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# Sunshine trading: Flashes of trading intent at the NASDAQ*


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**Abstract**

We use the introduction and the subsequent removal of the flash order facility (an actionable indication of interest, IOI) from Nasdaq as a natural experiment to investigate the impact of voluntary disclosure of trading intent on market quality. We find that flash orders significantly improve liquidity in Nasdaq. In addition overall market quality improves substantially when the flash functionality is introduced and deteriorates when it is removed. One explanation for our findings is that flash orders are placed by less informed traders and fulfil their role as advertisement of uninformed liquidity needs. They successfully attract responses from liquidity providers immediately after the announcement is placed, thus lowering the risk bearing cost for the overall market. Our study is important in understanding the impact of voluntary disclosure, in guiding future market design choices, and in the current debate on dark pools and IOIs.



*Keywords:* Actionable Indication of Interest (IOI); Flash orders; High-frequency Trading; Market quality; Market transparency; Sunshine trading.

*JEL Classification*: G10; G20; G14.



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# 1 Introduction

The recent proliferation of algorithmic trading, new trading venues and innovative new trading products raise many issues about financial regulation and market design. What is the impact of the financial innovations introduced by alternative trading systems (ATS) and electronic communication networks (ECN) on various market participants and market quality? What is the role of market transparency in today's fast moving markets? These questions have important implications for market liquidity, price efficiency, overall welfare and the trading strategies of market participants.

In this paper, we study the role of transparency in market design. To this end, we examine the introduction and removal of a specific trading product, *flash orders*, that offers traders the ability to announce their trading interest to other market participants for a fraction of a second. More specifically, flash orders are marketable orders that match or improve the national best bid or offer (NBBO) prices quoted at an away-exchange, which would normally be routed to the away exchange. These orders reflect voluntary announcements of trading intent and are essentially *actionable* indications of interest (IOIs) that advertise liquidity needs in an attempt to trigger a response from other traders. An actionable IOI expresses a trading interest with specified price, side, and number of shares and allows the buy-side trader to trade immediately on the indication directed to them, while submitters wait for the counterparty to hit their IOI, O'Hara (2010).[1]

An important feature of flash orders is that, while they would be marketable (i.e. taking liquidity) at the NBBO exchange if routed, they are treated as supplying liquidity at the Nasdaq and receive a maker rebate if they are executed. An additional benefit of flash orders is that if the order is executed, the submitter reduces his *explicit transaction costs* by avoiding the access fee incurred by routing. On the other hand, if a flash order is not executed it creates a potential delay cost to the submitter. The risk of delay makes flash orders less attractive for high frequency traders that try to exploit short lived information (e.g. statistical arbitrageurs). Therefore, flash orders are more likely to be used by uninformed traders that aim at minimizing transaction costs. If market participants regard flash orders as being mainly uninformed, their execution probability and fill rate maybe higher and hence result in lower *implicit costs.*

[1] An IOI functionality, frequently associated with "dark pool" liquidity, is mainly provided by ECN and ATS to facilitate trades among market participants with large orders and is an important trading outlet for long term retail and institutional investors.

We use the introduction and the removal of the flash order facility by Nasdaq OMX Group (Nasdaq hereafter) as a quasi natural experiment to study the impact of a pre-routing (i.e. pre-trade) display functionality on market quality. In the analysis, we consider the pre-routing feature of flash orders as a voluntary announcement of trading intent. Furthermore, we suggest that these orders are similar in nature to *sunshine trades* as modeled by Admati and Pfleiderer (1991), due to the pre-announcement characteristic. Sunshine trading is a strategy where a trader preannounces to other traders in the market that he or she will trade a specific number of shares or contracts several hours (or perhaps longer) before the order is actually submitted. While we do not explicitly test their model, we argue that if flash orders are mainly used by uninformed traders, the general model predictions may have some bearing in the high frequency trading environment. We use the model implications to guide our analysis and to interpret our results. Hence, we first attempt to determine who the main users of flash orders are, and to what degree flash orders act as a signalling device that helps to mitigate adverse selection costs and to co-ordinate liquidity supply and demand. We then assess whether the introduction and the removal of the flash order facility have an impact on market quality and discuss how our results align with the theoretical predictions of the Admati and Pfleiderer (1991) model.

To assess whether users of flash orders are informed traders we employ four different methods. First, we categorise the algorithms that place flash orders as agency and proprietary (Hasbrouck and Saar, 2010), we measure the adverse selection component for executed trades against flash orders and normal orders, we estimate the temporary and permanent price impact of executed orders against flash orders and normal limit orders (Hasbrouck, 1991), and finally we measure the contribution of trades against flash orders to stock's price change (e.g. Barclay and Warner, 1993). We find that flash orders are mainly placed by agency algorithms, suggesting that their main users are large institutional investors or intermediaries such as brokers.[2] These users are more likely to be uninformed. In addition, we find that adverse selection costs associated with flash order executions are substantially lower than those for non-flash executions, the price impact of these trades is very small and the weighted price contribution is 2%. The findings of lower trading costs associated with executed flashed orders indicate that market participants regard these orders as less informative and are willing to trade against them quickly at favorable prices. This is consistent with the Admati and Pfleiderer (1991) model, which suggests that preannounced orders are unlikely to be based on private information because of

[2]See Goldstein, Irvine, Kandel, and Wiener (2009) for details on the institutional brokerage market.

the reputation cost for brokers, the potential delay cost of preannouncement, and the potential risk of information leakage for informed traders.

We also study how liquidity in Nasdaq responds to flash order submissions and executions. The analysis shows that flash orders are useful as an advertisement for liquidity demand, because they reduce transaction costs in Nasdaq. The saving in trading costs comes from reductions of the bid-ask spread in Nasdaq and price improvements offered by liquidity providers. In addition, we find that flash orders have higher execution rates and better fill rates compared to non-flash orders submitted at the best prevailing quotes. Our results also show that flash order activity improves efficiency by narrowing the difference between the local Nasdaq quotes and the NBBO for individual stocks. Large deviations of Nasdaq quotes from the NBBO seem to trigger flash orders that help move the Nasdaq quotes quickly towards the NBBO.

Finally, we study the impact of flash orders on the overall market quality. We use two strategies for identification: (i) a ten day event study around the introduction and removal of the flash functionality from Nasdaq, and (ii) a difference-in-difference analysis over the sample period: April - October 2009. The event study approach minimizes the impact of any confounding effects in our analysis. The difference-in-difference analysis and regression allow us to implement controls and account for potential estimation problems. Comparing various liquidity and activity measures around the flash introduction and removal periods, overall market liquidity (measured by quoted spread, relative spread, and Amihud illiquidity ratio) improves (deteriorates) significantly when flash orders are introduced (removed). We find that market volatility improves (deteriorates) substantially when flash orders are introduced (removed). The results of the difference-in-difference analysis corroborate those of the event study. The pseudo event and cross-sectional analysis in the robustness section provide additional support for our findings. These results taken together imply a reduction in risk bearing costs in the market.

Admati and Pfleiderer (1991) argue that sunshine trading reduces the risk-bearing costs for both announcers and non-announcers, because it reduces the uncertainty of the liquidity demand of uninformed traders and the amount of noise in the price. Such a reduction in overall risk-bearing costs may be one possible driving force behind our results, as can be seen from the micro and macro analysis described above. The results seem to support the hypothesis that flash orders indicate to market participants that uninformed liquidity is available at a particular venue so that they can quickly route to it, if it represents the best available trading opportunity. Our findings indicate that advertising liquidity needs through flash orders successfully attracts liquidity providers and lowers price uncertainty and overall trading costs in the market. Hence, flashed orders appear to act as a coordinating mechanism for supply and demand and for the identification of informationless trades, which is in line with the predictions of the Admati and Pfleiderer (1991) model.

While we acknowledge the difference in announcement time between traditional sunshine trades (hours/days), as defined by Admati and Pfleiderer (1991), and flash orders (a fraction of a second), we suggest that the latter may be viewed as a high frequency version of the former, and that flash orders may provide a similar function in today's high frequency trading environment. In fact, the main implications of their model seem to align quite well with our results. Not only are submitters of flash orders uninformed but also: (i) trading costs of announcers are lower when preannouncement takes place than when it does not; (ii) adverse selection costs decrease with preannounced orders; (iii) market liquidity and price efficiency improve with preannouncement; and (iv) preannouncement affects price volatility as postulated in the model.

An important and immediate application of our results is to the on-going policy debate on the withdrawal of the flash order practice. In September 2009, the Securities and Exchange Commission (SEC) proposed to ban the use of flash orders in both U.S. equity and option markets. However, the SEC has not banned the use of flash orders and has not taken any decisions on restricting dark pools and IOIs.[3] Our work provides the first analysis of the effect of flash orders in particular, and actionable IOIs in general, on market quality and might be useful to guide the debate as well as the final decision taken from the SEC or other European and Asian regulators considering these issues.

This paper proceeds as follows. In the next section, we position our paper with respect to the existing literature. Section 3 provides a history of flash orders. Section 4 introduces the data used in the paper and presents descriptive statistics of flash order usage and the cross-sectional characteristics of stocks that are flashed. Section 5 investigates who submits flashed orders and why are they submitted. The results on the relation between flash orders and market quality are discussed in Section 6, while Section 7 provides further analysis. Section 8 concludes.

[3] See http://www.bloomberg.com/news/2011-01-21/sec-dark-pool-rule-may-not-arrive-in-11-nasdaq-s-hyndman-says.html?cmpid=yhoo.

## 2 Literature Review and Contribution

The role of market transparency on market quality is ambiguous and complex, as there is a tradeoff between the two.[4] On the one hand, an increase in transparency leads to lower information asymmetry which reduces adverse selection costs. On the other hand, transparency exposes liquidity traders to undue risk, which can reduce market liquidity, as liquidity providers are less willing to provide free-options to the market in the form of limit orders. Voluntary pre-trade disclosure retains the benefits of lower information asymmetry and reduces the free option problem by allowing for better coordination between liquidity providers and uninformed liquidity demanders.

The recent emergence of actionable IOIs in U.S. equity and option markets reopens the debate on the benefits and costs associated with voluntary pre-trade disclosure. Admati and Pfleiderer (1991) theoretically show that trading costs can improve when liquidity demanders preannounce their liquidity needs, i.e. "sunshine trading". Sunshine trading is beneficial because it allows for the coordination of liquidity supply and demand and the identification of informationless trades. Preannouncers indicate to the counterparty that they are uninformed by voluntarily disclosing their order, thus reducing the cost of adverse selection.[5] In addition, sunshine trading reduces the risk-bearing costs for both preannouncers and non-announcers, as it reduces the uncertainty of the liquidity demand of uninformed traders and the amount of noise in the price.

Our paper contributes to the literature on the impact of pre-trade transparency on market quality. Flood, Huisman, Koedijk, and Mahieu (1999) conduct an experimental study and find that transparency reduces trading cost and price efficiency, while Bloomfield and O'Hara (1999) in a different experiment find that transparency increases price informational efficiency but widens spreads. More recently, the empirical work of Boehmer, Saar, and Yu (2005), Hendershott and Jones (2005) and Madhavan, Porter, and Weaver (2005) uses the introduction/availability of information about the limit order book, as an indication of pre-trade transparency and finds contradicting results. The first two show that the availability of quote information is associated with increased market quality in the U.S., the latter finds that execution costs increase with pre-

[4]The literature on market transparency is vast and is often classified into pre- and post-trade transparency, see O'Hara (1995), Madhavan (2000) and Biais, Glosten, and Spatt (2005) for detailed discussions. A list of theoretical models on transparency includes: Biais (1993), Madhavan (1995, 1996), Pagano and Röell (1996), Bloomfield and O'Hara (2000), Baruch (2005), Moinas (2006).

[5]However, uninformed liquidity demanders might not always preannounce their trading intentions. Schoeneborn and Schied (2009) model the liquidity needs of traders with short trading horizons and argue that liquidity demanders' decision on whether to engage in sunshine or stealth trading depends on the expected behavior other market participants, who might either provide liquidity or predate them.

trade transparency in the Toronto Stock Exchange.[6] Foucault, Moinas, and Theissen (2007) find a significant improvement in liquidity after the switch of Euronext Paris to an anonymous limit order book. While prior works focus on the impact of mandatory pre-trade transparency and of limit order book information on market quality, there is little work on how pre-trade disclosure by uninformed liquidity demanders affects the limit order exposure strategies of liquidity providers and overall trading costs. Our paper helps to fill this gap by studying the role of voluntary pre-trade disclosure in a limit order book market and we align our finding with the theoretical model of Admati and Pfleiderer (1991).[7]

In a related paper, Hasbrouck and Saar (2009) categorize limit orders that are canceled within two seconds of submission as fleeting orders and investigate the new economic role of limit orders. An important insight from their work is that a new "equilibrium" has emerged in today's trading environment due to technological advancements: a more active trading culture and market fragmentation that transform the market from one that just posts visible limit orders to one that actively searches for liquidity. With a detailed data set at the order level and on actionable IOI, we find supporting evidence consistent with their suggestions that traders adopt high-frequency order submission strategies that signal liquidity demands in their search for liquidity.

This paper is also closely related to the literature on order exposure strategies. The first stream of the literature focuses on trader's choice between limit and market orders. The aggressiveness and number of limit orders is related to the depth and spread of the limit order book (Biais, Hillion, and Spatt, 1995; Griffiths, Smith, Turnbull, and White, 2000; Ranaldo, 2004). Furthermore, Ranaldo (2004) finds that limit order trades are more aggressive with increased recent volatility, while Handa and Schwartz (1996) and Ahn, Bae, and Chan (2001) find that market depth increases with higher transitory volatility.[8] The second stream of the literature investigates the use of hidden orders. Harris (1996, 1997) provide the economic rationale behind the use of hidden orders. The empirical literature suggests that hidden orders reduce implicit transaction costs (Bessembinder and Venkataraman, 2004) and do not affect trading vol-

[6] Bessembinder, Maxwell, and Venkataraman (2006), Goldstein, Hotchkiss, and Sirri (2007), and Edwards, Harris, and Piwowar (2007) investigate the impact of transparency in the corporate bond market and find that transparency improves market quality.

[7] Dia and Pouget (2011) study the impact of pre-opening orders for eight stocks listed in West African Bourse that operates three times a week and liken this to sunshine trading. They find that pre-opening large orders are not cancelled, pre-opening prices reveal information before trading hours and large volumes are traded without significant price movements in this infrequently and illiquidity market.

[8] Chakravarty and Holden (1995), Bae, Jang, and Park (2003), Anand, Chakravarty, and Martell (2005), and Ellul, Jain, Holden, and Jennings (2007) also study the choice between market and limit orders submissions.

ume (Anand and Weaver, 2004), but they get worse execution quality than visible limit orders (Bessembinder, Panayides, and Venkataraman, 2009).[9] While prior studies investigate order exposure strategies through regular and hidden limit orders, we examine the usage of flashed orders and compare their execution quality against limit orders. Our analysis shows that order exposure through actionable IOIs, which are more likely to be less informed, attracts trading interest from passive traders and have better execution quality. Thus, we provide insights on the order submission strategies of impatient uninformed liquidity takers.

More broadly, this paper contributes to the literature on voluntary disclosure in accounting and finance. Several papers show that voluntary disclosure reduces information asymmetry and consequently the cost of capital (Diamond and Verrecchia, 1991; Coller and Yohn, 1997), facilitates externally financed firm growth (Khurana, Pereira, and Martin, 2006), and voluntary disclosure of firm specific information allows for better monitoring by investors and ensures that managers undertake optimal investments (Fama and Jensen, 1983; Diamond and Verrecchia, 1991; Bushman and Smith, 2001; Khurana et al., 2006). Consistent with this literature, we show that voluntary disclosure of trading intention reduces the cost of asymmetric information and facilitates the coordination of the supply and demand of liquidity among traders.

