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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 the 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 the 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 fulfill their role as an 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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I Introduction

The recent proliferation of algorithmic trading, new trading venues, and innovative new trading products raises many issues about financial regulation and market design. What is the impact of the financial innovations by trading venues 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.

We study how introducing a facility for voluntarily disclosing trading intent affects equity market quality. To this end, we use the introduction and the removal of the flash order facility by NASDAQ OMX Group (NASDAQ). Flash orders are marketable orders that match or improve the national best bid or offer (NBBO) prices quoted at an away-exchange, orders that would normally be routed to and executed in the away exchange but are posted for up to 500 milliseconds to market participants in NASDAQ. These orders 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 a 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]

One important feature of flash orders is that the submission of a flash order imposes a potential delay cost on the submitter in NASDAQ, as opposed to submitting a marketable limit order that executes immediately in the away exchange. The risk of delay makes flash orders less attractive for high-frequency traders that try to exploit short-lived information (e.g., statistical arbitrageurs). Given this feature, we argue that flash orders are more likely to be used by uninformed traders that aim at minimizing transaction costs. Moreover, if market participants regard flash orders as coming mainly from uninformed traders, their overall execution probability and fill rate could be higher than comparable orders and result in lower *implicit costs* and price improvement. In the analysis, we consider the pre-routing feature of flash orders as a voluntary announcement of trading intent. We first attempt to determine who the main users of flash orders are. We then assess whether the introduction and the removal of the flash order facility have an impact on overall U.S. equity market quality.

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

To assess whether users of flash orders are informed, we categorize the algorithms that place flash orders as agency and proprietary (Hasbrouck and Saar, 2010). Then we estimate three measures aimed at gauging the informativeness of flash orders, or at understanding whether flash orders are being picked off by better-informed traders. To this end, we first measure the contribution of trades against flash orders to a stock's price change (e.g., Barclay and Warner, 1993); second, the adverse selection component for executed trades against flash orders and normal orders; and third, the temporary and permanent price impact of orders that execute against flash orders (Hasbrouck, 1991). 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 less informed. In addition, we find that adverse selection costs associated with flash order executions are substantially lower than those for non-flash executions, their permanent price impact is very small, and the weighted price contribution is only 2%. The findings of lower trading costs associated with executed flash orders indicate that market participants regard these orders as less informative and are willing to fill them quickly at favorable prices.

To examine the impact of flash orders on overall U.S. market quality, we use two identification strategies: (i) a ten-day event study around the introduction and removal of the flash functionality from the 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. A comparison of various liquidity and activity measures around the flash introduction and removal periods shows that overall market liquidity (measured by quoted and 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.

As a framework for interpreting our results, we suggest that flash orders are similar to *sunshine trades* as modeled by Admati and Pfleiderer (1991), due to the pre-announcement characteristic. Sunshine trading is a strategy whereby a trader preannounces to other traders

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

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. 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. 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.

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-analyses previously described. The results 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. Thus flash orders appear to act as a coordinating mechanism for supply and demand and for the identification of informationless trades, a finding 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 or days), as defined by Admati and Pfleiderer (1991), and flash orders (half 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. As Angel, Harris, and Spatt (2011) point out, the advancement of electronic technology has profoundly altered how exchanges, brokers, and dealers arrange most trades. Trading system performance is measured in milliseconds rather than hours, and high-speed communication networks allow faster coordination and execution of trades among traders and better service to clients. Thus expecting 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 is not unreasonable. Indeed, the main implications of their model align quite well with our results. Our results show that not only are submitters of flash orders uninformed but also that, as postulated in the model, (i) trading costs of announcers are lower when preannouncement takes place than when it does not; (ii) adverse selection costs decrease with pre-announced orders; (iii) market liquidity and price efficiency improve with preannouncement; and (iv) preannouncement affects price volatility.

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 banning the use of flash orders in both U.S. equity and option markets. However, the SEC has not yet banned the use of flash orders, nor has it made 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 may be useful for guiding both the debate and the final decision of the SEC or other European and Asian regulators considering these issues.

This paper proceeds as follows. Section II positions our paper with respect to the existing literature. Section III provides a history and discussion of flash orders. Section IV introduces the data and presents descriptive statistics on flash orders. Section V investigates who submits flash orders and whether they are associated with informed trading. Section VI discusses the results of the relation between flash orders and market quality, while Section VII provides further analysis. Section VIII concludes.

II 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 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

[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.

[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), and Moinas (2006).

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. Pre-announcers 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 pre-announcers 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. In an experimental study, Flood, Huisman, Koedijk, and Mahieu (1999) 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 or availability of information about the limit order book, as an indication of pre-trade transparency, and finds contradictory 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-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, little work focuses 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

[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 of other market participants, who might either provide liquidity or predate them.

[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 the West African Bourse, which operates three times a week, and liken pre-opening orders 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 infrequent and illiquid market.

today's trading environment due to technological advancements: a more active trading culture and market fragmentation that transform the market from one that merely 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 suggestion 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 volume (Anand and Weaver, 2004), but that they obtain 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 use of flash orders and compare their execution quality to that of limit orders. Our analysis shows that order exposure through actionable IOIs, which are more likely to be less informed, attracts trading interest from participants and results in better execution quality. Thus we provide insights into 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, which consequently reduces the cost of capital (Diamond and Verrecchia, 1991; Coller and Yohn, 1997) and facilitates externally financed firm growth (Khurana, Pereira, and Martin, 2006) and that voluntary disclosure of firm specific information allows 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

[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.

