15.00%	4.62%	2.617***	15.31%	4.19%	2.497***	14.73%	5.01%
	(9.51)			(8.96)			(7.11)		
$Ask\ Inner^U_{t-1}$	-2.571***	4.36%	16.24%	-2.775***	3.51%	17.74%	-2.394***	5.12%	14.90%
	(-10.45)			(-11.08)			(-7.01)		
$Bid\ Outer^U_{t-1}$	-0.004	7.04%	7.76%	0.601	7.58%	6.76%	-0.434*	6.56%	8.66%
	(-0.31)			(1.26)			(-1.86)		
$Ask\ Outer^U_{t-1}$	0.049	7.76%	7.05%	-0.273	6.89%	7.44%	0.315	8.54%	6.70%
	(0.38)			(-1.02)			(1.47)		
Adjusted R^2	1.50%			1.57%			1.44%		
# of stock-days	2,739,445			1,290,389			1,448,865		
Average # of stocks	1,228			1,166			1,289		

Table 5: Estimation results of the intraday return predictability from surprises in $MOIB$ and LOB (continued)

Panel B: Adjusted R^2 decomposition (dependent variable: Ret_t)

	Jan-2002 untill Dec-2010		Jan-2002 untill Jun-2006		Jul-2006 untill Dec-2010	
	Adjusted R^2		Adjusted R^2		Adjusted R^2	
	Absolute	Relative	Absolute	Relative	Absolute	Relative
$Constant$						
Ret^U_{t-1}	0.48%	31.87%	0.49%	31.42%	0.47%	32.29%
$MOIB^U_{t-1}$	0.31%	20.92%	0.31%	19.83%	0.32%	21.97%
$Bid\ Inner^U{}_{t-1}$	0.20%	13.40%	0.22%	13.81%	0.19%	13.00%
$Ask\ Inner^U{}_{t-1}$	0.21%	14.25%	0.24%	15.34%	0.19%	13.20%
$Bid\ Outer^U{}_{t-1}$	0.15%	9.79%	0.15%	9.83%	0.14%	9.77%
$Ask\ Outer^U{}_{t-1}$	0.15%	9.77%	0.15%	9.78%	0.14%	9.78%
$Total\ Inner^U$	0.41%	27.65%	0.46%	29.15%	0.38%	26.20%
$Total\ Outer^U$	0.30%	19.56%	0.30%	19.61%	0.28%	19.55%
$Total\ LOB^U$	0.71%	47.21%	0.76%	48.76%	0.66%	45.75%
$Total^U$	1.50%	100.00%	1.57%	100.00%	1.44%	100.00%
# of stock-days	2,739,445		1,290,389		1,448,865	
Average # of stocks	1,228		1,166		1,289	

Table 6: Second stage regression: Impact of algorithmic trading activity on intraday return predictability

This table shows the impact of algorithmic trading activity on intraday return predictability from the limit order book:

$$Y_{i,t} = \alpha_i + \gamma_t + \beta_1 AT_{i,t} + \beta_2 MCAP_{i.m-1} + \beta_3(1/PRC_{i,m-1}) + \beta_4 Turnover_{i,m-1} + \beta_5 Volatility_{i,m-1} + \epsilon_{i,t} \quad (4)$$

As proxy for algorithmic trading activity I use daily number of best bid-offer quote updates per \$10,000 of daily trading volume ($AT_{i,t}$). In order to identify causal effect of algorithmic trading activity, I instrument it with staggered introduction of NYSE Hybrid. The set of instruments include all explanatory variables with $AT_{i,t}$ substituted by $Hybrid_{i,t}$. I control for daily market capitalization, price, turnover, and volatility averaged over the previous calendar month. The specification includes stock (α_i) and day (γ_t) fixed effects. Standard errors are adjusted for double clustering. Panel A reports the effect of algorithmic trading on the coefficients from predictive regressions. Panel B reports the effect of algorithmic trading on the incremental adjustedR^2 from predictive regressions. The last two rows in each panel show the total number of stock-day observations and the average number of stocks per day. The estimation period is Jun-2006 untill May-2007. To be included in the sample, a stock should have NYSE as its primary exchange and have CRSP data available for all days under consideration. Data on common stocks and primary exchange code are obtained from CRSP database (PRIMEXCH=N, and SHRCD=10 or 11, EXCHCD =1 or 31). Data on consolidated trades, quotes, and 10 best levels of the limit order book are provided by TRTH. Data on NYSE Hybrid introduction comes from Terrence Hendershott's website. ***,**,* indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Effect of algorithmic trading on coefficients