This paper also contributes to the literature on dark pools and algorithmic trading. In a recent theoretical paper, Buti, Rindi, and Werner (2010) show that IOIs that inform some traders on the state of liquidity in dark pools can draw orders away from the transparent market, but they also show that IOIs provide information about dark pool liquidity, which increases the welfare of both informed and uninformed large traders. Angel, Harris, and Spatt (2011) provide an excellent overview about equity trading in the 21st century and liken IOIs to Craiglist advertisements that helps to coordinate the supply and demand of liquidity. They argue that IOIs lower the transaction cost of retail and institutional investors at the expense of informed traders. Understanding the characteristics of IOIs and how they are used by traders is important in shedding more light into dark pools. Despite its importance, there is no empirical work on IOIs due to data unavailability. Our work contributes to this literature by providing a detailed illustration of the characteristics, users, and trading strategies related to actionable IOIs. As actionable IOIs are mostly used by algorithmic traders in Nasdaq, our results also provide some insights on trading strategies used by algorithmic traders.

[9] Hasbrouck and Saar (2004) find that traders use fleeting orders in Island ECN to sweep for hidden orders.

# 3 A Short History and Discussion of Flash Orders

## 3.1 History

Flash orders have an extremely short duration, and they are not required to be included in the public consolidated quotation data according to paragraph (a)(1)(i)(A) of Rule 602 (quote rule) of Regulation National Market System (NMS).[10] The use of flash trading systems was first approved by the SEC under Chairman William Donaldson for the options market, Boston Options Exchange, in 2004. Flash orders were introduced when options trading took place mainly on exchange floors. They were expected to increase the speed and the likelihood of filling an order at the National Best Bid Offer (NBBO), since the floor quotes which constituted the NBBO were updated infrequently and could be unreliable.[11]

Flash trading was an obscure practice in the options market and was introduced in the equity market on January 27, 2006 by Direct Edge.[12] Direct Edge offered the "enhanced liquidity programme, ELP", where an IOI can be sent to the liquidity providers participating in their network, typically brokers and high-frequency proprietary traders, if an order cannot be matched on Direct Edge's book. The flash order can be routed or canceled if there is still no match, according to the users' instructions.

In response, Nasdaq and BATS Global Markets (BATS hereafter) introduced their own flash programs, where orders are flashed to their members before routing them to rival platforms, to protect their market share. On June 4, 2009, BATS introduced BATS Optional Liquidity Technology (BOLT) that included an optional display period during which a marketable order could be displayed to its users (and market data recipients) prior to being routed, canceled, or posted to the BATS book. Nasdaq introduced Flash Orders on June 05, 2009. According to Roseblatt Securities, executed flash orders constituted 3% of daily traded volume in the U.S. market for the period June - August 2009, a market share as large as AMEX or Boston Stock Exchange at the time. NYSE is the only major market center that has not offered any enhanced

[10] Regulation NMS approved by the SEC is a series of initiatives designed to promote fair and efficient price formation across U.S. financial markets through competition among market participants. Rule 602 requires exchanges to make their best bids and offers in U.S.-listed securities available in the consolidated quotation data that is disseminated to the public. Paragraph (a)(1)(i)(A) of Rule 602, however, excludes bids and offers communicated on an exchange that either are executed, cancelled, or withdrawn immediately after communication (less then 500 milliseconds).

[11] Manual flash orders have long been practiced on floor-based exchanges, where brokers announce orders to the floor crowd for potential price improvements. Flash orders in electronic markets were introduced to replicate this auction market process.

[12] Direct Edge was an ECN at the time but is currently an equity exchange.

liquidity provider program or flash-order functionality.[13]

Since mid-2009, there has been wide media coverage and intense debates by regulators, industry analysts, and commentators over the impact of flash trading on financial markets and participants, see a summary of arguments for and against in Table A1 in the Appendix. Nonetheless, many arguments in the current debate on flash orders have little or no empirical support. In view of the flash trading controversies and political pressure, both Nasdaq and BATS voluntarily discontinued support for flash orders on September 1, 2009, pending the review on flash orders by SEC. DirectEdge also withdrew ELP in March 2011. However, IOIs and actionable IOIs continue to be heavily used by dark pools both in the U.S. and Europe. On September 18, 2009, the SEC proposed the elimination of the flash order exception from Rule 602 of Regulation NMS. No decision has been taken to date.

## 3.2 Description

Flash orders, as implemented by Nasdaq, are actionable IOIs that expose submitted marketable orders for a pre-defined period of time to only its participants, at or improving the NBBO which is quoted at another trading venue. Thus, a "flashed" order may execute locally at the NBBO or better, while normally it would have been routed away to the other exchange offering the NBBO.

Nasdaq implemented two types of flash orders: Nasdaq Only Flash Orders (90%) and Flash Enhanced Routable Orders (10%), percentages from Nasdaq. After attempting to sweep the Nasdaq book, a Nasdaq Only Flash Order allows the order up to 500 milliseconds additional exposure to market participants and vendors via a Nasdaq direct data-feed interface at the most aggressive price possible that would not result in a trade through. Executed flashed orders receive a rebate. Orders that remain marketable after the flash period are deleted. Orders that become non-marketable and that do not execute in the flash period can be cancelled or re-inserted in the limit order book, see numerical example below.[14] After attempting to sweep the Nasdaq book, Flash Enhanced Routable Orders allow the order up to 30 milliseconds additional exposure to market participants and vendors in Nasdaq before being routed away. The market

[13]NYSE has vehemently protested against the trading practices of their competitors, especially those related to flash and dark pool trading. NYSE's concerns and complaints induced New York Senator Charles Schumer to request the SEC to ban flash trading and to increase monitoring of dark pool trading. Any ban or restriction of the flash functionality and provision of dark pool liquidity may help NYSE to win back market share in the U.S. equity market.

[14]A marketable order is any buy (sell) limit order with a limit price that is greater (less) than or equal to the current ask (bid) price.

could not distinguish between the two upon submission, and neither can we in our data.

| | Description | NBBO | Results |
|---|---|---|---|
| 1 | NASDAQ-only order arrives to Buy 2,000 @9.55 | 9.54x9.55 | Order attempts to execute to the maximum possible on the NASDAQ book |
| 2 | 500 shares are executed at 9.55 @ Nasdaq | 9.54x9.55 | Firm pays taker fee |
| 3 | Order is displayed for up to 500 milliseconds | 9.54x9.55 | NASDAQ displays a Buy order of 1,500@$9.55 via ITCH |
| 4 | 1,000 share executed on NASDAQ during flash period | 9.54x9.55 | Firm receives full liquidity provider rebate for 1,000 shares |
| 5 | Remaining shares could be marketable or non | | |
| 6 | If remaining 500 shares are marketable | 9.54x9.55 | Order cancels back to customer after flash period expires |
| 7 | If remaining 500 are non marketable | 9.55x9.56 | Shares can be deleted by customer or re-enter NASDAQ book |

The indication of interest by sunshine traders was carried out several hours before the order submission to trade, when the practice was first undertaken in 1980s. However trading in financial markets has changed substantially over the last 30 years with the rapid proliferation and growth of new information processing and communication technologies. As highlighted by Angel et al. (2011), the advancement of electronic technology has profoundly altered how exchanges, brokers, and dealers arrange most trades. Trading systems' performance is measured in milliseconds rather minutes or hours, and high-speed communication networks allow for faster coordination and execution of trades among traders as well as for better provision of services to clients. Thus, it is not unreasonable to expect the time for indication of trading interest before order submission to decrease from several hours in the 1980s to milliseconds in today's fast trading world.

## 4 Data Description

This paper uses the complete set of quotes and trades in the Nasdaq system for the sample period from April 01, 2009 to October 31, 2009. The flash order period covers June 5, 2009 - August 31, 2009. The data is obtained from Nasdaq ITCH-TotalView system on special order.[15] We retain stocks for which information is available in Trades and Quotes (TAQ), Center for Research in Security Prices (CRSP), and Compustat. Following the literature, we use only common stocks (Common Stock Indicator Type=1) and common shares (Share Code 10 and 11) and stocks that do not change primary exchange, ticker symbol or CUSIP over the sample period (Hasbrouck, 2009; Goyenko, Holden, and Trzcinka, 2009; Chordia, Roll, and Subrahmanyam, 2000). We also exclude stocks that exhibit a price lower than $5 and higher than $1,000 or market capitalization less than $1,000,000 over the sample period. Finally, we exclude stock/dates with reported negative bid-ask spreads and trading volume equal to zero. As a result we are left with a sample

[15]The intraday data where flash orders can be identified is available from June 10.

of 1,867 stocks and 265,000 firm/day observations. Because some of the stocks in our sample are affected by the Troubled Asset Relief Program (TARP), we also carry out our analysis with a subsample that excludes all financial stocks (SIC 6000-7000) and non-financial stocks that received TARP funds, for robustness.

We employ the complete dataset of new order messages, updates, cancelations, deletions, executions, hidden orders, and cross-network orders to build the complete limit order book (LOB) for 188 stocks following Kavajecz (1999). The LOB stocks are randomly selected from portfolios to represent different industry, size, book-to-market, and liquidity characteristics. Panels A and B of Table 1 show that the LOB sample is a good representation of the full data sample. Limiting the number of stocks is necessary for computational purposes, because we have to process more than 600 million datapoints per day. We use the LOB sample for the intraday analysis, while we use CRSP data for the event study and difference in difference exercise.

## 4.1 Market Quality Variables

In order to measure market quality for the U.S. equity market, we use daily data from CRSP. We employ two measures of spread: quoted and relative spread. The quoted spread measures the difference between the best prevailing ask and bid for a stock, i.e. the absolute "round trip" cost of trading a small amount of shares at the inner quote. The relative spread is the quoted spread divided by the bid-ask midpoint. To measure price impact at the market level, we calculate the Amihud (2002) illiquidity ratio (ILR), which is closely related to Kyle's lambda. ILR is calculated as $|r|$/VOLUME, where $|r|$ is the daily absolute returns and VOLUME is the daily total dollar volume (in million \$). Markets with lower short-term volatility are deemed to be more efficient, as high depth at the inner quotes makes the trade prices less volatile. We calculate short-term volatility as returns squared. We censor observations where spread and ILR ratio are at the $99^{th}$ percentile of the distribution. This is particularly important for ILR which exhibits large outliers when trading volumes are low.

From the LOB, we construct several measures of market quality. As flash orders cannot be posted during pre and post trading hours, all statistics are calculated within the trading hours 9:30-16:00 Eastern Standard Time.[16] To measure execution quality, we compute fill rates for flash and non-flash orders. Fill rates are defined as the percentage of original order volume that

[16]Trading begins and orders are accepted at 7:00 AM for all Nasdaq-listed stocks. Any open quotes or extended hours orders that lock or cross other open quotes or extended hours orders will execute. Pre-opening quotes are non-binding as market makers are not obliged to trade at pre-opening prices. Orders can be canceled.

is executed (Harris and Hasbrouck, 1996).

To measure whether users of flash orders are informed traders we employ four different methodologies: categorize the algorithms that place flash orders as agency and proprietary as advocated by Hasbrouck and Saar (2010), measure the adverse selection component for executed trades against flash orders and normal orders, estimate the temporary and permanent price impact of executed orders against flash orders and normal limit orders as in Hasbrouck (1991), and finally measure the contribution of a stock's price change due to trades against flash orders (see Barclay and Warner, 1993; Barclay and Hendershott, 2003; Choe and Hansch, 2005). The algorithm categorization is described in Section 5.1. To measure adverse selection, we decompose the effective spread into realized spread and adverse selection. As in Hendershott, Jones, and Menkveld (2011), the effective half spread, *espread* is defined as:

$$espread_t^j = q_t^j(p_t^j - m_t^j)/m_t^j,$$

where $j$ denotes the stock, $q_t^j$ is the buy (1)/sell(-1) trade indicator, $p_t^j$ is the traded price, and $m_t^j$ is the quote midpoint prevailing at the time of the trade. Trades are signed with respect to whether the initiating party (taker) is a buyer or seller. Hence, flash orders to buy that execute are signed as a seller initiated trade. For each stock and day, we use all Nasdaq quotes and trades to calculate the effective spread for each reported transaction. We calculate realized spread, $rspread_t^j$, and adverse selection, $adv\_selection_t^j$ as:

$$\begin{aligned} rspread_t^j &= q_t^j(p_t^j - m_{t+5min}^j)/m_t^j \\ adv\_selection_t^j &= q_t^j(m_{t+5min}^j - m_t^j)/m_t^j. \end{aligned}$$

The effective spread and its components are normalized by the number of shares traded in the transaction.

To measure the temporary and permanent price impact of different orders, we estimate a VAR model for every stock on each date and produce the impulse response functions. The basic bivariate VAR model estimated for each stock for each date is,

$$r_t^j = \sum_{i=1}^{P} a_i^j r_{t-i}^j + \sum_{i=0}^{P} b_i^j q_{t-i}^j + v_{1,t}^j, \tag{1}$$

$$q_t^j = \sum_{i=1}^{P} c_i^j r_{t-i}^j + \sum_{i=1}^{P} d_i^j q_{t-i}^j + v_{2,t}^j, \tag{2}$$

where $t$ is the event time counter (messsage time), $i$ is the event lag up to a maximum of $P$, and $r$ denotes the quote midpoint change.[17] To examine to what degree the information content of executed flash orders is different from regular trades, we estimate the above VAR separately for trades against regular limit orders and trades against flash orders. We exclude stock/days where there are no flash orders in order to make better comparisons.

To calculate the weighted price contribution of flash orders, suppose that during the time period $t$ there are $N$ trades for stock $j$. Each trade belongs to one of two categories: executed against flash orders or regular limit orders. The price contribution of trades executed against flash orders is: $PC^j_{flash,t} = \frac{\sum_{n=1}^{N} \delta_{n,flash} r^j_{n,t}}{\sum_{n=1}^{N} r^j_{n,t}}$ where $\delta_{n,flash}$ is an indicator variable equal to 1 if the $n^{th}$ trade executes against a flash order, and 0 otherwise. $r^j_{n,t}$ is the log return between the price of trade *n-1* and $n$ for the $n^{th}$ trade. $PC^j_{flash,t}$ is a stock specific measure, while we are interested in the two categories across stocks. We use the weighted average across stocks of the price contributions of trades against flash orders, weighted price contribution ($WPC$). The weight for each stock's $PC$ is the ratio of its absolute cumulative return to the total absolute cumulative return for all the stocks $WPC_{flash,t} = \sum_{j=1}^{188} (\frac{|R^j_t|}{\sum_{j=1}^{J} |R^j_t|} PC^j_{flash,t})$ where $R^j_t = \sum_{n=1}^{N} r^s_{n,t}$.

Autocorrelation is a measure of market efficiency, the lower the autocorrelation of returns the more efficient is the market. As Boehmer and Kelley (2009) and Boehmer, Chava, and Tookes (2010), we calculate intraday first order autocorrelation $|AR|$ using 30-minute quote midpoint return data and correct for the negative bias in autocorrelations: $\hat{\rho}(k) = \rho(k) + \frac{T-k}{(T-1)^2}[1 - \rho^2(k)]$ where $\rho(k) = \frac{Cov(r, r_{t+k})}{Var(r_t)}$, Fuller (1976). We also calculate 5-minute autocorrelation for robustness. Table A2 in the Appendix A provides a list of all the variables and their definitions.

## 4.2 Matching Sample

We need to construct a matching control group that is not directly affected by flashed orders for the difference in difference analysis. One potential control group are U.S. stocks that are not traded on Nasdaq. However, there are only 10 such stocks during our sample period, which are too few to constitute a good control sample. An alterneative is to use Canadian stocks, represented by the Toronto Stock Exchange (TSE) listed companies, as our control group. While this is clearly not a perfect control, it is a reasonable alternative given the similarity of market

[17] Note that the contemporaneous/instantaneous realization of $q^j_t$ enters the return equation. Thus, it assumes that trades precede quote revisions. This is needed for identification and ensures that innovations $v^j_{1,t}$ and $v^j_{2,t}$ are uncorrelated. The innovation to the return equation is typically interpreted as quote revisions associated with public information, while the innovations to the trade equation is interpreted as related to (unpredictable) informed trading. Hence, the permanent response of quote revisions to innovations in the trade equation should capture the adjustments to private information.

structures and regulation and the absence of controls on the free flow of capital between the two countries. Moreover, U.S. and Canadian trading hours fully overlap, Canadian stocks trade as ordinary securities as opposed to American Depositary Receipts in the U.S. market, and competition across the two markets is vigorous.[18] One potential concern related to the Canadian match is the relatively low market capitalization of its stocks. In our robustness section, we also include stocks from the London Stock Exchange (LSE) in the matching group together with the TSE stocks, to increase the size of the control group. LSE stocks are a good alternative to TSE, as they have higher market capitalizations.