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

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. However, 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 21^{st} century and liken IOIs to Craigslist advertisements because they help 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 traders use IOIs is important to better understanding dark pools. Despite its importance, no empirical work exists on IOIs due to data unavailability. Our work provides a detailed illustration of the characteristics, users, and trading strategies related to actionable IOIs. As actionable IOIs are mostly used by algorithmic traders in the NASDAQ, our results also provide some insights into trading strategies used by algorithmic traders.

III Flash Orders: Description, History, and Discussion

A Description

Flash orders, as implemented by the NASDAQ, are actionable IOIs that expose submitted marketable orders at/or improving the NBBO, which is quoted at another trading venue, for a predefined period to only its participants. Therefore, a “flash” order may execute locally at the NBBO or better, while normally it would have been routed for execution to the other exchange offering the NBBO. Orders can only be flashed when a new order message is submitted or an order is updated; thus the same order can be flashed more than once, e.g. at submission and when updated.

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 possible price that would not result in a trade-through on the NASDAQ.

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 following numerical example).[10] 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 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-marketable		
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

B History

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

Flash trading, originally an obscure practice in the options market, was introduced in the equity market on January 27, 2006, by Direct Edge.[12] Direct Edge offered the "enhanced liquidity program, ELP," whereby 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

[10]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.

[11]Regulation NMS, approved by the SEC is a series of initiatives for promoting 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 are executed, cancelled, or withdrawn immediately after communication (less then 500 milliseconds).

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

matched on Direct Edge's book. The ELP order can be routed or canceled if there is still no match, according to the users' instructions.

In response, the NASDAQ and BATS Global Markets (BATS) introduced their own flash programs, where orders are flashed to their members before getting routed to rival platforms, to protect their market share. On June 4, 2009, BATS introduced BATS Optional Liquidity Technology (BOLT), which included an optional display period during which a marketable order could be displayed to its users (and market data recipients) before being routed, canceled, or posted to the BATS book. The NASDAQ introduced Flash Orders on June 5, 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 the AMEX or the Boston Stock Exchange at the time. The NYSE is the only major market center that has not offered any enhanced liquidity provider program or flash-order functionality.[13]

Given the flash trading controversies and political pressure, both the NASDAQ and BATS voluntarily discontinued support for flash orders on September 1, 2009, pending SEC review. 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. To date no decision has been made.

C Discussion and Regulatory Concerns

Since mid-2009, there have 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).[14] The first concern is that "flashing of order information could lead to a two-tiered market in which the public does not have access, through the consolidated quotation data streams, to information about the best available prices for U.S.-listed securities that is available to some market participants through proprietary data feeds." Our data does not allow us to address this concern about the two-tiered market.

[13]The NYSE has vehemently protested against the trading practices of their competitors, especially those related to flash and dark pool trading. The 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 the NYSE to win back market share in the U.S. equity market.

[14]See SEC Release No. 34-60684, File No. S71-21-09, Elimination of Flash Order Exception from Rule 602 of Regulation NMS.

The second concern is that high-speed trading firms may use flash orders, and that flash orders may significantly decrease incentives for market participants, who do not have access or the technology to use flash orders, to display their trading interest publicly. However, the impact of flash orders on liquidity provision is unclear. Manual flash orders have long been practiced on floor-based exchanges, where brokers announce orders to the floor crowd for potential price improvements. Harris and Namvar (2011) highlight that such actions from floor traders, "flash order system on the floor," are to seek additional liquidity from other participants in the exchange. Thus, liquidity might even improve rather than decrease. Flash orders in electronic markets were supposed to replicate this auction market process. This view is supported by the International Security Exchange, which argues that flash orders attract more liquidity by tapping into undisplayed trading interest, from traders concerned about pick-off risk.

Although our analysis cannot differentiate the display of trading interest or liquidity provision for market participants in all the U.S. exchanges, our results show that market quality for all market participants increases with the availability of flash-like functionality. This finding supports the view that flash orders, much like shouting orders on the floor, attract undisplayed trading interests and improve liquidity. Our findings have important policy implications because they provide detailed empirical evidence that might resolve the debate on at least one of the regulatory concerns about flash orders.

IV Data and Descriptive Statistics

A Data

The main data source used in this paper consists of the complete set of quotes and trades in the NASDAQ system for the sample period from April 1 through October 31, 2009. The flash order period covers June 5 through August 31, 2009. The data is obtained from NASDAQ ITCH-TotalView.[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=0), 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

[15] The intra-day data in which flash orders can be identified is available from June 10, 2009.

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 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), for robustness 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.

We employ the complete dataset of new order messages, updates, cancelations, deletions, executions, hidden orders, and crossing-network orders to build the complete limit order book (LOB) message by message for 188 stocks (10% of our sample) following Kavajecz (1999). We randomly select the LOB stocks from portfolios representing different industry, size, book-to-market, and liquidity characteristics. Panels A and B of Table I 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 observations per day. 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.

Panel C of Table I presents the main characteristics of the LOB. The size of executed flash orders is larger than other orders. Following Goldstein and Kavajecz (2000) we calculate the cumulative depth as the sum of all shares available at a particular price or better on the LOB, at successively distant prices. 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 794 shares per tick for the first five levels of the LOB.