	$Ret^U_{i,t-1}$	$MOIB^U_{i,t-1}$	$Bid\ Inner^U_{i,t-1}$	$Ask\ Inner^U_{i,t-1}$	$Bid\ Outer^U_{i,t-1}$	$Ask\ Outer^U_{i,t-1}$
$AT_{i,t}$	-0.004***	0.095**	0.337***	-0.275***	-0.006	0.001
	(-3.67)	(2.40)	(9.21)	(-6.66)	(-0.17)	(0.05)
$\ln(MCAP)_{i,m-1}$	-0.010***	0.162	1.158***	-1.026***	0.182*	-0.153
	(-2.78)	(1.13)	(8.28)	(-7.19)	(1.71)	(-1.30)
$1/PRC_{i,m-1}$	-0.321***	54.778***	8.288**	-7.782*	8.490**	-4.437
	(-3.28)	(11.14)	(1.97)	(-1.82)	(2.47)	(-1.32)
$Turnover_{i,m-1}$	-0.045***	-1.594***	1.373***	-0.952***	0.022	-0.029
	(-8.02)	(-7.68)	(6.70)	(-4.45)	(0.12)	(-0.18)
$Volatility_{i,m-1}$	0.748***	56.901***	-4.218	-0.311	-9.770**	9.048**
	(6.13)	(10.24)	(-0.80)	(-0.06)	(-2.45)	(2.31)
Stock FE	YES	YES	YES	YES	YES	YES
Day FE	YES	YES	YES	YES	YES	YES
Double clustering	YES	YES	YES	YES	YES	YES
R^2	0.14	0.35	0.06	0.06	0.01	0.01
# of stock-days	296,130	296,130	296,130	296,130	296,130	296,130
Average # of stocks	1,180	1,180	1,180	1,180	1,180	1,180

Table 6: Second stage regression (continued)

Panel B: Effect of algorithmic trading on incremental Adjusted R^2

	$Adj\ R^2_{i,t}$	$Ret^U_{i,t-1}$	$MOIB^U_{i,t-1}$	$Bid\ Inner^U_{i,t-1}$	$Ask\ Inner^U_{i,t-1}$	$Bid\ Outer^U_{i,t-1}$	$Ask\ Outer^U_{i,t-1}$
$AT^{BBO}_{i,t}$	0.211***	0.080***	0.052***	0.025***	0.026***	0.007**	0.006*
	(9.11)	(7.93)	(8.20)	(5.64)	(5.26)	(2.17)	(1.76)
$\ln(MCAP)_{i,m-1}$	0.380***	0.234***	0.004	0.049***	0.079***	0.001	-0.005
	(6.31)	(7.88)	(0.24)	(4.05)	(5.72)	(0.09)	(-0.60)
$1/PRC_{i,m-1}$	-4.410**	-1.681**	-1.461***	-0.692**	-0.550	0.163	0.129
	(-2.53)	(-2.19)	(-2.83)	(-2.08)	(-1.41)	(0.68)	(0.50)
$Turnover_{i,m-1}$	1.209***	0.508***	0.260***	0.132***	0.140***	0.047***	0.037**
	(10.72)	(9.88)	(8.52)	(5.89)	(5.59)	(3.07)	(2.12)
$Volatility_{i,m-1}$	-27.372***	-11.065***	-4.728***	-3.027***	-3.631***	-1.430***	-1.355***
	(-12.40)	(-10.42)	(-7.97)	(-7.12)	(-7.55)	(-4.73)	(-4.34)
Stock FE	YES	YES	YES	YES	YES	YES	YES
Day FE	YES	YES	YES	YES	YES	YES	YES
Double clustering	YES	YES	YES	YES	YES	YES	YES
R^2	0.06	0.04	0.06	0.03	0.04	0.02	0.02
# of stock-days	296,130	296,130	296,130	296,130	296,130	296,130	296,130
Average # of stocks	1,180	1,180	1,180	1,180	1,180	1,180	1,180

Table 7: Realized volatility portfolios and intraday return predictability from surprises in $MOIB$ and LOB

This table shows the average estimation results of predictive regressions of one-minute mid-quote returns on lagged surprises in returns, lagged surprises in market order imbalance ($MOIB$), and lagged surprises in depth concentration at the inner and outer levels of the ask and bid sides of the limit order book for NYSE-listed common stocks during the sample period (2002-2010):

$$Ret_t = \alpha + \beta_1 Ret^U_{t-1} + \beta_2 MOIB^U_{t-1} + \beta_3 Bid\ Inner^U_{t-1} + \beta_4 Ask\ Inner^U_{t-1} + \beta_5 Bid\ Outer^U_{t-1} + \beta_6 Ask\ Outer^U_{t-1} + \epsilon_t \quad (3)$$