All TSE and LSE data is downloaded from Datastream and converted to U.S. dollars using the end of day Canadian Dollar/U.S. Dollar and U.S. Dollar/British Pound exchange rate. We exclude cross-listed stocks and stocks that exhibit a price lower than $5 or market capitalization less than $1,000,000 at any time over the sample period, as for the CRSP sample. The final match sample includes 481 TSE and 741 LSE stocks.

### 4.3 Limit Order Book

Panel C of Table 1 presents the main characteristics of the LOB. The size of executed flashed orders is larger than other orders. This is in line with the Admati and Pfleiderer (1991) model. The cumulative depth is calculated as the sum of all shares available at a particular price or better on the LOB, at successively distant prices, following Goldstein and Kavajecz (2000). The table presents depth at 5 and 10 levels away from the best quotes. On average there are 4,610 and 9,486 shares in the first five and 10 levels of the book, respectively. On average, the cumulative depth on both the bid and ask side increases by 800 shares per tick for the first five levels of the LOB.

### 4.4 Descriptive Statistics for Flashed Orders

First, we compare and contrast the usage and execution performance of flashed orders relative to regular limit orders. We, then, present some general statistics on the cross-sectional characteristics of flashed stocks, where we investigate how flash intensity is related to stock characteristics such as market capitalization and trading volume. Panel A of Figure 1 presents the total number

[18] Jorion and Schwartz (1986) and Foerster and Karolyi (1993) find that Canadian stocks have very similar market characteristics in Toronto as in the U.S.. Eun and Sabherwal (2003) find that prices on the TSE and U.S. exchange are cointegrated and mutually adjusting. Bacidore and Sofianos (2002) find no significant statistical differences in the intraday participation and stabilization rates of NYSE specialist between U.S. stocks and cross-listed Canadian stocks.

orders that are flashed at least once. The daily number of submitted flash orders is about four million and it constitutes about 5% of the total number of submitted orders in Nasdaq.

**Intraday Characteristics of Flash Order Usage**

Panel B of Figure 1 presents the intra-day variation of flashed orders at a five minute interval across the trading day. There is a distinct pattern in the submission of orders that are flashed. Orders are flashed less frequently at the beginning of the day, less than 1% of total orders and increase up to 4% at the end of the day.

Panel A of Table 2 presents an overview of the type of orders that are flashed, and what happens to these orders. 5% of all orders in Nasdaq are flashed at least once. 87% of these are flashed upon initial submission rather than during an update. 14% of the orders that are flashed at least once are executed compared to 4% of non-flashed orders. The statistics suggest that non-flashed orders are executed proportionally less frequently than flashed orders. In addition, the average daily proportion of flashed orders that are executed to total executed orders is 16%. In other words, 16% of the total number of executed orders in Nasdaq have been flashed at least once. Despite the fact that flash order submissions are a small proportion of total submitted orders, 5%, they constitute a substantial part of executed orders, 16%.

Panel B of Table 2 shows that the average fill rate of orders that are flashed at least once is 9.17% and is much higher than that of non-flashed aggressive limit orders (at or improving the best price) during the flash period. The low fill rates are mainly due to quotes moving away from the posted price or order cancelations. The difference in fill rates of all non-flash orders before and after the introduction and removal of the flash functionality from Nasdaq, using a ten day event window, suggests that the average fill rate of non-flashed orders decreased during the flash period. These results indicate that users of flash orders have better execution quality than non-users, and the execution quality of non-users deteriorates as in Admati and Pfleiderer (1991).

Panel C of Table 2 presents statistics on when flash orders are executed. The largest part of executions occurs right after flashed orders are entered into the LOB. Only 30% of the 516,187 executed flashed orders are executed during the flash period, 24% during an order submission and 6% during an update. This finding is consistent with Angel et al. (2011)'s suggestion that IOIs are similar to Craigslist advertisements of available uninformed liquidity.

**Cross-sectional Characteristics and Flash Intensity**

Table 3 provides statistics on stock characteristics: price, dollar volume traded, number of trades, market capitalization, and market quality measures: quoted and relative spreads, ILR, and volatility within terciles based on the number of flash messages (one order may be flashed more than once). Panel A of Table 3 provides statistics based on stocks sorted by the daily number of flash messages. Note that the same stock might be placed in different terciles in different days, as stocks do not have the same number of flashes every day. Results in Panel B are based on stocks sorted by the average number of flash orders across the flash period. The second measure is important because we use it to sort stocks in the pre and post flash periods.

Panels A and B of Table 3 show a monotonic improvement in the liquidity variables from the first to the third tercile, when sorted according to the number of flash orders. Stocks that are most frequently preannounced are also stocks with the highest market capitalization, the highest numbers of trades and traded volume, and the lowest spreads and volatility.[19] Table A4 in the Appendix presents the liquidity characteristics for stocks double sorted by market characteristics: volume and market capitalization, and flash messages. The same pattern of higher liquidity for the most flashed stocks emerges.

# 5 Flash Orders: Who and Why?

Traders must always decide on their order submission strategy: when and where to submit a market or a limit order. Traders who submit market orders demand liquidity ("takers") and those who submit limit orders are liquidity suppliers ("makers"). The decision on one's order submission strategy depends on the trading problem at hand. Traders who face early deadlines (rebalancing/liquidity needs) or those with short lived private information will be more impatient and are more likely to submit market orders or aggressive limit orders. We can think about them as impatient uninformed liquidity traders and impatient informed traders. When the deadline is distant and the spread is wide, liquidity traders are often patient and submit limit orders. As the deadline draws nearer and their orders are not filled, they become impatient and might resort to using more aggressive limit orders and market orders to assure execution. Thus, liquidity traders are liquidity makers when they are patient and takers when the deadline to invest or divest due to exogenous cash flow needs draws nearer, see Harris (1998).

[19] The same results hold when TARP stocks are excluded, as presented in Table A3 in the Appendix.

Informed traders have private information about the underlying value of an asset but this information is often transitory. Thus, they can be impatient as they strive to exploit their information superiority before the information becomes common knowledge. For this reason, informed traders with short-lived information are more likely to use market orders to trade quickly. Depending on the deadline of their information superiority, they might also use limit orders if the spread is wide and deadline is distant. Thus, informed traders can be liquidity makers as well as takers.

Actionable IOIs are orders that are more aggressive than limit orders but less aggressive than market orders, i.e. they are not ensured immediate execution. As actionable IOIs reveal one's trading needs and intention, the response by other liquidity suppliers to IOIs depends critically on whether the IOI submitter is perceived to informed or uninformed. If actionable IOIs are submitted by uninformed liquidity demanders, they will trigger responses from liquidity suppliers and will execute with lower transaction costs because of lower adverse selection. Admati and Pfleiderer (1991) argue that preannounced orders, like actionable IOIs, are likely to be informationless trades because of the potential costs of preannouncement for an informed trader. As preannouncement entails a delay in the execution of the order, this delay cost is likely to be more costly for informed traders than for liquidity traders. This is because short-lived private information might become common knowledge during the execution delay. Moreover, preannouncements reveal the private information of informed traders. If other traders acquire information through observing preannounced orders, the trading profit of informed traders will be severely reduced. However, preannouncements of trading intentions by uninformed liquidity demanders are unlikely to be front-run.[20]

## 5.1 Identifying Flash Order Submitters

In order to investigate if actionable IOIs are uninformed orders, we study the kind of algorithmic traders that use flash orders. In addition, we investigate the adverse selection costs for flashed and non-flashed orders, the temporary and permanent price impact and the price contribution

[20] Front running is an exploitation of information about future order placement of other traders by trading in the same direction before the order is executed. Admati and Pfleiderer (1991) provides a good example on why front-running is unlikely. If a large sale is preannounced and the public can observe this preannouncement, all market participants will have a similar valuation of the stock, conditioning on this information. Thus, it is unlikely that any trader will buy from the front runner at an unfavorable price conditioning on the preannouncement information. A trader that is willing to buy at the unfavorable price is an impatient liquidity demander, with high demand for immediacy. Hence, the front runner is providing a valuable market making service by transferring through time the demand to buy and sell, which is unlikely to be detrimental to preannouncers in a competitive market.

of flash order executions compared to non-flash trades.

### Proprietary and Agency Algorithms

As flashed orders are only actionable for a maximum of 500 milliseconds, it is only machines from algorithmic traders that can respond to them . Trading algorithms can be classified in two categories: agency and proprietary, see Hasbrouck and Saar (2010). Agency algorithms (AA) are frequently used by buy-side institutions like mutual funds, pension funds, and insurance firms, who submit nonmarketable limit orders as part of their strategies. They are normally used to break large orders into small portions to be sent to multiple trading venues over time. It is more likely that these traders are uninformed. Algorithms which aim to profit from the trading environment are classified as proprietary algorithm (PA). These algorithms are often associated with electronic market makers, hedge funds, proprietary trading desks of large financial firms, and independent statistical arbitrage firms. Some PAs aim to identify the trading needs of other market participants (such as those of buy-side institutions) and profit at the expense of these less sophisticated participants. A typical characteristic of PAs is the repeated submissions and cancelations of orders that aim to trigger actions from other algorithms.[21] The observation of such trading patterns might be associated with PAs and is called a "strategic run". All orders that are not part of a strategic run can be considered as agency algorithms.

We construct "strategic runs" for flashed and non-flashed orders, to identify whether flash order submitters are PAs or AAs. We construct strategic runs in two ways using messages posted in Nasdaq trade and quotes data. First, we follow Hasbrouck and Saar (2010) and link sequences of submissions, cancelations, and executions that are likely to be part of a PA's dynamic strategy. We link an individual limit order with its subsequent cancelation or execution using the unique order reference numbers supplied with the data. Then, we link a cancelation to either a subsequent submission of a nonmarketable limit order, when the cancelation is followed within one second by a limit order submission, or an execution, when the cancelation is followed by an execution, in the same direction and for the same size. If a limit order is partially executed and the remainder is canceled, we look for a subsequent resubmission or execution of the canceled quantity.[22] As highlighted in Hasbrouck and Saar (2010), such methodology might introduce

[21] An example of such an algorithm is a "pinging" algorithm used by sell-side investors to identify reserve book orders. In pinging, the PA issues an order ultra fast and if nothing happens, it cancels it. But if it is successful, the PA learns about hidden information on the reserve book orders that it can use to its advantage.

[22] See Hasbrouck and Saar (2010) for a detailed description and examples of strategic runs.

some noise into the identification of low-latency activity as it is not certain that the subsequent resubmission and execution are linked to the initial individual limit order, but it is useful in identifying runs during the period when Nasdaq did not have the "update" function.

From 2008, Nasdaq provides the possibility to change and update the price and/or volume of orders without having to cancel and resubmit them (message type U). We use update messages in our second approach to measure strategic runs, as they serve the same purpose as the cancel and submit orders that are identified in Hasbrouck and Saar (2010). We identify an update strategic run by tracking the reference number associated with an individual limit order and subsequent update messages in the same direction or a subsequent execution within one second. Different from Hasbrouck and Saar (2010), with the update function, we are certain that order update sequences and alterations are related to the initial individual limit order that we track. Orders with updates are not included in Hasbrouck and Saar (2010) runs by construction.

However, PAs might make use of both mechanisms to fulfil their strategies, thus Table 4 shows the number of runs and the associated messages for flashed and non-flashed orders for Hasbrouck and Saar (2010) runs (HS) and update runs. One update corresponds to two messages in the HS run (cancel+resubmit), thus the number messages in an update run is normalized to be comparable to the HS runs. *Total* is the sum of HS and update runs, which we can add given because they are mutually exclusive by construction. A run is classified under flash, if there is a flash message that is part of the run. We present the monthly runs in order to be able to compare with the results in Hasbrouck and Saar (2010), who study and report results for two separate months. The total number of monthly runs and their message length is comparable to those in Hasbrouck and Saar (2010), given the smaller sample and the smaller size stocks included in our sample. The total number of runs is smaller for the month of June because our sample only starts on June 10. A run is considered to be strategic when it includes more than 10 messages. Most flash runs, HS and Update, are part of runs shorter than 10 messages. On average less than 3% of the runs with a flashed order are longer than 10 messages, and this is consistent through the different months and different algorithm submission strategies. Over 7% of non-flashed orders are part of runs longer than 10 messages, which is double the strategic runs in flashed orders. The results imply that flash orders are predominantly submitted by agency/buy-side investors.

### Adverse Selection Costs

One of the main reasons to submit preannounced orders in the Admati and Pfleiderer (1991) model is to signal to other market participants that the trader is uninformed. As a result, the preannounced trade would get a lower effective spread due to lower adverse selection. Panel A of Table 5 presents the difference in the mean and median effective and realized spread and adverse selection costs for flashed and non-flashed orders, aggregated by stock. Executed flashed orders exhibit lower effective and realized spreads and lower adverse selection costs than other executed orders, as the model posits.

### Hasbrouck Decomposition

In Figure 2, we show the average cumulative impulse response of a one unit positive shock (i.e. a buy). Panel A shows the average response for executions against regular orders and flash orders for all trade sizes, and Panel B shows the average response to trades against regular and flash orders for different trade size categories. We define trades as small if the trade size less than or equal to 10 shares, medium if the trade size is between 10 and 100 shares, and large if trade size is greater than 100 shares.

Panel A of Figure 2 shows the typical Hasbrouck (1991) result that quote revisions are not instantaneous. In additions, the permanent price impact of a trade (at t=20) is on average about five times larger for regular orders compared to flash orders. This result substantiates further our previous results that flash orders are associated with uninformed trading. Interestingly, we also see that the initial impact of executions of flash orders are very close to zero, or even slightly negative. This suggests that executions against flash orders do not shift the midpoint price in the same direction as the trade. This is likely due to the fact that trades against flash orders do not take out depth from the LOB. Panel B of Figure 2 shows that for a one unit shock, the permanent impact of regular orders regardless of trade size is much greater compared to flash orders. Furthermore, the difference in responses between trade sizes is very small for flash orders compared to regular order executions.[23]

[23] We also check whether impulse function responses change during the sample period and find that they do not fluctuate across days. Results are available upon request from the authors.

### Weighted Price Contribution

Results in Panel B of Table 5 show that the cumulative contribution of flash orders to total returns is small but negative, while non flash executed trades have a large and positive contribution. This result implies that flash trades are not informative when it comes to the daily total change in price. These results taken together indicate that the market prices flashed orders as coming from uniformed traders, as the model predicts.

## 5.2 Why Submit Flash Orders?

Flashed orders are used when the Nasdaq quotes are not the NBBO.[24] We first construct the NBBO for our sample of 188 stocks using the TAQ database following Hasbrouck (2010).[25] We then merge the Nasdaq LOB data with the NBBO. The NBBO is fixed over each second, while the quotes at the Nasdaq may move within the second. We construct a distance measure, *SRATIO*, to examine the status of the Nasdaq spread relative to the NBBO spread at points in time when there is flash activity. SRATIO is the ratio of the local spread to the NBBO spread minus one for each message. Thus, the SRATIO measures the relative deviation of the Nasdaq spread from the NBBO spread, for example when SRATIO>0 the Nasdaq spread is greater than the NBBO spread.[26]

### Flash Order Submissions

First, we study how the SRATIO changes around new flash order submissions. We set up an event study around flash order submissions with an event window of 50 messages before and after the submission. Only events where flash orders are not preceded by other flash orders in the pre-event window are used.[27]

Figure 3 shows the change in the SRATIO surrounding flash order submissions to buy and sell. The first flash order submission is centered at message time 0. The bars show the total

[24]Flash orders that are motivated by liquidity needs may also occur when the NBBO is at the Nasdaq if the volume at the best quotes is low.

[25]TAQ data is reported in one second intervals, and the Nasdaq ITCH data is time stamped at the millisecond. In TAQ there are quotes from several exchanges at each second, but we do not know at which millisecond the quote is received. Thus, we use the best quotes across all exchanges for each second as our proxy for the prevailing NBBO for each second.

[26]Since the best prevailing NBBO quotes are sampled at the 1 second frequency while the best Nasdaq quotes are sampled at the millisecond frequency, the Nasdaq spread can become lower than the NBBO spread within the second.