To investigate the impact of flash orders on the U.S. equity market quality, we use end-of-day daily data from CRSP. We employ two measures of spread: quoted and relative. 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 return and VOLUME is the daily total dollar volume (in million \$). Markets with lower short-term volatility are deemed more efficient, as high depth at the inner quotes makes the trade prices less

Table I
Sample Characteristics

The table shows the daily and intra-day sample characteristics. *Price* is the stock price in \$, *Volume* is daily trading dollar volume in \$ millions, *Trades* is the daily number of trades in the 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 1, 2009, to October 31, 2009. Panel B presents the statistics for the 188 stocks used for rebuilding the limit order book and used for the intraday analysis. Panel C presents the intra-day characteristics of the limit order book stocks. *Flash Trade Size* is 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* are 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

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. The censoring is particularly important for ILR, which exhibits large outliers when trading volumes are low.

B Descriptive Statistics for Flashed Orders

First, we compare and contrast the usage and execution performance of flash 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. Finally, we perform an intra-day event study in message time around flash events to examine what happens to spreads and depth around flash order submissions and executions on NASDAQ.

Characteristics of flashed orders

Panel A of Figure 1 presents an initial overview of the flash order activity during the flash period. The figure shows the daily total number of 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 on the NASDAQ. Panel B of Figure 1 presents the intra-day variation of flashed orders at 5-minute intervals 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.

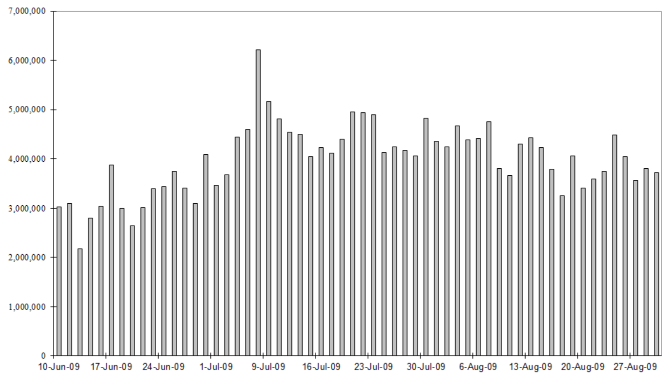
Panel A of Table II presents an overview of the type of orders that are flashed and what happens to these orders. Five percent of all unique orders in the NASDAQ are flashed at least once, and 87% of these are flashed upon initial submission rather than during an update. Fourteen percent of the orders 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 flash orders that are executed to total executed orders is 16%. Even though flash order submissions are a small proportion (5%) of total submitted orders, they constitute a substantial part (16%) of executed orders on the NASDAQ.

To measure execution quality, we compute fill rates for flash and non-flash aggressive limit orders (at or improving the best price). Fill rates are defined as the percentage of original order

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 intra-day variation in flashed orders submissions accumulated at the 5 minute interval.

Panel A: Daily



Panel B: Intraday - 5 minute interval

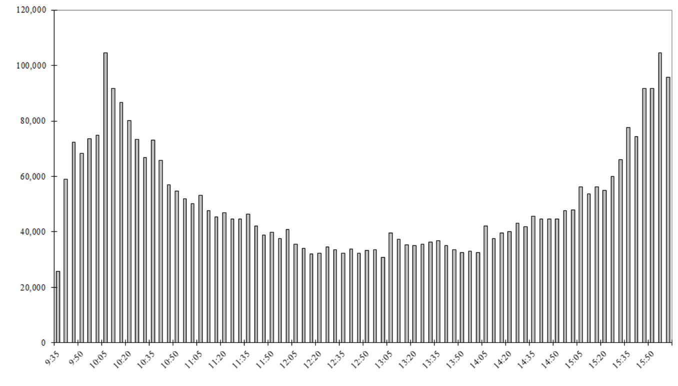


Table II
Order Submission and Execution Quality

The table shows statistics on the daily average number of orders submitted at the NASDAQ and their 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 (*Flash Order Submission*) and orders flashed during an update (*Flash Order Update*). *Flash Order Total* is the total number of orders that are flashed at least once. The average number of daily non-flash orders is *Non-Flash Orders*, and the average total number of daily orders is *Total Orders*. *Flash Order %* 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 into *Flash* and *Non-Flash* 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 executed sometime after entering the LOB. *,**,*** represent significance at the 10, 5, and 1% level, respectively.

Panel A. Order Submissions

	Flash Order Submission	Flash Order Update	Flash Order Total	Non-Flash Orders	Total Orders	Flash Order %
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

volume that is executed (Harris and Hasbrouck, 1996). Panel B of Table II 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-flash aggressive limit orders 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 for 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-flash orders decreased during the flash period. These results indicate that users of flash orders get better execution quality than non-users, and execution quality for non-users deteriorates as in Admati and Pfleiderer (1991).

Panel C of Table II presents statistics on when flash orders are executed. The largest part of executions occurs right after flash orders are entered into the LOB. Of the 516,187 executed flashed orders, 30% 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 of flashed stocks

Table III provides cross-sectional descriptive statistics on various 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. The same stock might be placed in different terciles in different days, as stocks do not have the same number of flashes every day. Panel A of Table III provides statistics based on stocks sorted by the daily number of flash messages. 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 III 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 flashed are also stocks with the highest market capitalization, the highest numbers of trades and traded volume, and the lowest spreads and volatility.[16] 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.