Surprises are computed as residual values from $VAR(k)$ regression per stock-day, number of lags, k, can take values from 1 to 5 and is selected by AIC criteria. Superscript U indicates that this a residual value from $VAR(k)$. I run this regression on the stock-day basis. For each day I sort all the stocks into four portfolios based on one-day lagged realized volatility (realized volatility is computed from one-minute mid-quote returns). The table reports average coefficients together with average Newey-West t-statistics (Panel A), and adjusted R^2 decomposition (Panel B). Coefficient for order imbalance is scaled by 10^9. All other coefficients are scaled by 10^4. To compute average Newey-West t-statistic, I use a time-series of estimated coefficients for each stock to compute Newey-West t-statistics and average it across stocks. The ordering of the variables used to decompose the adjusted R^2 is identical to the order in which they appear in the table. The last two rows show the total number of stock-day observations and the average number of stocks per day. To be included in the sample, a stock should have NYSE as its primary exchange. Data on common stocks and primary exchange code are obtained from CRSP database (PRIMEXCH=N, and SHRCD=10 or 11, EXCHCD =1 or 31). Data on consolidated trades, quotes, and 10 best levels of the limit order book are provided by TRTH. ***,**,* indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Coefficient estimates (dependent variable: Ret_t)

	RV1 (low)	RV2	RV3	RV4 (high)
$Constant$	0.005	0.003	-0.001	-0.016
	(0.06)	(0.01)	(0.00)	(-0.17)
Ret^U_{t-1}	-0.011*	-0.009	-0.013**	-0.027***
	(-1.70)	(-1.51)	(-2.03)	(-2.81)
$MOIB^U_{t-1}$	1.175***	2.397***	4.420***	11.630***
	(7.40)	(7.28)	(6.74)	(6.10)
$Bid\ Inner^U_{t-1}$	1.642***	2.089***	2.585***	3.781***
	(4.22)	(4.35)	(4.23)	(4.08)
$Ask\ Inner^U_{t-1}$	-1.714***	-2.135***	-2.625***	-3.813***
	(-4.61)	(-4.75)	(-4.71)	(-4.55)
$Bid\ Outer^U_{t-1}$	-0.072	-0.075	-0.005	0.156
	(-0.14)	(-0.21)	(-0.08)	(0.08)
$Ask\ Outer^U_{t-1}$	0.102	0.094	0.063	-0.068
	(0.25)	(0.24)	(0.11)	(-0.12)
Adjusted R^2	1.50%	1.44%	1.47%	1.68%
# of stock-days	684,531	683,138	683,801	682,742
Average # of stocks	307	306	307	306

Table 7: Realized volatility portfolios and intraday return predictability from surprises in $MOIB$ and LOB (continued)

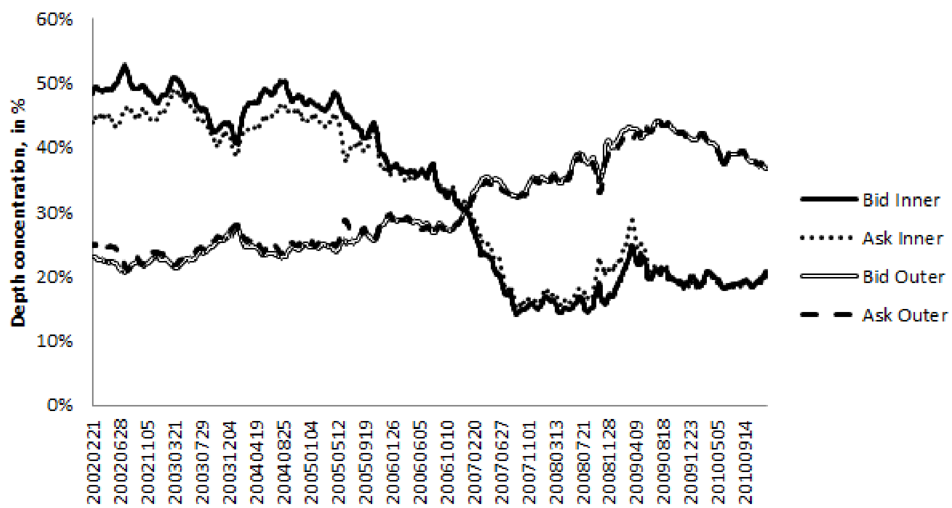
Panel B: Adjusted R^2 decomposition (dependent variable: Ret_t)