[27]We also investigate the case when there are no flash orders subsequent to the initial flash order. This lowers the number of events, but does not affect the results qualitatively. The results are available from the authors upon request.

number of flash submissions (buys+sells) across all events, and at message time 0 the bar shows the total number of events in the sample. The first thing to note from Panel A of Figure 3 is that the SRATIO increases prior to the flash event at time 0 on the x-axis. This suggests that an important determinant of order flashing is that the quotes at the Nasdaq move away from the NBBO. The rate of flash order submissions decreases after the initial flash, as the Nasdaq spread moves closer to the NBBO. As long as Nasdaq quotes are worse than the NBBO one would expect there to be flash interest. The figure shows a very similar pattern for buy and sell orders.

Overall, there appears to be an improvement in spreads which follows right after flashed orders. They make the local market more efficient and reduce the spread at the Nasdaq and hence the spread gap with the national market. Market participants choose to flash their orders for the possibility of a price improvement, quicker execution, getting paid a maker fee, and avoiding paying the routing fees.

**Flash Order Executions**

We also investigate flash order executions. We perform a similar analysis as above, but instead of conditioning on new flash order submissions, we now condition on flash order executions. As previously discussed, a flash order is quite different from a marketable limit order. We compare and contrast the Nasdaq spread and changes in the full depth of the LOB around the execution of each of these types of orders. In the LOB set up, the main difference between a marketable limit order and a flashed order is that the marketable limit order executes immediately at the best prevailing quote, while a flash order fishes for liquidity at the NBBO quotes without the certainty of execution. In addition, a flash order that executes does not take liquidity from the Nasdaq LOB directly as a marketable limit order does. However, there might be an indirect effect if responding traders cancel their limit orders resting in the LOB to fill the flashed orders.

Panel A of Figure 4 shows the average spread around marketable limit order and flash order executions. Marketable limit orders arrive when the spread is low and the spread is improving prior to their submission, which is consistent with liquidity takers consuming liquidity when the spread is low, i.e. the liquidity take cycle in Foucault, Kadan, and Kandel (2011). The spread increases immediately after marketable limit orders execute as the best level(s) of the LOB is taken out. In contrast, a flash order arrives when the bid-ask spread is large, and when it executes the spread improves substantially, i.e. liquidity is filled in the make cycle. The average price improvement that executed flashed orders get, compared to the best prevailing quote in Nasdaq, is 0.09% both for buys and sells. The improvements after flash order executions are probably partly due to competitive liquidity providers coming with quote improving limit orders.

Panel B of Figure 4 shows the cumulative change in total depth of the LOB for marketable limit order executions and flash order executions. When a marketable limit order executes, the total depth of the limit order book decreases immediately, while when a flash order executes the depth in the limit order book is replenished. These two figures show that flashed orders act as a call for liquidity and result in the coordination of supply and demand, as posited by Admati and Pfleiderer (1991).

## 6 Flash Orders and Market Quality

We start with an analysis of the effect of flash orders within the U.S. market, through an event study and a panel regression of market quality on dummy variable for the flash period. First, we conduct an event study around the introduction and removal of the flash functionality. We use ten day event windows, five days prior and after the introduction and removal of the flash functionality, to investigate the change in market quality variables caused by flashed orders. The ten-day event window is chosen to eliminate the possibility of corporate or market wide events confounding our analysis, while still keeping a reasonably long sample period. The pre-introduction period is from May 28-June 4, the post-introduction period is June 5-11, the pre-removal period is August 25-31, and the post removal period is September 1-8.

Panel A of Table 6 shows the proportional changes [(Post-Pre)/Pre] in the market quality variables. Results based on the mean and median of various illiquidity measures suggest that there are statistically significant improvements (deteriorations) in liquidity after the introduction (removal) of the flash functionality. There is an 11 percent improvement in liquidity during the flash period for both the quoted and the relative spread and they are statistically significant. In addition, short term volatility decreases (increases) significantly after the introduction (removal) of flashed orders.[28] To better understand the impact of flash orders on market quality, we conduct the event study on the sample sorted into three terciles based on market capitalization. Panel B of Table 6 shows that there is a significant improvement in liquidity and a reduction

[28] The results for the non-TARP sample confirm the findings, see Table A5 in the Appendix. Also, the same results hold when using the whole market sample, i.e. including all stocks and all types of shares above $5, shown in Table A6 in the Appendix.

in volatility for mid-cap and large stocks. Flash orders appear to have less impact on smaller stocks.[29]

We also run a panel regression of the liquidity variables on a flash period dummy and a group of controls for the period April 1 - October 31, 2009. This analysis helps us to determine whether there is a longer term impact of the introduction and removal of flash orders, beyond the event study window. We run a two-way fixed effect panel regression controlling for price, market capitalization, dollar trading volume and the daily volume-weighted average price (VWAP). Results in Panel C of Table 6 show that the flash period dummy has a large coefficient and is highly statistically significant. The results indicate that spreads, relative spreads and volatility decreased substantially during the flash period confirming the event study results.[30] Although the results suggest a positive impact of flash orders on market quality, these findings might be influenced by various unobserved confounding effects at the stock price and size level. A linear regression method is causal, if we include all the appropriate control variables, such that the conditional independence assumption holds. Thus, we also use a matched sample approach as an alternative methodology for causal inference, because it does not require the specification of a functional form for the outcome equation and is less susceptible to misspecification bias.

## 6.1 Difference in Difference Analysis

**Propensity Score Matching**

Our matching procedure relies on a matching of propensity scores in the spirit of Rosenbaum and Rubin (1983) and Heckman, Ichimura, and Todd (1998). The matching procedure begins by defining the treatment and control groups, which correspond to the CRSP sample of stocks and TSE stocks, respectively. Each CRSP stock is matched with a control firm from TSE that has the closest propensity score, with replacement. We denote the two month period prior to the introduction of the flash facility by t=-1 and the three month flash period as t=0. The propensity score is the estimated probability of belonging to the CRSP group in period t=0 based on firm characteristics in period t=-1. We estimate this probability using a logistic regression, where the dependent variable is equal to 1 if it is a CRSP stock and zero otherwise. The firm

[29] This result is confirmed by the non-TARP subsample in Table A5 in the Appendix. Tables A7 and A8 in the Appendix show that the same results hold when sorting according to flashed orders and double sorting by market capitalization and flash orders.

[30] We also replicate these results using TAQ data aggregated at the daily level and find qualitatively similar results. We use CRSP data in order to be able to compare with our match group, but TAQ results are available from the authors upon demand.

characteristics used are: price, log market capitalization and relative bid-ask spread. We use the predicted probabilities (i.e., propensity scores) to match each firm from the treatment group with a firm from the control group based on the smallest absolute difference between the estimated propensity scores, with replacement. Figure 5 shows the propensity score distribution for the treatment (CRSP) and control (TSE) groups after matching. The densities of the propensity scores after matching are very close and there is a clear overlap of the distributions, implying a good match between the samples. In addition, Table A10 in the Appendix shows that the normalized differences between the treatment and control groups are small and within the 0.25 limits proposed by Imbens and Rubin (2011).

**Event Study**

Table 7 presents changes in market quality surrounding the introduction and removal of flash orders for a ten day event window. Panel A of Table 7 shows that short term volatility, quoted spread and realized spread decrease significantly after the introduction of flash orders, while ILR does not change. With the introduction of the flash order, the quoted spread and relative spread in the U.S. decrease by 19 basis points and 3 percent over the matched group, respectively. The average quoted spread and realized spread at Nasdaq increase by an additional 5.2 basis points and 2.7 percent when the flash functionality is removed.[31] When stocks are sorted according to market capitalization, the improvement in market quality comes from the large and medium cap stocks. Flash orders appear to have limited impact on smaller stocks.

**Regression Analysis**

To further control for the possibility that the observed relation between flash order introduction and removal and market quality is due to changes in the two markets over time, we study market quality changes around the duration of the flash order functionality in Nasdaq in a two-way fixed effect panel regression. The sample period, April 1 - October 31, 2009 covers two months before and after the introduction and removal of the flash order functionality from Nasdaq. We compare the 1820 CRSP sample stocks to the 1820 matched TSE control stocks without flash functionality.

[31] The results are robust to using a longer event window of 20 days, Table A9 in the Appendix. The magnitude of the decrease, relative to the matched group, in quoted and relative spread is even larger over the 20 days window with a decrease of 24 basis points and 5.3 percent respectively. When the flash facility is removed, the change in both the quoted and realized spreads is positive but insignificant. Short term volatility also increases after the removal of flash orders.

We estimate the following two-way fixed effects model for a variety of left-hand side variables $Y_{it}$ measured for matched pair $i$ on day $t$:

$$Y_{it} = \mu_i + \phi_t + \beta D_{it}^{\text{flash period}} + \theta X_{it} + \epsilon_{it} \tag{3}$$

where $Y_{it}$ is the difference between CRSP and TSE match in the: quoted spread, realized spread, ILR and short term volatility. $\mu$ and $\phi$ capture the match pair fixed effect and time fixed effects. $D^{\text{flash period}}$ is equal to one during the flash period, and zero otherwise. $X_{it}$ is a vector of pairwise differences for the following control variables: market capitalization, dollar trading volume, and VWAP. The matched pair fixed effect accounts for any differences between two stocks in a pair that are present during the non-flash period. The time fixed effects remove the impact of any broad market changes in our variables of interest. The control variables pick up time variation in the matching variables due to size, trading volume and share price level. Statistical inference is based on Thompson (2010) two-way clustered robust standard errors.

Panel B of Table 7 shows the full-sample panel regression results. During the flash period, one pays 2 basis points less in terms of quoted spread than the matched group compared to two months before and after the flash period. One pays 1.6 percent less in terms of relative spread. We also find that short term volatility decreases during the flash period. These results also hold for the non-TARP subsample, in Panel B of Table A9.

We recognize that albeit there are many good reasons for the Toronto Stock Exchange stocks to be good matches for the U.S. listed stocks, the number of stocks available for matching from TSE is limited. Therefore, we use LSE stocks as an additional control group to TSE. The final match sample includes 1121 stocks. Table A10 in the Appendix provides the normalized difference between the treatment and control group after matching. This difference is very small and an indication of the good match between the two groups. The results in Table A11 are very similar to the results presented above on the TSE match only. The flash dummy variable is large and highly statistically significant across the different equations. The improvement in market quality during the flash period is always strong, regardless of the methodology we employ.

## 6.2 Other Measures of Market Quality

An additional measure of market quality is return autocorrelation. After the correction for the negative bias in the autocorrelation of returns, the mean and median autocorrelation at the 5 and 30 minute aggregation investigated remain negative and are statistically different from zero. Table 8 shows change in intra-day return autocorrelations at the five and thirty minute frequency for the introduction and removal of the flash facility. The 5 and 30 minute return autocorrelation decreases significantly after the introduction of flashed orders. The thirty minute return autocorrelations also decreases after the removal of the flash facility, but it does not change at the 5 minute frequency. This constitutes additional evidence of the improvement in market efficiency as posited in the Admati and Pfleiderer (1991) model.

### 6.3 Summary

Our findings seem to support the hypothesis that flash orders indicate to brokers that uninformed liquidity is available at a particular venue so that they can quickly route to it, if it represents the best available trading opportunity. The market wide results of the event study, regression analysis, with and without a control group, and difference in difference, show that the improvement in Nasdaq quality leads to an improvement in the overall market. Our findings indicate that advertising for liquidity needs through flash orders successfully attracts liquidity providers and lowers price uncertainty and overall trading costs in the market. Admati and Pfleiderer (1991) argue that sunshine trading reduces risk-bearing costs for both announcers and non-announcers, because it reduces the uncertainty of the liquidity demand of uninformed traders and the amount of noise in the price. Such a reduction in overall risk-bearing costs may be on possible explanation for our results above.

## 7 Robustness

### 7.1 Cross Sectional Relation of Flash Orders and Market Quality

So far we have carried out a time series analysis on how the introduction and removal of the flash facility affects market quality in Nasdaq through event study and regression analysis, and across exchanges using difference-in-difference regressions. In this section, we investigate the role of flashed orders on liquidity and volatility using cross sectional analysis as a robustness.

If flash orders really affect market quality as demonstrated in our time series exercise, then the difference in the number of flash orders across firms should also explain the cross-sectional differences across firms liquidity and volatility. We follow Boehmer and Kelley (2009) in the design of this analysis. Specifically, for each day during the flash sample period, we run cross-section regressions of market quality variables and the number of flash orders per stock in the day or the previous day, controlling for the effect of size, volume, volatility, price and the lagged dependent variable (DV). We draw inferences from the time series of the estimated coefficients with Newey-West standard errors. In addition we also run a pooled regression for the whole flash sample period.

The results in Panel A of Table A12 in the Appendix show that there is a positive and significant contemporaneous relation between the daily number of flash orders and liquidity after controlling for size, volume, volatility, lagged price and the lagged dependent variable. Thus, larger numbers of flashed orders are associated with greater liquidity and smaller volatility. Regarding the control variables, illiquidity decreases with the market capitalization and the trading volume of a stock, but it increases with volatility. Results from the pooled regression in Panel B remain qualitatively similar. The cross-sectional analysis results are consistent with the conclusions from the time series analysis, which suggest that flash orders improve liquidity and lower volatility.

### 7.2 Effect of Flash Orders on Pseudo Outcomes

The next test focuses on estimating the effect of a treatment that is known not to have an effect. This is one approach in causal inference to assess the assumption of unconfoundedness and is analogous to Heckman, Ichimura and Todd (1997). We estimate a "pseudo" average treatment effect by analyzing two control groups as if one of them is the treatment group. In particular, we construct a sample of pseudo events drawn from the non-flash period, more specifically two months pre and post flash period. We use a longer sample period than in the main analysis because we would like to have more observations for our statistical inference and ensure non-overlap with the event study in Section 6. We test for the null hypothesis that the treatment effect on our variables of interest, $V$, of the pseudo event studies are not different from the event (flash) study. We consider each day starting from February 06, 2009 till May 08, 2009 and from September 29, 2009 till December 31, 2009 as a pseudo event date, for the pre and post flash period respectively. As in the event study in the earlier section, our variables of interest, $V$, are quoted spread, relative spread, illiquidity ratio and return volatility.

For each pseudo event date, we construct the mean and median of our variables of interest for 5 days before and after the pseudo event date. Like the event study we have carried out for the flash period, we then create the difference in pre and post period for these pseudo events. For the pre-flash pseudo events from February 06, 2009 till May 08, 2009, we calculate the percentage change in means and medians of the variable of interest $((V_{post} - V_{pre})/V_{pre}))$ for pseudo event $i$ and call this $Introduction_i^{pseudo}$. We carry out the same procedure for post-flash pseudo events $j$ from September 29, 2009 till December 31, 2009, and calculate the percentage change in means and medians, which we call $Removal_j^{pseudo}$. Panel A of Table A13 in the Appendix shows the mean and median change across the pre and post event periods, as for the flash period in Table 6. All means and medians are statistically not different from zero, with the exception of the relative spread mean in the introduction period. Differently from the flash period, these pseudo changes in market quality are not different from zero.

We test for the difference of the treatment effect of the pseudo events from the actual event by taking the difference of $Introduction$ for the flash and pseudo event for each pseudo event day $i$ ($Introduction^{flash} - Introduction_i^{pseudo}$). We do this for $Removal$ as well and test if the difference is statistically different from zero. Panel B of Table A13 in the Appendix presents the results for the pseudo event analysis for the pre and post flash period respectively. For the pre flash period period, the negative average difference between the treatment effects of actual and pseudo events implies that the improvement in liquidity at the introduction of flash orders is much higher on average than those of the pseudo events. The difference both in means and medians is statistically different from zero. For the post-flash pseudo event analysis, the positive difference between the actual and pseudo removal event implies that the market deteriorated substantially more during the removal of the flash functionality than in any post flash pseudo events. The difference both in means and medians again is statistically different from zero.

# 8 Conclusions

In this paper, we empirically analyze the implications of voluntary disclosure on the trading costs of the announcer and market quality. We use the introduction and removal of actionable indications of interest, flash orders, by Nasdaq as a natural experiment to study the implications of sunshine trading.