[16]The same results hold when TARP stocks are excluded (see table A3 in the appendix).

Table III
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

Intra-day patterns around flash order submissions and executions

Flash orders are used when the best NASDAQ quotes are at or worse than the NBBO.[17] We first construct the NBBO for the 188 LOB stocks using the TAQ database following Hasbrouck (2010).[18] Then we 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. To examine the status of the NASDAQ spread relative to the NBBO spread at points in time when there is flash activity, we construct a distance measure, the SRATIO, 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, e.g., when SRATIO>0 the NASDAQ spread is greater than the NBBO spread.[19]

We first investigate how the SRATIO changes around new flash order submissions. To do so, we set up an event study around flash order submissions with an event window of 50 messages before and after the submission. Thus the submission of the flash order is centered at message

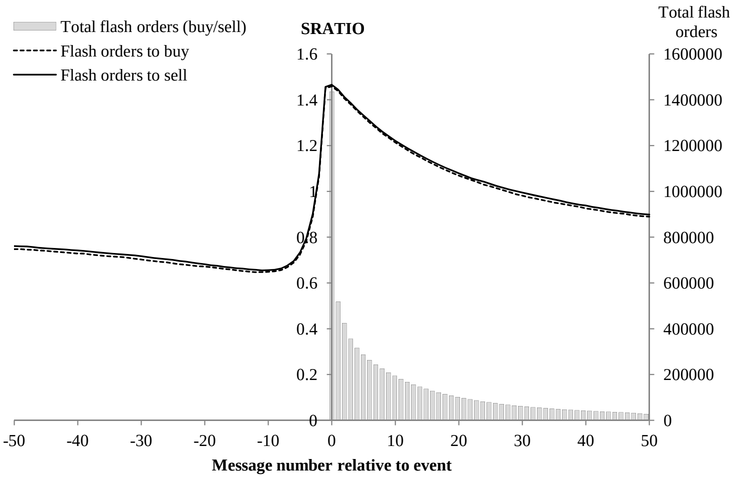
[17] If the volume at the best quotes is low, flash orders that are motivated by liquidity needs may also occur when the NBBO is at the NASDAQ.

[18] TAQ data is reported in one second intervals, and the NASDAQ ITCH data is time stamped at the millisecond. While in TAQ there are quotes from several exchanges at each second, 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.

[19] As the best prevailing NBBO quotes are sampled at the one-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. The average clock time for the event window is 16.5 seconds.

Figure 2
Flash Order Submissions

The figure shows 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).



number 0. Only events in which flash orders are not preceded by other flash orders in the pre-event window are used.[20]

Figure 2 shows the change in the SRATIO surrounding flash order submissions to buy and sell. The bars show the total number of flash submissions (buys+sells) during the event window. Figure 2 shows that the SRATIO increases prior to the flash event at time 0 on the x-axis. The rate of flash order submissions decreases after the initial flash, as the NASDAQ spread moves closer to the NBBO. As long as the NASDAQ quotes are worse than the NBBO, one would expect flash interest. The figure shows a very similar pattern around flash orders to buy and to sell. Overall, there is an improvement in the NASDAQ spreads right after flash orders. Flash orders appear to make the local market more efficient, and reduce the spread at the NASDAQ and the spread gap with the national market.

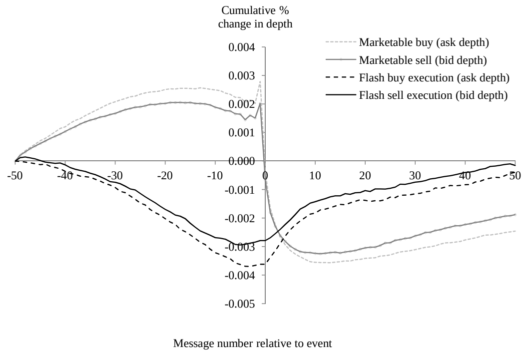
We also examine what happens around flash order executions. We perform a similar event study as before, but instead of conditioning on new flash order submissions, we now condition on flash order executions. As previously discussed, a flash order, because it supplies liquidity,

[20]We also investigate the case when there are no flash orders subsequent to the initial flash order, and the results (available upon request) do not change qualitatively.

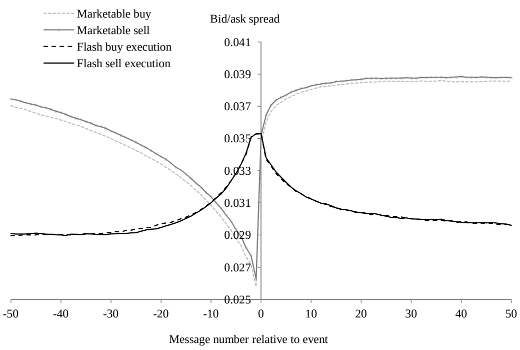
Figure 3
Flash Order versus Marketable Limit Order Executions

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 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 B 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 A: Limit order book depth around market and flash order executions



Panel B: NASDAQ spread around market and flash order executions



is very different from a marketable limit order. We compare 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.