	RV1 (low)		RV2		RV3		RV4 (high)	
	Adjusted R^2		Adjusted R^2		Adjusted R^2		Adjusted R^2	
	Absolute	Relative	Absolute	Relative	Absolute	Relative	Absolute	Relative
$Constant$								
Ret^U_{t-1}	0.48%	32.07%	0.45%	31.67%	0.46%	31.43%	0.54%	32.15%
$MOIB^U_{t-1}$	0.29%	19.42%	0.29%	20.08%	0.31%	21.01%	0.38%	22.88%
$Bid\ Inner^U{}_{t-1}$	0.21%	14.00%	0.20%	13.82%	0.20%	13.44%	0.21%	12.52%
$Ask\ Inner^U{}_{t-1}$	0.22%	14.95%	0.21%	14.78%	0.21%	14.35%	0.22%	13.17%
$Bid\ Outer^U{}_{t-1}$	0.15%	9.78%	0.14%	9.80%	0.15%	9.92%	0.16%	9.68%
$Ask\ Outer^U{}_{t-1}$	0.15%	9.78%	0.14%	9.86%	0.14%	9.84%	0.16%	9.60%
$Total\ Inner^U$	0.43%	28.95%	0.41%	28.60%	0.41%	27.79%	0.43%	25.69%
$Total\ Outer^U$	0.30%	19.56%	0.28%	19.66%	0.29%	19.76%	0.32%	19.28%
$Total\ LOB^U$	0.73%	48.51%	0.69%	48.26%	0.70%	47.55%	0.75%	44.97%
$Total^U$	1.50%	100.00%	1.44%	100.00%	1.47%	100.00%	1.68%	100.00%
# of stock-days	684,531		683,138		683,801		682,742	
Average # of stocks	307		306		307		306	

Figure 1: Limit order book composition

This figure shows the equally-weighted average of the depth concentration at the inner and outer levels for the ask and bid sides of the limit order book for the NYSE-listed common stocks during 2002-2010. Please refer to Table 2 for detailed variables description. I use the following procedure to construct time-series of the equally-weighted averages of the variables. First, I winsorize one-minute observations per stock-day at the 1% and 99% levels. Second, the average of the one-minute observations per stock-day is calculated for each variable. Third, I winsorize daily observations at the 1% and 99% levels for the whole sample period. Then, the summary statistics across all stock-days are computed for each variable. Then, I plot one-month moving average of each variable. To be included in the sample, a stock should have NYSE as its primary exchange. Data on common stocks and primary exchange code are obtained from CRSP database (PRIMEXCH=N, and SHRCD=10 or 11, EXCHCD =1 or 31). Data on consolidated trades, quotes, and 10 best levels of the limit order book are provided by TRTH.

Panel A: Depth concentration at the inner and outer levels of the limit order book



Panel B: Cutoff point between inner and outer levels of the limit order book

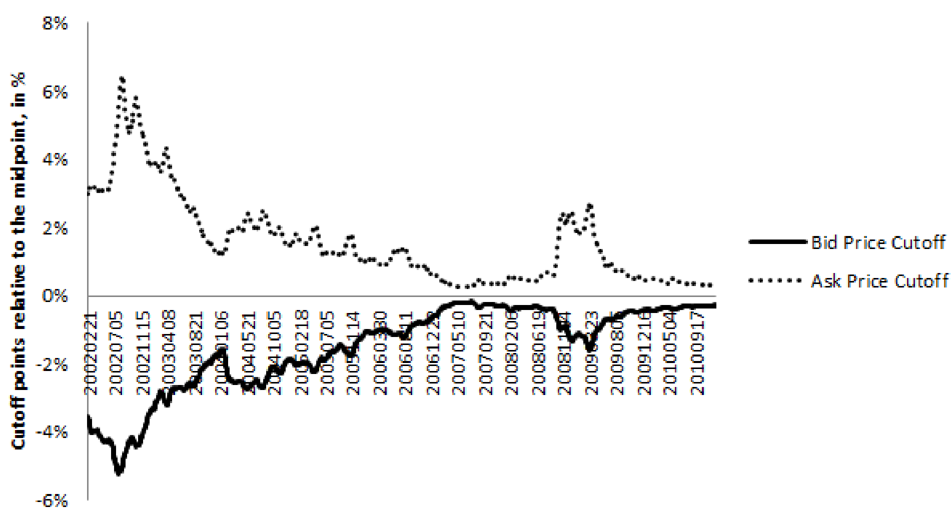


Figure 2: NYSE Hybrid Market introduction

This figure shows the staggered way of NYSE Hybrid Market introduction for the stocks included in the analysis from October 1, 2006 to January 31, 2007. To be included in the sample, a stock should have NYSE as its primary exchange and have CRSP daily data available for the period from June 2006 to May 2007. Data on common stocks and primary exchange code are obtained from CRSP database (PRIMEXCH=N, and SHRCD=10 or 11, EXCHCD =1 or 31). Data on Hybrid introduction are from Terrence Hendershott's website.