We find that flash orders are mainly submitted by agency algorithms, indicating that the main users of flash orders are large institutional investors. Executed flashed orders have lower adverse selection costs, implying that the market treats them as less informed. Our findings are consistent with Admati and Pfleiderer (1991), where they argue that the potential delay cost of preannouncement and information leakage by informed traders ensure that preannounced trades are unlikely to contain information. Identification of uninformed traders allows other market participants to lower the adverse selection cost they impose and encourages the provision of liquidity. We find that flash intensity increases when the local quotes for individual stocks diverge from the NBBO and flash orders drive the Nasdaq spread towards the NBBO. It appears that flashed orders are used to advertise demand for liquidity and to avoid routing costs. The signalling of liquidity demand attracts volume to Nasdaq immediately after an order is flashed. The use of flash orders leads to improved execution quality. Furthermore, the removal of flash orders leads to an overall increase in adverse selection costs. Thus, flashed orders improve the market quality in Nasdaq.

The improvement in Nasdaq market quality leads to an improvement in the overall market. Comparing various liquidity and activity measures around the flash introduction and flash removal periods, overall market liquidity improves (decreases) significantly when flash orders are introduced (removed). Market efficiency also improves (deteriorates) when flash orders are introduced (removed). The difference in difference analysis shows that market liquidity for large and medium size stocks that are flashed more frequently improves significantly during the flash period and deteriorates after its removal, while that of small stocks does not change.

Admati and Pfleiderer (1991) argue that while sunshine trading decreases the adverse selection cost of preannounced trades, it increases the adverse selection cost of the non-announcers. However, sunshine trading reduces the risk-bearing costs for both announcers and non-announcers, because it reduces the uncertainty of the liquidity demand of the uninformed traders and the amount of noise in the price. Overall, the improvement in trading cost of the uninformed traders comes at the expense of the informed traders as informed traders are able to extract less consumer surplus from the uninformed as the price becomes less noisy. This reduction in overall risk-bearing costs appears to be the driving force behind our results.

An important and immediate application of our results is to the on-going policy debate on the withdrawal of the flash trade practice in the U.S.. Our analysis and results help to understand the impact and implications of similar competition enhancing mechanisms that might are also used by dark pools, like Getco and Knight Link, who are establishing new trading venues in Europe and Asia. Nonetheless, further research on the option and European markets where flash orders are still widely used would be useful. Furthermore, our results inform future decisions on market design and transparency.

**Table 1**
**Sample Characteristics**

The table shows the daily and intraday sample characteristics. *Price* is the stock price in \$, *Volume* is daily trading dollar volume in \$ millions, *Trades* is the daily number of trades in NASDAQ, *Market Cap.* is the market capitalization in \$ millions, *Spread* is the bid-ask spread, ask price - bid price in \$, *Rel. Spread* is Spread/((ask+bid)/2) in %, *ILR* is the illiquidity ratio $|return|$/dollar volume for a million shares, *Volatility* is $return^2$. Panel A presents the statistics for 1867 stocks in the sample over the period April 01, 2009 to October 31, 2009. Panel B presents the statistics for the 188 stocks used to rebuild the limit order book and are used for the intraday analysis. Panel C presents the intraday characteristics of the limit order book stocks. *Flash Trade Size* the average size of trades for flashed orders, *Trade Size* is the average size of trades for non-flash orders, *Slope 5* and *10* are the slopes for the first five and ten levels of the book, respectively, and *Depth 5* and *10* is the cumulative number of shares standing in the first five and ten levels of the book, respectively. All variables are defined in Table A2.

| | Price | Volume | Trades | Market Cap. | Spread | Rel. Spread | ILR | Volatility |
|---|---|---|---|---|---|---|---|---|
| *Panel A. CRSP Daily Sample* | | | | | | | | |
| Mean | 27 | 54 | 5,450 | 4,893 | 0.083 | 0.489 | 0.2962 | 0.0012 |
| Median | 21 | 8 | 1,130 | 910 | 0.020 | 0.109 | 0.0016 | 0.0002 |
| 25th | 14 | 2 | 260 | 324 | 0.010 | 0.057 | 0.0003 | 0.0000 |
| 75th | 33 | 37 | 2,809 | 2,809 | 0.050 | 0.240 | 0.0010 | 0.0009 |
| St. Dev. | 29 | 176 | 15,191 | 17,202 | 0.234 | 1.583 | 2.9206 | 0.0051 |
| *Panel B. Limit Order Book Sample* | | | | | | | | |
| Mean | 29 | 52 | 4,658 | 4,310 | 0.102 | 0.589 | 0.3583 | 0.0011 |
| Median | 20 | 7 | 1,042 | 708 | 0.030 | 0.122 | 0.0020 | 0.0002 |
| 25th | 13 | 1 | 18 | 255 | 0.010 | 0.064 | 0.0004 | 0.0000 |
| 75th | 30 | 27 | 3,500 | 2,258 | 0.060 | 0.280 | 0.0143 | 0.0009 |
| St. Dev. | 47 | 208 | 10,570 | 13,288 | 0.269 | 1.770 | 3.0870 | 0.0088 |

*Panel C. Intraday Sample Characteristics*

| | Flash Trade Size | Trade Size | Slope 5 | Slope 10 | Depth 5 | Depth 10 |
|---|---|---|---|---|---|---|
| Mean | 202 | 106 | 794 | 630 | 4,610 | 9,486 |
| Median | 145 | 96 | 169 | 167 | 2,069 | 5,767 |
| 25th | 101 | 83 | 45 | 47 | 1,433 | 3,954 |
| 75th | 226 | 108 | 564 | 568 | 3,666 | 9,363 |
| St. Dev. | 247 | 184 | 1,974 | 1,358 | 8,636 | 12,748 |

**Table 2**
**Order Submission and Execution Quality**

The table shows statistics on the daily average number of orders submitted at Nasdaq and execution quality. Panel A shows statistics related to the daily average of orders that involve at least one flash, divided into two categories, orders flashed at submission (*F. O. Submission*) and orders flashed during an update (*F.O. Update*). *F.O. Total* is the total number of orders that are flashed at least once. The average number of daily non flashed orders is *Orders Non Flashed*, and the average total number of daily orders is *Total Orders*. *F.O. %* presents the share of the *Total Orders* (New, Executed or Deleted) that are flashed. *% Executed* is the percentage of submitted orders that are executed. Panel B shows the fill rates during the flash period split in flashed and non-flashed orders, and the difference in fill rates at the introduction and removal of flash orders. *Introduction* is the difference in fill rates for the first five days of flash introduction and five days before (post-pre), and *Removal* is the difference between five days after the removal of flash and five days prior (post-pre). Panel C shows the average composition of the 14% of executed flash orders. % is the proportion of executed flashed orders executed at submission, executed after updates, or executed right after entering the book. *Later execution* are flashed orders that are executed sometime after entering the LOB. *,**,*** represent significance at the 10, 5, and 1% level, respectively.

*Panel A. Order Submissions*

| | F. O. Submission | F. O. Update | F. O. Total | Non Flash Orders | Total Orders | F.O. % |
|---|---|---|---|---|---|---|
| No. Orders | 3,228,724 | 499,140 | 3,727,864 | 64,581,142 | 68,309,006 | 5% |
| | 87% | | | | | |
| Executed | 350,163 | 166,023 | 516,187 | 2,714,660 | 3,230,847 | 16% |
| | 68% | | | | | |
| Deleted | 2,878,561 | 333,117 | 3,211,677 | 61,866,482 | 65,078,159 | 5% |
| % Executed | | | 14% | 4% | 5% | |

*Panel B. Fill Rates*

| | Flash | Non-Flash | Introduction | Removal |
|---|---|---|---|---|
| Mean | 9.17% | 3.85% | -1.00%*** | 0.06% |

*Panel C. Flash Executions*

| | Mean | % |
|---|---|---|
| Execution at submission | 3.40 | 24.54 |
| Execution at update | 0.77 | 5.59 |
| Execution right after entering book | 7.63 | 55.16 |
| Later execution | 2.04 | 14.71 |

## Table 3
## Flash Stock Characteristics

The table shows the characteristics of the stocks according to the number of daily flashed orders (Panel A), and the mean number of flashed orders over the sample period (Panel B). Tercile 1 represents the stocks with the least flashes (at least 1), while tercile 3 the stocks with most flashes. There are approximately 620 stocks in each tercile. All variables are defined in Table A2.

| Tercile | Volume | Trades | Size | Spread | Rel. Spread | ILR | Volatility | Flash |
|---|---|---|---|---|---|---|---|---|
| *Panel A. Number of Daily Flashed Orders* | | | | | | | | |
| 1 (low) | 2 | 578 | 410 | 0.1714 | 1.088 | 0.72444 | 0.00129 | 13 |
| 2 | 20 | 2,977 | 1,825 | 0.0366 | 0.139 | 0.03753 | 0.00098 | 185 |
| 3 (high) | 140 | 21,066 | 13,734 | 0.0191 | 0.076 | 0.00410 | 0.00071 | 10172 |
| *Panel B. Period Mean Flashed Orders* | | | | | | | | |
| 1 (low) | 2 | 497 | 348 | 0.1956 | 1.315 | 1.01489 | 0.00148 | 20 |
| 2 | 22 | 3,413 | 1,829 | 0.0328 | 0.114 | 0.01621 | 0.00110 | 272 |
| 3 (high) | 158 | 22,852 | 14,372 | 0.0203 | 0.083 | 0.00258 | 0.00096 | 10414 |

## Table 4
## Strategic Runs

The table shows the monthly total number of runs grouped according to the number of messages per run (*Run Length*) for 188 LOB stocks during the flash period. The runs are presented for flashed and non-flashed runs. A run is classified under flash, if there is a flash message that is part of the run. HS Run is a run as defined by Hasbrouck and Saar (2010), Update Run is a run consisting of subsequent update messages, Total Run is the sum of HS and Update runs. Strategic Runs is the percentage of runs with more than ten messages, Total runs is the total number of runs per period.

| | HS Run | | | | Update Run | | | | Total Run | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Run Length | Non Flash | | Flash | | Non Flash | | Flash | | Non Flash | | Flash | |
| *Panel A. June* | | | | | | | | | | | | |
| 3-4 | 3,860,761 | 54.46% | 164,606 | 74.88% | 546,395 | 80.68% | 688,504 | 77.57% | 4,407,156 | 65.98% | 853,110 | 77.04% |
| 5-10 | 1,634,840 | 23.06% | 49,130 | 22.35% | 112,296 | 16.58% | 172,677 | 19.46% | 1,747,136 | 26.16% | 221,807 | 20.03% |
| 11-14 | 177,301 | 2.50% | 2,641 | 1.20% | 9,572 | 1.41% | 16,626 | 1.87% | 186,873 | 2.80% | 19,267 | 1.74% |
| 15-20 | 117,222 | 1.65% | 1,421 | 0.65% | 4,625 | 0.68% | 6,549 | 0.74% | 121,847 | 1.82% | 7,970 | 0.72% |
| 21-100 | 187,616 | 2.65% | 1,678 | 0.76% | 2,870 | 0.42% | 2,531 | 0.29% | 190,486 | 2.85% | 4,209 | 0.38% |
| 101-1000 | 23,859 | 0.34% | 299 | 0.14% | 1,207 | 0.18% | 632 | 0.07% | 25,066 | 0.38% | 931 | 0.08% |
| 1001-5000 | 790 | 0.01% | 38 | 0.02% | 302 | 0.04% | 52 | 0.01% | 1,092 | 0.02% | 90 | 0.01% |
| >5000 | 73 | 0.00% | 2 | 0.00% | 1 | 0.00% | | 0.00% | 74 | 0.00% | 2 | 0.00% |
| Strategic Runs | | 7.15% | | 2.77% | | 2.74% | | 2.97% | | 7.87% | | 2.93% |
| Total Runs | 6,002,462 | | 219,815 | | 677,268 | | 887,571 | | 6,679,730 | | 1,107,386 | |
| *Panel B. July* | | | | | | | | | | | | |
| 3-4 | 6,531,985 | 60.70% | 340,753 | 75.36% | 1,098,713 | 77.73% | 1,636,214 | 77.59% | 7,630,698 | 65.03% | 1,976,967 | 77.20% |
| 5-10 | 2,910,182 | 27.04% | 99,865 | 22.08% | 277,389 | 19.62% | 425,000 | 20.15% | 3,187,571 | 27.17% | 524,865 | 20.50% |
| 11-14 | 317,495 | 2.95% | 5,475 | 1.21% | 21,008 | 1.49% | 30,409 | 1.44% | 338,503 | 2.88% | 35,884 | 1.40% |
| 15-20 | 196,474 | 1.83% | 2,687 | 0.59% | 9,628 | 0.68% | 11,971 | 0.57% | 206,102 | 1.76% | 14,658 | 0.57% |
| 21-100 | 327,803 | 3.05% | 2,873 | 0.64% | 4,604 | 0.33% | 4,040 | 0.19% | 332,407 | 2.83% | 6,913 | 0.27% |
| 101-1000 | 35,092 | 0.33% | 477 | 0.11% | 1,723 | 0.12% | 1,000 | 0.05% | 36,815 | 0.31% | 1,477 | 0.06% |
| 1001-5000 | 677 | 0.01% | 59 | 0.01% | 422 | 0.03% | 97 | 0.00% | 1,099 | 0.01% | 156 | 0.01% |
| >5000 | 89 | 0.00% | 3 | 0.00% | | 0.00% | | 0.00% | 89 | 0.00% | | 0.00% |
| Strategic Runs | | 8.16% | | 2.56% | | 2.64% | | 2.25% | | 7.80% | | 2.31% |
| Total Runs | 10,319,797 | | 452,192 | | 1,413,487 | | 2,108,731 | | 11,733,284 | | 2,560,920 | |
| *Panel C. August* | | | | | | | | | | | | |
| 3-4 | 6,992,449 | 64.98% | 349850 | 74.39% | 1,677,283 | 79.76% | 2,248,948 | 79.50% | 8,669,732 | 67.57% | 2,598,798 | 78.77% |
| 5-10 | 2,911,205 | 27.05% | 109,178 | 23.22% | 363,498 | 17.29% | 499,405 | 17.65% | 3,274,703 | 25.52% | 608,583 | 18.45% |
| 11-14 | 304,753 | 2.83% | 4,967 | 1.06% | 29,243 | 1.39% | 41,479 | 1.47% | 333,996 | 2.60% | 46,446 | 1.41% |
| 15-20 | 186,866 | 1.74% | 2,365 | 0.50% | 15,136 | 0.72% | 20,930 | 0.74% | 202,002 | 1.57% | 23,295 | 0.71% |
| 21-100 | 310,883 | 2.89% | 3,620 | 0.77% | 10,712 | 0.51% | 13,138 | 0.46% | 321,595 | 2.51% | 16,758 | 0.51% |
| 101-1000 | 21,208 | 0.20% | 282 | 0.06% | 5,220 | 0.25% | 4,643 | 0.16% | 26,428 | 0.21% | 4,925 | 0.15% |
| 1001-5000 | 571 | 0.01% | 24 | 0.01% | 1,836 | 0.09% | 428 | 0.02% | 2,407 | 0.02% | 452 | 0.01% |
| >5000 | 68 | 0.00% | 2 | 0.00% | 30 | 0.00% | | 0.00% | 98 | 0.00% | | 0.00% |
| Strategic Runs | | 7.66% | | 2.39% | | 2.96% | | 2.85% | | 6.91% | | 2.78% |
| Total Runs | 10,728,003 | | 470,288 | | 2,102,958 | | 2,828,971 | | 12,830,961 | | 3,299,257 | |

**Table 5**
**Information Content of Flash Orders**

The table presents effective spread decomposition and the weighted price index in Nasdaq, for 188 stocks. Panel A presents the effective (*espread*) and realized (*rspread*) spreads and adverse selection costs (*adv_selection*). We show mean and median spreads and costs. *Diff* is the difference between flashed and non-flashed orders spreads and adverse selection costs. Panel B presents the weighted price contribution of flash and non-flash executed orders. The price contribution of trades executed against flash orders is: $PC^{s,t}_{flash} = \frac{\sum_{n=1}^{N} \delta_{n,flash} r_n^{s,t}}{\sum_{n=1}^{N} r_n^{s,t}}$ where $\delta_{n,flash}$ is an indicator variable equal to 1 if the $n^{th}$ trade executed against a flash order, and 0 otherwise and $r_n^{s,t}$ is the return for the $n^{th}$ trade. The weight for each stock's $PC$ is the ratio of its absolute cumulative return to the total absolute cumulative return for all the stocks $WPC^t_{flash} = \sum_{s=1}^{S}(\frac{|R^{s,t}|}{\sum_{s=1}^{S}|R^{s,t}|} PC_j^{s,t})$ where $R^{s,t} = \sum_{n=1}^{N} r_n^{s,t}$.