Panel A of Figure 3 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 LOB decreases immediately, whereas when a flash order executes the depth in the LOB is replenished. Panel B of Figure 3 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, consistent with liquidity takers consuming liquidity when the spread is low. 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.

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). The average price improvement that executed flashed orders get, compared to the best prevailing quote in the NASDAQ, is 0.09% both for buys and sells. The improvements after flash order executions are due to competitive liquidity providers posting quote improving limit orders. 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.

V 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 or 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 consider these two types 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 may 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).

Although informed traders have private information about the underlying value of an asset, 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 may also use limit orders if the spread is wide and the 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 the submitter's trading needs and intention, the response by other liquidity suppliers to IOIs depends critically on whether the IOI submitter is perceived to be informed or uninformed. If uninformed liquidity demanders submit actionable IOIs, these IOIs 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 orders because of the potential costs of preannouncement for an informed trader. As flashing an order entails a delay in the execution of the order, this delay cost is likely to be higher for informed traders than for liquidity traders, e.g., because short-lived private information might become common knowledge during the execution delay. Moreover, flashing reveals the private information of informed traders. If other traders acquire information through observing flash orders, the trading profit of informed traders will be severely reduced. However, flashing of trading intentions by uninformed liquidity demanders are unlikely to be front-run.[21]

To understand who uses flash orders and the information content of flash order submitters and their counterparties, we employ different methodologies. First, we examine what type of algorithms employ flash orders in their strategies. We do so by categorizing algorithms into agency and proprietary in the spirit of Hasbrouck and Saar (2010) and by looking at the occurrences of flash orders within each type. Second, we employ three measures for understanding whether flash orders are associated with private information events: 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 adverse selection component for executed trades against flash orders and normal orders, and the permanent price impact of trades against flash orders, as in Hasbrouck (1991).

[21] 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 pre-announcement information. A trader that is willing to buy at the unfavorable price is an impatient liquidity demander, with high demand for immediacy. Thus the front runner is providing a valuable market making service, which is unlikely to be detrimental to pre-announcers in a competitive market, by transferring through time the demand to buy and sell.

A Identifying Flash Order Submitters

As flash orders are actionable only for a maximum of 500 milliseconds, only machines from algorithmic traders 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 such as mutual funds, pension funds, and insurance firms, which submit non-marketable limit orders as part of their strategies. They are normally used for breaking large orders into small portions to be sent to multiple trading venues over time. It is likely that these traders are uninformed. Algorithms that aim to profit from the trading environment are classified as proprietary algorithms (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 submission and cancelation of orders that aim to trigger actions from other algorithms.[22] 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 agency algorithms.

To identify whether flash order submitters are PAs or AAs, we construct runs for flash and non-flash orders. We construct runs in two ways using messages posted in the NASDAQ trade and quote data. Following Hasbrouck and Saar (2010), we link sequences of submissions, cancellations, and executions that are likely to be part of a PA's dynamic strategy. First, we link an individual limit order with its subsequent cancelation or execution using the unique order reference numbers supplied with the data. Second, 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.[23] An *HS* run is the number of messages in a linked cancel-and-resubmit sequence. As Hasbrouck and Saar (2010) point out, such a methodology may introduce some noise into the identification

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

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

of low-latency activity as it is not certain that the subsequent resubmission and execution are linked to the initial individual limit order. However, this methodology is useful for identifying runs during the period when the 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). Our second approach to measuring runs is to use "update" messages, as they serve the same purpose as the cancel-and-resubmit orders that Hasbrouck and Saar (2010) identify. An *Update* run is the number of times an order is updated. We construct it 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. Unlike Hasbrouck and Saar (2010), we are certain that order update sequences and alterations are related to the initial individual limit order that we track. Orders with updates do not exist in the Hasbrouck and Saar (2010) sample.

However, PAs may make use of both mechanisms to fulfill their strategies. Thus Table IV shows the number of runs and the associated messages for flash and non-flash orders for *HS* (Hasbrouck and Saar, 2010) and *Update* runs. One update corresponds to two messages in the HS run (cancel+resubmit), thereby normalizing the number of messages in an update run to be comparable to the HS runs. *Total* is the sum of HS and Update runs, which we can add because they are mutually exclusive by construction. A run is classified as flash, if a flash message is part of the run. We present the monthly runs to be able to compare with the results in Hasbrouck and Saar (2010), who study and report results for two separate months. Given the smaller sample and the smaller size stocks included in our sample, the total number of monthly runs and their message length is comparable to those in Hasbrouck and Saar (2010). The total number of runs is smaller for June because our sample starts only on June 10, 2009.

A run is considered 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 flash order are longer than 10 messages, and this finding is consistent over the different months. Over 7% of non-flash orders are part of runs longer than 10 messages, double the strategic runs in flash orders. The results imply that flash orders are predominantly submitted by agency or buy-side traders.