*Panel A. Spread Decomposition*

| | espread | rspread | *adv_selection* |
|---|---|---|---|
| | | Mean | |
| Flash | 0.037 | - 0.009 | 0.036 |
| Non-flash | 0.307 | 0.051 | 0.084 |
| Difference | -0.270 | -0.060 | -0.048 |
| p-val | 0.00 | 0.00 | 0.09 |
| | | Median | |
| Flash | 0.029 | 0.000 | 0.020 |
| Non-flash | 0.053 | 0.000 | 0.027 |
| Difference | -0.024 | 0.000 | -0.007 |
| p-val | 0.00 | 0.04 | 0.00 |

*Panel B. Weighted Price Index*

| | Flash | Non-Flash |
|---|---|---|
| Mean | 0.0199 | 0.9801 |
| Median | 0.0158 | 0.9842 |
| 25th | 0.0009 | 0.9552 |
| 75th | 0.0448 | 0.9991 |
| St. Dev. | 0.0462 | 0.0462 |

## Table 6
## Flash Order Impact on Market Quality

The table presents the proportional change ((post-pre)/pre) in market quality variables after the introduction and removal of flash orders in the equity market using end-of-day CRSP data. *Introduction* is the proportional change between the first five days of flash introduction and five days before ((post-pre)/pre), and *Removal* is the proportional change between five days after the removal of flash and five days prior ((post-pre)/pre). The table presents results for the whole sample of 1867 stocks. Panel A presents the change in the impact on the whole market. *Mean* presents the change in mean and *Median* the change in median. Panel B presents the proportional change in the mean of market quality variables after the introduction and removal of flash orders for stocks sorted according to market capitalization. Panel C shows the regression results for a two-way fixed effects panel regression of market quality variables on a flash period dummy. VWAP is the log volume weighted average price. Flash Dummy is a binary variable that is one for the period June 5 - August 31, 2009, and zero otherwise. All other variables are defined in Table A2. *,**,*** represent significance at the 10, 5, and 1% level, respectively.

*Panel A. Whole Market*

| | Spread | Rel. Spread | ILR | Volatility |
|---|---|---|---|---|
| **Introduction** | | | | |
| Mean | -0.11*** | -0.11** | -0.06 | -0.36*** |
| Median | -0.33*** | -0.23*** | -0.17*** | -0.54*** |
| **Removal** | | | | |
| Mean | 0.01 | 0.04 | -0.11 | 0.31*** |
| Median | 0.00 | 0.10*** | 0.26*** | 0.62*** |

*Panel B. Sorted by Market Capitalization*

| | Spread | Rel. Spread | ILR | Volatility |
|---|---|---|---|---|
| **Introduction** | | | | |
| 1 (low) | -0.08* | -0.09* | -0.06 | -0.28*** |
| 2 | -0.15*** | -0.17*** | 0.04 | -0.35*** |
| 3 (high) | -0.20*** | -0.24*** | -0.15** | -0.54*** |
| **Removal** | | | | |
| 1 (low) | 0.01 | 0.04 | -0.11 | 0.19 |
| 2 | -0.01 | 0.10*** | 0.07 | 0.40*** |
| 3 (high) | 0.01 | 0.07*** | 0.35*** | 0.62*** |

*Panel C. Regression Analysis*

| | Spread | Rel. Spread | ILR | Volatility |
|---|---|---|---|---|
| Market cap. | -0.059*** | -0.381*** | -0.732*** | -0.016*** |
| Price | 0.002** | 0.005*** | 0.013*** | -0.000*** |
| Volume | 0.020*** | 0.115*** | 0.182*** | 0.080*** |
| Flash Dummy | -0.001*** | -0.004** | 0.002 | -0.003*** |
| VWAP | -0.008*** | -0.050*** | -0.140*** | 0.017*** |
| Adj. $R^2$ | 0.69 | 0.65 | 0.21 | 0.32 |

## Table 7
## Difference in Difference Match Group

The table shows results for the difference in difference analysis. Panel A shows the mean difference in difference between the CRSP and Toronto Stock Exchange market quality variables (treatment-control) for an event study with a ten day event window. *Introduction* is the difference in market quality measures between the flash introduction and before (post-pre), and *Removal* is the difference between the removal of flash and prior (post-pre). We show the results for the whole sample and the results for U.S. stock sorted according to market capitalization. Panel B shows two-way fixed effect regressions of the market quality difference between the Nasdaq and Toronto Stock Exchange (TSE) (treatment-control) on a flash period dummy for the sample period: April 1 - October 31, 2009. *Market Cap. Diff.* is the difference in market capitalization between Nasdaq and TSE stocks, *Volume Diff.* is the difference in volume between Nasdaq and TSE stocks, *VWAP* is the log volume weighted average price. The coefficients for *Volume Diff.* and *VWAP* have been multiplied by 1,000. *Flash Dummy* is a binary variable that is one for the period June 5 - August 31, 2009, and zero otherwise. All other variables are defined in Table A2. *,**,*** represent significance at the 10, 5, and 1% level, respectively.

| | Introduction | Removal |
|---|---|---|
| *Panel A. Event Study* | | |
| *Whole Sample* | | |
| Spread | -0.0187*** | 0.0052 |
| Rel. Spread | -0.0301* | 0.0270* |
| ILR | 0.0189 | 0.0337 |
| Volatility | -0.0023*** | 0.0065*** |
| *Market Cap Sorted* | | |
| Tercile 1 (low) | | |
| Spread | 0.0045 | 0.0029 |
| Rel. Spread | 0.0744 | 0.0281 |
| ILR | 0.0769 | 0.0863 |
| Volatility | -0.0016 | 0.0069*** |
| Tercile 2 | | |
| Spread | -0.0256*** | 0.0122*** |
| Rel. Spread | -0.0658*** | 0.0559*** |
| ILR | 0.0007 | 0.0003 |
| Volatility | -0.0019** | 0.0060*** |
| Tercile 3 (high) | | |
| Spread | -0.0356*** | 0.0006 |
| Rel. Spread | -0.1022*** | -0.0032 |
| ILR | -0.0226* | 0.0129 |
| Volatility | -0.0035*** | 0.0065*** |

*Panel B. Regression Analysis*

| | Market Cap. Diff. | Volume Diff. | VWAP | Flash Dummy | Adj. R2 |
|---|---|---|---|---|---|
| Spread | 0.004*** | -0.001 | -0.009** | -0.002** | 0.56 |
| Rel. Spread | -0.005** | -0.001 | -0.050*** | -0.016*** | 0.17 |
| ILR | -0.007 | -0.007 | -0.030 | -0.011 | 0.13 |
| Volatility | 0.000 | 0.069 | 0.018 | -0.002*** | 0.23 |

**Table 8**
**Return Autocorrelation**

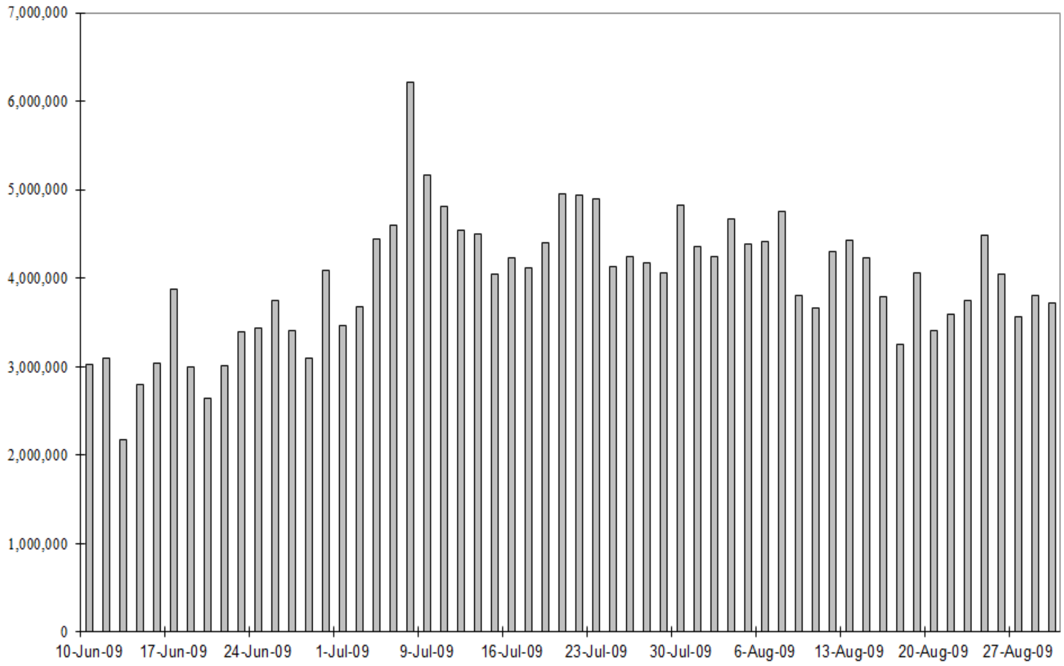
The table shows the return autocorrelation for 188 stocks for an event study with a ten day event window for the introduction and removal of flash orders. *Introduction* is the difference in autocorrelation measures between the flash introduction and before (post-pre), and *Removal* is the difference between the removal of flash and prior (post-pre). Panel A presents the results for the 30 minutes return autocorrelation and Panel B the results for the 5 minute return autocorrelation.

| | Introduction | Removal |
|---|---|---|
| *Panel A. 30 Minutes* | | |
| Mean | 0.0463 | -0.046 |
| p-val | 0.00 | 0.00 |
| Median | 0.050 | -0.033 |
| p-val | 0.00 | 0.01 |
| *Panel B. 5 Minutes* | | |
| Mean | 0.076 | 0.027 |
| p-val | 0.00 | 0.40 |
| Median | 0.084 | -0.007 |
| p-val | 0.00 | 0.25 |

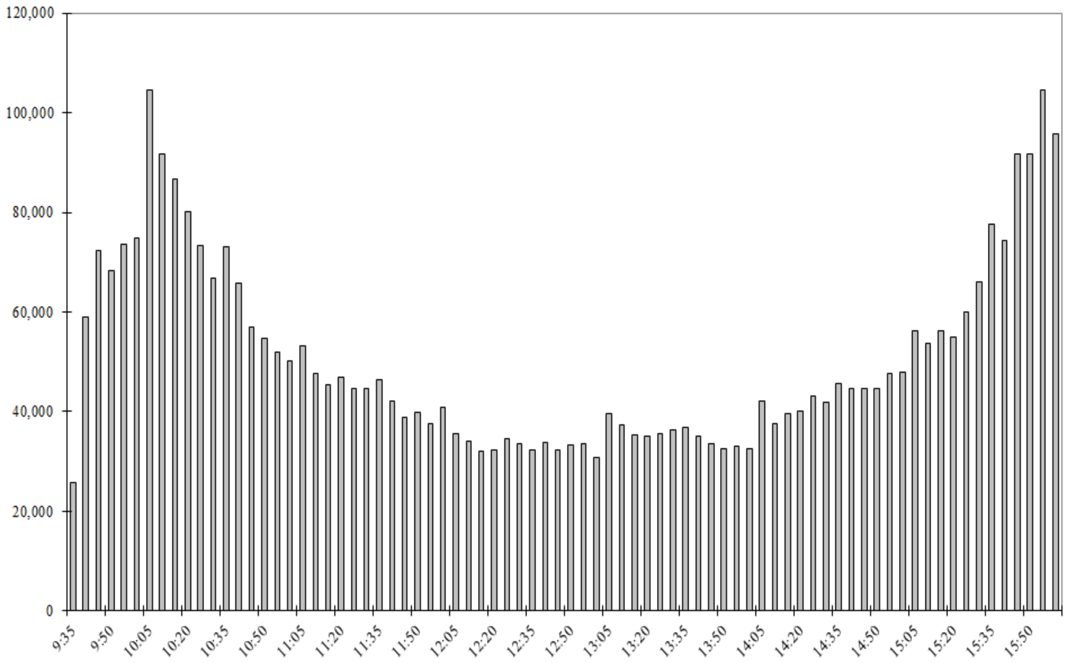
**Figure 1**
**Flashed Orders at Nasdaq**

The figure presents the time series evolution of orders that are flashed at least once. Panel A presents the daily number of flashed orders. Panel B presents the intraday variation in flashed orders submissions accumulated at the 5 minute interval.

*Panel A: Daily*



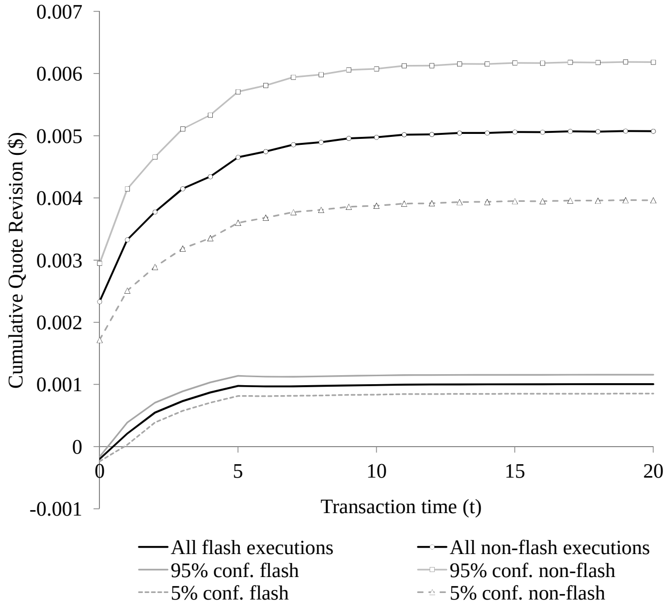

*Panel B: Intraday - 5 minute interval*



## Figure 2
## Quote Revision Process

The figures shows the impulse response functions (IRF) associated with executions against regular limit orders and flash orders. The IRFs are the average across dates and stocks. Note that the sample of flash order executions and regular executions are for the same stock and date combinations to make the response functions comparable. The IRFs are the cross-sectional average IRFs, where the IRF is first averaged across all dates for each stock and then averaged across stocks. The dotted lines show the 5th and 95th confidence bands for the cross sectional IRFs. Panel A shows the quote revision process for trades against regular limit orders versus flash orders for all trade sizes, and Panel B shows the quote revision process associated with different trade sizes. Small trades are defined as trades equal to or less than 10 shares, medium sized trades are trades of size between 10 and 100 shares, and large trades as trades of size greater than 100 shares.

*Panel A: Executions - All Trade Sizes*




*Panel B: Executions - Different Trade Sizes*

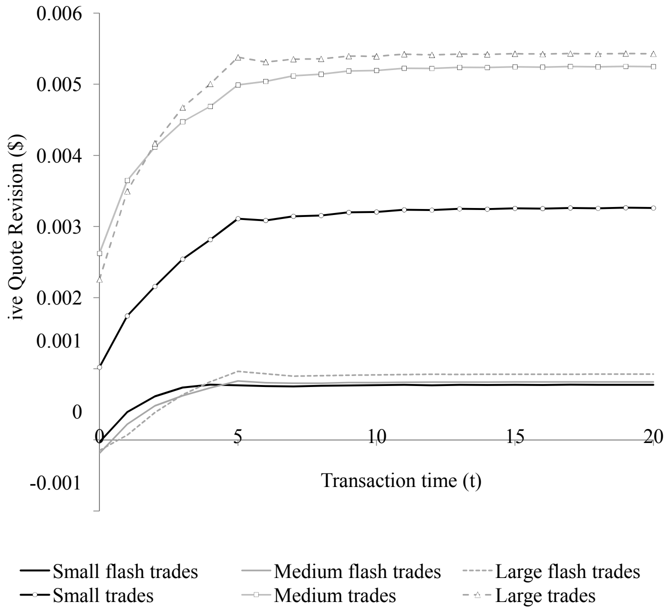
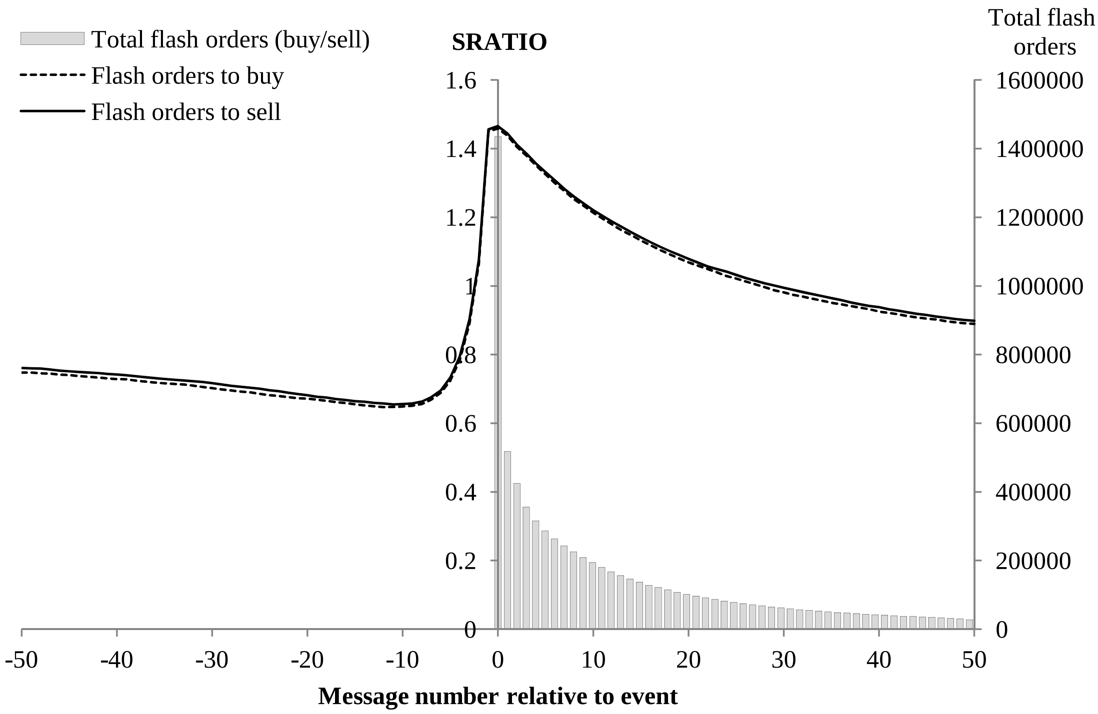


**Figure 3**
**Flash Order Submissions**

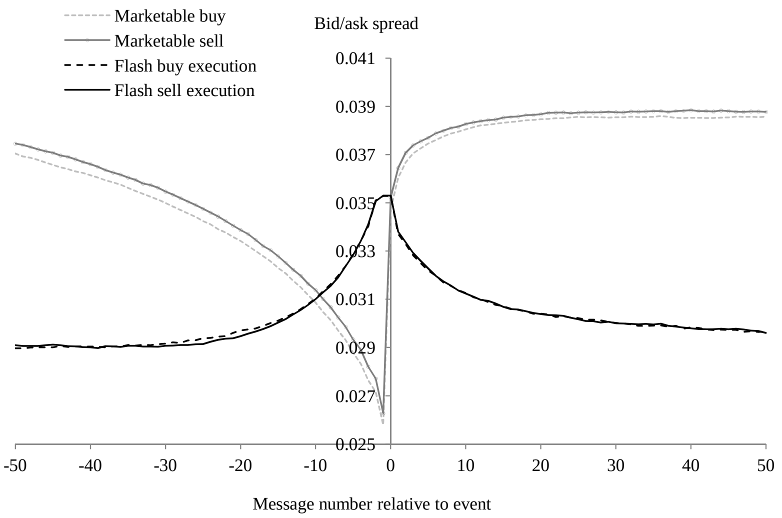
The figures show the cross sectional average SRATIO for 50 messages before and after the flashed order events for 188 stocks. The SRATIO is calculated as the Nasdaq spread (ask-bid) divided by the best prevailing NBBO spread (ask-bid) minus one. The x-axis is the number of messages relative to the flashed order submission, which is the event of interest centered at zero, and the y-axis shows the SRATIO. The SRATIO for buy orders is the dotted line and for sell orders is solid line, and the number of flash orders is in bars, (secondary y-axis).



## Figure 4
## Flash Order versus Marketable Limit Order Executions

The figure shows Nasdaq liquidity around the execution of flashed and marketable limit orders for 188 stocks. Event time 0 is the execution time, and the event window is 50 messages before and after the execution. Panel A shows the Nasdaq bid-ask spread (ask-spread) around the execution of the two types of orders: flashed orders and marketable limit orders. The y-axis shows the average Nasdaq bid-ask spread. Panel B shows the change in cumulative depth (the total depth of the limit order book) around the execution of the two types of orders. The y-axis portrays the average cumulative % change in the total depth of the limit order book.

*Panel A: Nasdaq spread around market- and flash order executions*




*Panel B: Limit order book depth around market- and flash order executions*

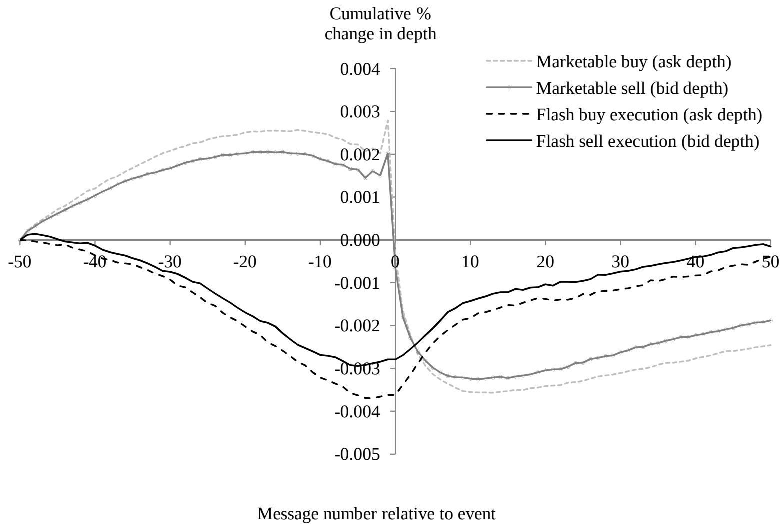
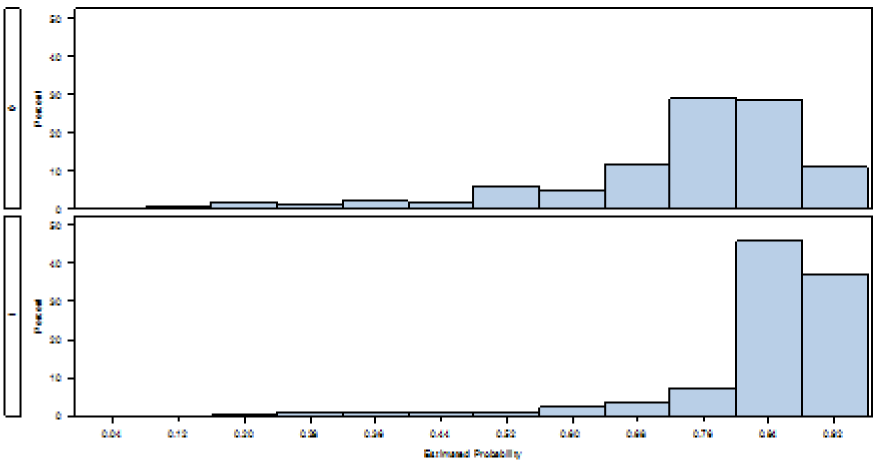


**Figure 5**
**Propensity Score Distribution**

The figure shows the propensity score distribution of the treated (U.S.) and control (TSE) groups. The treated group is in panel 1 and the control group in panel 0. The logit regression to estimate the propensity scores is run over the period April 1 - June 4.



# A Appendix

**Table A1**
**Arguments on Flash Orders**

| Against | For |
|---|---|
| **Market Quality** | |
| Discourage the public display of trading interest and harm quote competition among markets, reduce incentives for public display of quotations. | Increase in volume and reduction of spreads, increase in liquidity |
| Deprive those who publicly display their interest at the best price from receiving a speedy execution at that price. Harm price discovery. | Attract liquidity from market participants who are not willing to display their trading interest publicly. Flash orders may provide an opportunity for better execution than if orders were routed elsewhere. |
| Front-running (flashed orders that do not receive an execution in the flash process are less likely to receive a quality execution elsewhere.) Quotes being taken away. | Increase the chance of execution at the best price and lower cost. |
| Harm the interest of long-term investors to the benefit of high-frequency traders. | Decrease volatility and provide more liquidity in volatile markets. |
| Diverts a certain amount of order flow that otherwise might be routed directly to execute against displayed quotations in other markets. | Orders to be routed could go to dark pool, thus flash reduce dark pool volume. |
| **Fairness** | |
| Detract from the fairness and efficiency of the national market system as the best quotations from specific markets are made available to a limited number of market participants. | |
| “Last mover” advantage, cannot have price and time priority because flash order comes at same price but later time and is still executed immediately, i.e. before outstanding orders. | |
| Maximize an exchange’s competitive advantage, since exchanges compete on volume of executed trades. | Reduce flight to overseas markets |
| Those who are highly concerned about information leakage generally would be unlikely to flash their order information to a large number of professional traders. | |

**Table A2**
**Variable Definitions**

| Variable | Acronym | Definition | Units |
|---|---|---|---|
| **Market Wide** | | | |
| Dollar volume | Volume | (Share volume*price)/1000000 | $ million |
| Number of daily trades | Trades | | |
| Firm size | Mkt Cap | (Price*Outstanding Shares)/1000000 | $ million |
| Spread | | $ask - bid$ | $ |
| Relative Spread | Rel. Spread | $(ask - bid) * 100/((ask + bid)/2)$ | % |
| Amihud Illiquidity Ratio | ILR | $\|return\|$/dollar volume | price change per $ million |
| Volatility | | $return^2$ | |
| **Limit Order Book** | | | |
| Midpoint price | $m_t$ | $(ask_1 + bid_1)/2$ | $ |
| Realized spread | rspread | direction*(price-$m_{t+5min}$ )/$m_t$ | % |
| Adverse selection | $adv\_selection$ | direction*($m_{t+5min}$-$m_t$)/$m_t$ | % |
| Effective Spread | espread | direction*(price-$m_t$)/$m_t$ | % |
| Slope 5 Ask | $slope_{A5}$ | $(askdepth_5 - askdepth_1)/(ask_5 - ask_1)$ | number of shares per level in the book |
| Slope 5 Bid | $slope_{B5}$ | $(biddepth_5 - biddepth_1)/(bid_5 - bid_1)$ | number of shares per level in the book |
| Slope 5 | | $(slope_{A5} + slope_{B5})/2$ | number of shares per level in the book |
| Slope 10 | | $(slope_{A10} + slope_{B10})/2$ | number of shares per level in the book |
| Depth 5 | | (ask $depth_5$+bid $depth_5$)/2 | cumulative number of shares |
| Depth 10 | | (ask $depth_{10}$+bid $depth_{10}$)/2 | cumulative number of shares |

**Table A3**
**Flash Stock Characteristics - Non TARP**

The table shows the characteristics of the non-TARP sample according to the number of daily flash orders (Panel A) and the mean number of flashed orders over the sample period (Panel B). Tercile 1 represents the stocks with the least flashes (at least 1), while tercile 3 the stocks with most flashes. There are approximately 620 stocks in each tercile. All variables are defined in Table A2.

| Tercile | Volume | Trades | Size | Spread | Rel. Spread | ILR | Volatility | Flash |
|---|---|---|---|---|---|---|---|---|
| *Panel A. Total Flashed Orders* | | | | | | | | |
| 1 (low) | 3 | 798 | 477 | 0.1066 | 0.573 | 0.19763 | 0.00130 | 15 |
| 2 | 21 | 3,100 | 1,857 | 0.0327 | 0.117 | 0.03203 | 0.00102 | 187 |
| 3 (high) | 139 | 22,367 | 14,138 | 0.0187 | 0.074 | 0.00467 | 0.00071 | 9744 |
| *Panel B. Period Mean Flashed Orders* | | | | | | | | |
| 1 (low) | 3 | 693 | 417 | 0.1166 | 0.635 | 0.25543 | 0.00141 | 25 |
| 2 | 22 | 3,399 | 1,832 | 0.0315 | 0.112 | 0.01833 | 0.00109 | 248 |
| 3 (high) | 152 | 23,878 | 14,631 | 0.0201 | 0.081 | 0.00290 | 0.00089 | 9815 |

## Table A4
## Market Quality After Double Sorting on Stock Characteristics and Flashed Stocks

The table shows the market quality measures of the sample after sorting according to stock characteristics and the mean number of flashed orders a day. Panel A shows the results for sorting according to volume and Panel B according to market capitalization. All variables are defined in Table A2.

| Tercile | Spread | Rel. Spread | ILR | Volatility | Flash |
|---|---|---|---|---|---|
| *Panel A. Volume* | | | | | |
| Volume Tercile 1 - Low | | | | | |
| 1 (low) | 0.36836 | 2.94035 | 2.49553 | 0.00154 | 11 |
| 2 | 0.03575 | 0.13256 | 0.10303 | 0.00172 | 221 |
| 3 (high) | 0.02103 | 0.07357 | 0.00024 | 0.00087 | 13,419 |
| Volume Tercile 2 | | | | | |
| 1 (low) | 0.16094 | 0.96392 | 0.62878 | 0.00148 | 18 |
| 2 | 0.03286 | 0.11497 | 0.00679 | 0.00110 | 233 |
| 3 (high) | 0.02143 | 0.08080 | 0.00723 | 0.00103 | 9,805 |
| Volume Tercile 3 - High | | | | | |
| 1 (low) | 0.10813 | 0.50922 | 0.33260 | 0.00144 | 28 |
| 2 | 0.03210 | 0.10934 | 0.00310 | 0.00097 | 302 |
| 3 (high) | 0.01940 | 0.08787 | 0.00076 | 0.00095 | 9,637 |
| *Panel B. Market Cap* | | | | | |
| Market Cap Tercile 1 - Low | | | | | |
| 1 (low) | 0.38485 | 3.10508 | 2.83379 | 0.00166 | 14 |
| 2 | 0.04229 | 0.13994 | 0.01800 | 0.00106 | 244 |
| 3 (high) | 0.02174 | 0.06960 | 0.00020 | 0.00077 | 11,306 |
| Market Cap Tercile 2 | | | | | |
| 1 (low) | 0.17652 | 1.11403 | 0.69302 | 0.00151 | 20 |
| 2 | 0.03196 | 0.11277 | 0.00399 | 0.00096 | 287 |
| (high) | 0.02055 | 0.07517 | 0.00037 | 0.00096 | 11,312 |
| Market Cap Tercile 3 - High | | | | | |
| 1 (low) | 0.11294 | 0.54561 | 0.31588 | 0.00137 | 24 |
| 2 | 0.03193 | 0.11099 | 0.02115 | 0.00116 | 269 |
| 3 (high) | 0.01975 | 0.09124 | 0.00446 | 0.00101 | 9,675 |

## Table A5
## Flash Order Impact on Market Quality Non TARP Stocks

The table presents the proportional change in market quality variables after the introduction and removal of flash orders for 1420 non-TARP stocks. *Introduction* is the proportional change between the first five days of flash introduction and five days before ((post-pre)/pre), and *Removal* is the proportional change between five days after the removal of flash and five days prior ((post-pre)/pre). Panel A presents the change in the impact on the whole market. *Mean* presents the change in mean and *Median* the change in median. Panel B shows the proportional change in the mean of market quality variables after the introduction and removal of flash orders for stocks sorted according to market capitalization. $^{*}$,$^{**}$,$^{***}$ represent significance at the 10, 5, and 1% level, respectively. All variables are defined in Table A2.