Table IV
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. A run is a sequence of cancel and resubmit orders or of update orders. 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%	349,850	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	

B Informativeness of Flash Orders

To examine the informativeness of flash orders we apply three standard methods: examining how much trades that execute against flash orders contribute to price changes, measuring the adverse selection component associated with trades that hit flash orders, and estimating the permanent price impact associated with trades against flash orders. All these methods assess the informativeness associated with the initiating party of a trade (i.e., the taker); flash orders, by definition, are the passive party in a trade. Thus these measures capture whether flash order submitters are being picked off by better-informed traders. Alternatively, due to the symmetry of these measures, we can also infer to what degree flash order submitters are systematically better informed than those that hit the flash orders. For example, buyer (seller) initiated trades against flash orders to sell (buy) would systematically experience an adverse price movement subsequent to the trade in the same direction as the flash order to sell (buy). Alternatively, if flash orders are generally not associated with private information events (on either side), we would expect a very small post trade movement, in either direction, after flash order executions.

Weighted price contribution

First we look at the weighted price contribution of flash orders (see Barclay and Warner, 1993). During a 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 $R^j_t = \sum_{n=1}^{N} r^s_{n,t}$.

Results in Panel A of Table V 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 associated with private information when it comes to the daily total change in price.

Table V
Information Content of Flash Orders

The table presents the weighted price index and effective spread decomposition in NASDAQ, for 188 stocks. Panel A 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 B 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 A. 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

Panel B. 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

Spread decomposition

Second, we measure the adverse selection associated with trades against flash orders by decomposing 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. For each stock and day, we use all NASDAQ quotes and trades to calculate the effective spread for each reported transaction. The effective spread and its components are normalized by the number of shares traded in the transaction. We calculate realized spread, $rspread_t^j$, and adverse selection, $adv\_selection_t^j$ as:

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

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 pre-announced trade would get a lower effective spread due to lower adverse selection. Panel B of Table V presents the difference in the mean and median effective and realized spread and adverse selection costs for flash and non-flash orders, aggregated by stock. Executed flash orders exhibit lower effective and realized spreads and lower adverse selection costs than other executed orders, consistent with the Admati and Pfleiderer (1991) model.

Hasbrouck decomposition

Third, we measure the permanent price impact of flash orders by estimating a VAR model for every stock on each date, and produce the impulse response functions based on Hasbrouck (1991). 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.[24] To examine to what degree the information content of executed flash orders is different from regular trades, we estimate the VAR separately for trades against regular limit orders and trades against flash orders. To make better comparisons, we exclude stock-days for which there are no flash orders.

Figure 4 shows 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 orders, 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 is less than or equal to 10 shares, medium if the trade size is between 10 and 100 shares, and large if the trade size is greater than 100 shares.

Panel A of Figure 4 shows the typical Hasbrouck (1991) result that quote revisions are not instantaneous. In addition, the permanent price impact of a trade (at t=20) is on average about five times larger for regular orders than for flash orders. This finding suggests that flash orders are facing less pick-off risk than regular limit orders. Nonetheless, the response function associated with flash orders does not suggest that the traders hitting the flash orders are trading against better-informed traders. Moreover, the results indicate that neither side of flash order trades is adversely selected, consistent with our results that flash orders are not associated with private information events.

Panel B of Figure 4 shows that for a one unit shock, the permanent impact of regular orders regardless of trade size, is much greater than that of flash orders. More importantly, the difference in responses across trade sizes for flash orders is very small.[25]

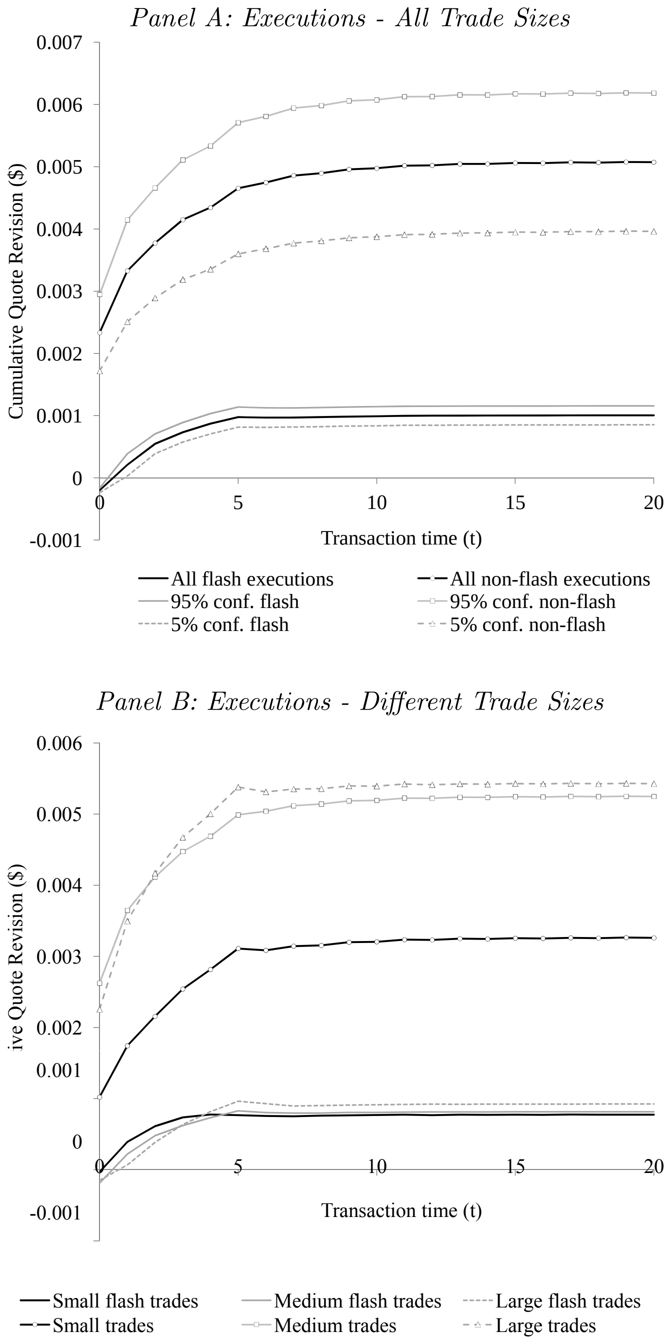
Overall, these results indicate that flash orders are not associated with informed trading. Moreover, while the flash orders seem to face less pick-off risk than regular limit orders, the traders hitting the flash orders do not appear to experience a systematically adverse price movement after the trade. This finding therefore suggests that flashed orders come mainly from uninformed traders, consistent with the Admati and Pfleiderer (1991) model assumptions.