*Panel A. Whole Market*

| | Spread | Rel. Spread | ILR | Volatility |
|---|---|---|---|---|
| **Introduction** | | | | |
| Mean | -0.14*** | -0.17** | -0.22 | -0.39*** |
| Median | -0.33*** | -0.24*** | -0.20*** | -0.56*** |
| **Removal** | | | | |
| Mean | 0.06 | 0.07 | 0.09 | 0.42*** |
| Median | 0.00 | 0.09*** | 0.29*** | 0.69*** |

*Panel B. Sorted by Market Capitalization*

| | Spread | Rel. Spread | ILR | Volatility |
|---|---|---|---|---|
| **Introduction** | | | | |
| 1 (low) | -0.11* | -0.16** | -0.22 | -0.25*** |
| 2 | -0.10 | -0.17*** | 0.13 | -0.44*** |
| 3 (high) | -0.22*** | -0.25*** | -0.22*** | -0.59*** |
| **Removal** | | | | |
| 1 (low) | 0.06 | 0.07 | 0.09 | 0.46** |
| 2 | 0.07 | 0.08*** | -0.01 | 0.33** |
| 3 (high) | 0.05 | 0.08*** | 0.35*** | 0.49*** |

## Table A6
## Flash Order Impact on Market Quality - Other Samples

The table presents the proportional change in market quality variables after the introduction and removal of flash orders for two additional samples. *Introduction* is the proportional change between the first five days of flash introduction and five days before ((post-pre)/pre), and *Removal* is the proportional change between five days after the removal of flash and five days prior ((post-pre)/pre). *Mean* presents the change in mean and *Median* the change in median. Panel A presents the results for the whole sample, unrestricted to common stocks and common shares, of 4095 stocks, while Panel B presents the results for 2162 non-TARP stocks unrestricted to common stocks and common shares. $p$-values are presented in brackets. All variables are defined in Table A2.

*Panel A. All Sample*

| | Spread | Rel. Spread | ILR | Volatility |
|---|---|---|---|---|
| **Introduction** | | | | |
| Mean | -0.07 | -0.08 | 0.05 | 0.00 |
| | (0.01) | (0.00) | (0.46) | (1.00) |
| Median | -0.25 | -0.15 | -0.14 | -0.54 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| **Removal** | | | | |
| Mean | 0.03 | 0.06 | 0.13 | 0.02 |
| | (0.23) | (0.03) | (0.08) | (0.71) |
| Median | 0.03 | 0.06 | 0.13 | 0.02 |
| | (1.00) | (0.00) | (0.00) | (0.00) |

*Panel B. Non TARP*

| | Spread | Rel. Spread | ILR | Volatility |
|---|---|---|---|---|
| **Introduction** | | | | |
| Mean | -0.12 | -0.15 | -0.12 | -0.13 |
| | (0.00) | (0.00) | (0.49) | (0.50) |
| Median | -0.33 | -0.21 | -0.22 | -0.57 |
| | (0.00) | (0.00) | (0.34) | (0.00) |
| **Removal** | | | | |
| Mean | 0.06 | 0.07 | 0.08 | 0.15 |
| | (0.12) | (0.11) | (0.03) | (0.46) |
| Median | 0.00 | 0.07 | 0.25 | 0.78 |
| | (1.00) | (0.00) | (0.33) | (0.00) |

## Table A7
## Flash Order Impact on Market Quality in Terciles by Total Flash

The table presents the proportional change in the mean of the market quality variables after the introduction and removal of flash orders for stocks sorted according to the number of flashed orders. *Introduction* is the proportional change between the first five days of flash introduction and five days before ((post-pre)/pre), and *Removal* is the proportional change between five days after the removal of flash and five days prior ((post-pre)/pre). All variables are defined in Table A2. *,**,*** represent significance at the 10, 5, and 1% level, respectively.

| | Spread | Rel. Spread | ILR | Volatility |
|---|---|---|---|---|
| *Panel A. Whole Sample* | | | | |
| Introduction | | | | |
| 1 (low) | -0.06 | -0.09* | -0.04 | -0.28*** |
| 2 | -0.27*** | -0.26*** | -0.80 | -0.37*** |
| 3 (high) | -0.27*** | -0.21*** | -0.68 | -0.53*** |
| Removal | | | | |
| 1 (low) | -0.02 | 0.02 | -0.11 | 0.24* |
| 2 | 0.11** | 0.14*** | -0.39 | 0.24* |
| 3 (high) | 0.10*** | 0.09*** | 0.98* | 0.79*** |
| *Panel B. Non TARP* | | | | |
| Introduction | | | | |
| 1 (low) | -0.05 | -0.15*** | -0.16 | -0.30*** |
| 2 | -0.27*** | -0.27*** | -0.81 | -0.37*** |
| 3 (high) | -0.27*** | -0.21*** | -0.68 | -0.55*** |
| Removal | | | | |
| 1 (low) | 0.03 | 0.04 | 0.22 | 0.47* |
| 2 | 0.11*** | 0.14*** | -0.39 | 0.20** |
| 3 (high) | 0.08 | 0.07*** | 1.07*** | 0.67*** |

## Table A8
## Flash Order Impact on Market Quality Double Sorted by Market Cap and Total Flash

The table presents the proportional change in the mean of market quality variables after the introduction and removal of flash orders for stocks double sorted according to market capitalization and the flash ratio. *Introduction* is the proportional change between the first five days of flash introduction and five days before ((post-pre)/pre), and *Removal* is the proportional change between five days after the removal of flash and five days prior ((post-pre)/pre). All variables are defined in Table A2. *,**,*** represent significance at the 10, 5, and 1% level, respectively.

| | Spread | Rel. Spread | ILR | Volatility |
|---|---|---|---|---|
| | | *Panel A. Introduction* | | |
| | | Market Cap Tercile 1 (Low) | | |
| 1 (low) | -0.06 | -0.07 | -0.07 | -0.38*** |
| 2 | -0.17 | -0.16 | 0.52 | -0.40*** |
| 3 (high) | -0.26*** | -0.23*** | -0.29*** | -0.65*** |
| | | Market Cap Tercile 2 | | |
| 1 (low) | -0.15* | -0.17** | -0.19 | -0.11 |
| 2 | -0.14 | -0.19*** | -0.55* | -0.20 |
| 3 (high) | -0.28*** | -0.23*** | -0.18*** | -0.54*** |
| | | Market Cap Tercile 3 (High) | | |
| 1 (low) | 0.04 | -0.04 | 0.50 | -0.38*** |
| 2 | -0.33*** | -0.31*** | -0.92* | -0.41*** |
| 3 (high) | -0.28*** | -0.21*** | -0.69 | -0.49*** |
| | | *Panel B. Removal* | | |
| | | Market Cap Tercile 1 (Low) | | |
| 1 (low) | -0.06 | 0.00 | -0.12 | -0.22 |
| 2 | 0.34 | 0.30 | -0.47 | -0.05 |
| 3 (high) | 0.09 | 0.10** | 0.34*** | 0.56*** |
| | | Market Cap Tercile 2 | | |
| 1 (low) | 0.05 | 0.09 | 0.12 | 0.06 |
| 2 | 0.15** | 0.17** | -0.45 | 0.30*** |
| 3 (high) | 0.12** | 0.09** | 0.29*** | 0.38** |
| | | Market Cap Tercile 3 (High) | | |
| 1 (low) | -0.04 | 0.00 | -0.32 | 0.98** |
| 2 | 0.06 | 0.10** | -0.38 | 0.27 |
| 3 (high) | 0.09* | 0.08*** | 1.19 | 1.08*** |

## Table A9
## Difference in Difference - 20 Day Window

The table shows the mean difference in difference between the Nasdaq and Toronto Stock Exchange market quality variables (treatment-control) of a 20 day pre/post window event study. *Introduction* is the difference between the flash introduction and before (post-pre), and *Removal* is the difference between the removal of flash and prior (post-pre). Panel A shows the results for the whole sample, and the results sorted according to market capitalization. Panel B shows two-way fixed effect regressions for non-TARP stocks of the market quality difference between the Nasdaq and Toronto Stock Exchange (TSE) (treatment-control) on a flash period dummy for the sample period: April 1 - October 31, 2009. *Market Cap. Diff.* is the difference in market capitalization between Nasdaq and TSE stocks, *Volume Diff.* is the difference in volume between Nasdaq and TSE stocks, *VWAP* is the log volume weighted average price. The coefficients for *Volume Diff.* and *VWAP* have been multiplied by 1,000. *Flash Dummy* is a binary variable that is one for the period June 5 - August 31, 2009, and zero otherwise. All other variables are defined in Table A2. *,**,*** represent significance at the 10, 5, and 1% level, respectively.

*Panel A. Event Study*

| | Introduction | Removal |
|---|---|---|
| **Whole Sample** | | |
| Spread | -0.024*** | 0.003 |
| Relative Spread | -0.053*** | 0.008 |
| ILR | -0.023 | 0.029 |
| Volatility | 0.000 | 0.002*** |
| **Market Cap Sorted** | | |
| **Tercile 1 (Low)** | | |
| Spread | -0.008 | 0.002 |
| Relative Spread | 0.017 | -0.006 |
| ILR | -0.057 | 0.071 |
| Volatility | 0.000 | 0.002*** |
| **Tercile 2** | | |
| Spread | -0.030*** | 0.008*** |
| Relative Spread | -0.089*** | 0.041*** |
| ILR | -0.001 | -0.001 |
| Volatility | 0.000 | 0.002*** |
| **Tercile 3 (High)** | | |
| Spread | -0.036*** | -0.001 |
| Relative Spread | -0.091*** | -0.011 |
| ILR | -0.009 | 0.015 |
| Volatility | -0.001** | 0.001*** |

*Panel B. Non TARP*

| | Market Cap | Dollar Volume | VWAP | Flash Dummy | Adj. $R^2$ |
|---|---|---|---|---|---|
| Spread | 0.005*** | -0.004 | -0.008* | -0.002* | 0.58 |
| Rel Spread | -0.004** | 0.004 | -0.050*** | -0.011*** | 0.21 |
| ILR | -0.008*** | -0.006 | -0.030 | -0.005 | 0.16 |
| Volatility | 0.000 | 0.081 | 0.016 | -0.001*** | 0.26 |

**Table A10**
**Matching Quality Statistics**

The table shows normalized mean differences between the treatment and control groups for the period April 1 - June 4, 2009. All other variables are defined in Table A2.

| | Canada | U.K. and Canada |
|---|---|---|
| Price | 0.00 | 0.10 |
| Volume | 0.30 | 0.23 |
| Market Cap | -0.17 | 0.02 |
| Spread | -0.21 | -0.25 |
| Rel. Spread | -0.19 | -0.25 |
| ILR | 0.10 | 0.12 |

## Table A11
## U.K. and Canada Match Group

The table shows results for the difference in difference regression where the match group is the combined stocks of Toronto Stock Exchange and London Stock Exchange. The results are for two-way fixed effect regressions of the market quality difference between the Nasdaq and matched group (treatment-control) on a flash period dummy for the sample period: April 1 - October 31, 2009. Market Cap is the difference in market capitalization between Nasdaq and matched stocks, Volume is the difference in volume between Nasdaq and matched stocks, VWAP (volume weighted average price) is the difference in VWAP between Nasdaq and matched stocks. The coefficients for Volume and VWAP have been multiplied by 1000. Flash Dummy is a binary variable that is one for the period June 5 - August 31, 2009, and zero otherwise. All variables are defined in Table A2. *,**,*** represent significance at the 10, 5, and 1% level, respectively.

| | Market Cap | Dollar Volume | VWAP | Flash Dummy | Adj. $R^2$ |
|---|---|---|---|---|---|
| Spread | 34.78*** | -0.007 | 0.00*** | -0.01*** | 0.52 |
| Rel Spread | -75.74*** | -0.006 | -0.07*** | -0.01*** | 0.44 |
| ILR | -259.9*** | 0.118*** | -0.08*** | -0.02*** | 0.20 |
| Volatility | -7.11*** | 0.032*** | 0.025*** | 0.00*** | 0.28 |

## Table A12
## Cross-sectional effect of the number of flash orders on market quality

The table shows the regression of market quality variables on the number of flash orders placed for each stock for the period June 5 to August 31, 2009. Panel A shows the contemporaneous cross sectional regression, while Panel B shows the pooled regression. Panel A presents the mean coefficient over 57 daily cross-sectional regressions. *Flash* is the number of flashed orders a stock experienced, *lag Price* is the lagged logged price, *lag DV* is the lagged dependent variable, the rest of the variables are defined in Table A1 in the Appendix. The coefficient for *Flash* and *Market Cap.* has been multiplied by 1,000,000 and the coefficient for dollar volume has been multiplied by 10,000. We test for significance using the time-series variation in the regression coefficients over these fifty-seven periods and report the significance level based on Newey-West standard errors. *,**,*** represent significance at the 10, 5, and 1% level, respectively.

| | Spread | Relative Spread | ILR | Volatility |
|---|---|---|---|---|
| *Panel A. Average Daily Regression* | | | | |
| Flash | -0.090** | -2.260*** | -0.850*** | -0.010*** |
| Market Cap. | -0.050** | 0.320*** | 0.770*** | -0.020*** |
| Volume | -0.240*** | -0.142 | -0.680*** | 0.030*** |
| Volatility | 1.650*** | 11.500*** | 32.610*** | - |
| lag Price | 0.010*** | -0.060*** | -0.030*** | 0.000*** |
| lag DV | 0.710*** | 0.670*** | 0.510*** | 0.540*** |
| *Panel B. Pooled Regression* | | | | |
| Flash | -0.100*** | -2.190*** | -1.120*** | -0.010*** |
| Market Cap. | -0.110*** | 0.120* | 0.530*** | -0.020*** |
| Volume | -0.200*** | -0.115 | -0.356 | 0.030*** |
| Volatility | 0.544 | 3.551 | 15.004 | - |
| lag Price | 0.020*** | -0.060*** | -0.040*** | 0.000*** |
| lag DV | 0.660*** | 0.610*** | 0.260*** | 0.168 |

## Table A13
## Pseudo Event Analysis

The table shows the pseudo event results. We construct ten day event windows for each day for the pre-flash pseudo event period February 06, 2009 till May 08, 2009 and the post-flash pseudo event period, from September 29, 2009 till December 31, 2009. For each event date, we create the average and median of the market quality variables, $V$ for 5 days before and after the event date. We then create the difference in pre and post period in the same way as in Table 6. Panel A presents the proportional change ((post-pre)/pre) in the mean and median of market quality variables for the introduction and removal pseudo event windows. $Introduction_i^{pseudo}$ for each pseudo event is calculated as $(V_{post} - V_{pre})/V_{pre})$ for both means and medians. The same calculation is carried out for Removal. t-stat is the t-statistic for the difference from zero. Panel B presents the the average difference between the flash period and the pseudo event change in market quality for the pre and post event period. It represents the average of the difference in pre and post event period changes in $V$ between pseudo events $i$ and introduction of flash, as per Table 6, $(Introduction^{flash} - Introduction_i^{pseudo})$. t-statistics are presented in square brackets.

| | Spread | Relative Spread | ILR | Volatility |
|---|---|---|---|---|
| *Panel A. Pseudo Period* | | | | |
| $Introduction^{pseudo}$ | | | | |
| Mean | -0.01 | -0.01 | 0.00 | 0.03 |
| t-stat | -1.52 | -2.01 | -0.08 | 1.06 |
| Median | 0.03 | -0.01 | 0.00 | 0.04 |
| t-stat | 0.88 | -0.88 | 0.03 | 1.01 |
| $Removal^{pseudo}$ | | | | |
| Mean | 0.01 | 0.02 | 0.03 | 0.00 |
| t-stat | 0.87 | 1.29 | 1.62 | -0.07 |
| Median | 0.01 | 0.01 | 0.02 | 0.00 |
| t-stat | 0.84 | 0.66 | 1.03 | -0.03 |
| *Panel B. Flash-Pseudo* | | | | |
| Introduction | | | | |
| Mean | -0.10 | -0.10 | -0.06 | -0.39 |
| t-stat | -18.34 | -17.30 | -3.39 | -13.75 |
| Median | -0.36 | -0.22 | -0.17 | -0.58 |
| t-stat | -11.38 | -25.04 | -8.30 | -15.59 |
| Removal | | | | |
| Mean | 0.00 | 0.02 | -0.15 | 0.32 |
| t-stat | -0.31 | 1.62 | -7.20 | 10.36 |
| Median | -0.01 | 0.09 | 0.24 | 0.62 |
| t-stat | -0.84 | 8.35 | 10.65 | 15.47 |

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