[24]The contemporaneous realization of q_t^j enters the return equation. Thus it assumes that trades precede quote revisions. This assumption is necessary for identification, and it ensures that innovations $v_{1,t}^j$ and $v_{2,t}^j$ 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 are interpreted as related to (unpredictable) informed trading. Thus the permanent response of quote revisions to innovations in the trade equation should capture the adjustments to private information.

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

Figure 4
Quote Revision Process

The figures show the impulse response functions (IRF) associated with executions against regular limit orders and flash orders. The IRFs are the average across dates and stocks. The sample of flash order executions and regular executions is for the same stock and date combinations making 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 5^{th} and 95^{th} 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 between 10 and 100 shares, and large trades as trades greater than 100 shares.



VI Flash Orders and Market Quality

We start the investigation of the impact of flash orders on market quality, 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. To investigate the change in market quality variables caused by flash orders, we use ten-day event windows, five days before and after the introduction and removal of the flash functionality. We chose the ten-day event window 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 May 28-June 4, 2009, the post-introduction period is June 5-11, 2009, the pre-removal period is August 25-31, 2009, and the post removal period is September 1-8, 2009.

Panel A of Table VI 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. Both the quoted and the relative spread decrease by 11% when flash orders are introduced. In addition, short-term volatility decreases (increases) significantly after the introduction (removal) of flash orders.[26] 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 VI shows a significant improvement in liquidity and a reduction in volatility for mid-cap and large stocks. Flash orders appear to have less impact on smaller stocks.[27]

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, (log) market capitalization, dollar trading volume, and the daily volume-weighted average price (VWAP). Results in Panel C of Table VI show that the flash period dummy has a large coefficient and is highly statistically significant. The results indicate that quoted and relative spreads, and

[26] The results for the non-TARP sample confirm the findings (see table A5 in the appendix). The same results also hold when we use the entire market sample, i.e., include all stocks and all types of shares above $5 (see table A6 in the appendix).

[27] 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 flash orders and double sorting by market capitalization and flash orders.

Table VI
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 entire sample of 1867 stocks. Panel A presents the change in the impact on the entire 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. *Price* is the stock price, *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. The coefficients for Volume and VWAP are multiplied by 1,000. All other variables are defined in Table A2. All regressions include a constant (not reported to conserve space). p-values calculated using Thompson (2010) two-way clustered robust standard errors. *,**,*** 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
Flash Dummy	-0.001***	-0.004**	0.002	-0.003***
Log 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***
VWAP	-0.008***	-0.050***	-0.140***	0.017***
Adj. R^2	0.69	0.65	0.21	0.32

volatility decreased substantially during the flash period, confirming the event study results.[28] In further results we also include a dummy variable for days when there are earning announcements and an interaction term between earning announcements and flash orders. The coefficients of both these variables are statistically insignificant.[29]

A linear regression method is causal, if we include all the appropriate control variables, such that the conditional independence assumption holds. Although the results suggest that market quality improves due to flash orders, these findings might be influenced by various unobserved confounding effects at the stock price and size level. We therefore 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.

A Difference-in-Difference Analysis

Matching sample

For the difference-in-difference analysis, we need to construct a matching control group that is not directly affected by flash orders. One potential control group is U.S. stocks not traded on the NASDAQ. However, there were only 10 such stocks during our sample period, too few to constitute a good control sample. An alternative is to use Canadian stocks, represented by the Toronto Stock Exchange (TSE)-listed companies, as our control group. While this control is clearly not perfect, it is a reasonable alternative given the similarity of market 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.[30] One potential concern related to the Canadian match is the relatively low market capitalization of its stocks. In our robustness section, to increase the size of the control group, we also include stocks listed in the London Stock Exchange (LSE) in the

[28] We also replicate these results using TAQ data aggregated at the daily level and find qualitatively similar results. While we use CRSP data for comparison with our match group, TAQ results are available from the authors upon request.

[29] Results are not presented to conserve space, but are available from the authors upon request.

[30] Jorion and Schwartz (1986) and Foerster and Karolyi (1993) find that Canadian stocks have very similar market characteristics in Toronto to those 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 the NYSE specialist between U.S. stocks and cross-listed Canadian stocks.

control group together with the TSE-listed stocks. As they have higher market capitalizations, the LSE-listed stocks are a good alternative to the TSE-listed ones.

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 we did for the CRSP sample. The final control sample includes 481 TSE and 741 LSE stocks.

Propensity score matching

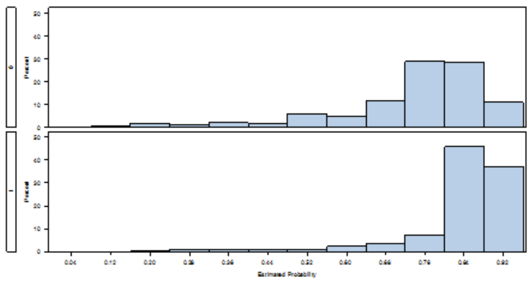
Our matching procedure relies on a matching of propensity scores in the spirit of Rosenbaum and Rubin (1983) and Heckman, Ichimura, and Todd (1998). The matching procedure begins by defining the treatment and control groups, which correspond to the CRSP and the TSE stocks, respectively. Each CRSP stock is matched with a control firm from the TSE that has the closest propensity score. 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 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 VII presents changes in market quality surrounding the introduction and removal of flash orders for the difference between U.S. and Canadian stocks for a ten-day event window. Panel A

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 is in panel 0. The logit regression to estimate the propensity scores is run over the period April 1-June 4, 2009.



of Table VII shows that short-term volatility, quoted and relative spread decrease significantly after the introduction of flash orders, while ILR does not change. With the introduction of flash orders, the quoted and relative spreads in the U.S. decrease by 19 basis points and 3% over the control group, respectively. The average quoted and realized spreads in the U.S. increase by an additional 5.2 basis points and 2.7% 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 the 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 the NASDAQ. We compare the 1820 CRSP sample stocks to the 1820 matched TSE control stocks

[31] The results are robust to using a longer event window of 20 days (see table A9 in the appendix). The magnitude of the decrease, relative to the control group, in quoted and relative spread is even larger over the 20-day window with a decrease of 24 basis points and 5.3% 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.

Table VII
Difference in Difference

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 (TSE) 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 entire 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 CRSP and 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 CRSP and TSE stocks, *Volume Diff.* is the difference in volume between CRSP 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. All regressions include a constant (not reported to conserve space). p-values calculated using Thompson (2010) two-way clustered robust standard errors. *,**,*** represent significance at the 10, 5, and 1% level, respectively.

Panel A. Event Study

	Introduction	Removal
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

	Spread	Rel. Spread	ILR	Volatility
Flash Dummy	-0.002**	-0.016***	-0.011	-0.002***
Log Market Cap.	0.004***	-0.005**	-0.007	0.000
Volume	-0.001	-0.001	-0.007	0.069
VWAP	-0.009**	-0.050***	-0.030	0.018
Adj. R^2	0.56	0.17	0.13	0.23

without flash functionality.

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. μ and ϕ 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 VII shows the full-sample panel regression results. During the flash period, a trader pays 2 basis points less in terms of quoted spread than the control group compared to two months before and after the flash period. A trader pays 1.6% 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 sub-sample in Panel B of Table A9.

We recognize that despite many good reasons for the TSE stocks to be good matches for the U.S.-listed stocks, the number of stocks available for matching from the TSE is limited. Therefore, we use the LSE stocks as an additional control group to the TSE. Table A10 in the Appendix provides the normalized difference between the treatment and control group after matching. This difference is very small, indicating the good match between the two groups. The results in Table A11 are very similar to the earlier results on the TSE match. 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 which methodology we employ.

Table VIII
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-minute 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

B Market Efficiency

Autocorrelation is a measure of market efficiency: the lower the autocorrelation of returns, the more efficient is the market. Like Boehmer and Kelley (2009) and Boehmer, Chava, and Tookes (2010), we calculate intra-day first-order autocorrelation $|AR|$, using 30-minute and 5-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).

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 VIII shows the change in intra-day return autocorrelations at the 5- and 30-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, i.e., autocorrelation becomes less negative, and thus the positive change. The 30-minute return autocorrelation also decreases after the removal of the flash facility, but it does not change at the 5-minute frequency. This finding constitutes additional evidence of the improvement in market efficiency, as posited in the Admati and Pfleiderer (1991) model.

C Summary

Our findings support the hypothesis that flash orders signal 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. The market-wide results of the event study, the regression analysis (with and without a control group), and the difference-in-difference analysis, 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 one possible explanation for these results.

VII Robustness

A Cross Sectional Relation of Flash Orders and Market Quality

Thus far we have carried out a time series analysis on how the introduction and the removal of the flash facility affects market quality in the U.S. through event study, panel regression, and difference-in-difference regression analysis. In this section, we investigate the role of flash orders on liquidity and volatility using cross-sectional analysis for robustness.

If flash orders 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, 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 run a pooled regression for the entire flash sample period.

The results in Panel A of Table A12 in the Appendix show 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 flash orders are associated with greater liquidity and lower volatility. For the control variables, illiquidity decreases with the market capitalization and the trading volume of a stock but increases with volatility. In further analysis we also include a dummy variable for days when there are earning announcements and an interaction term between earning announcements and flash orders.[32] The coefficients of both these variables are statistically insignificant. Results from the pooled regression in Panel B are qualitatively similar. This result is consistent with the conclusions from the time series analysis, suggesting that flash orders improve liquidity and lower volatility.

B Effect of Flash Orders on Pseudo Outcomes

Our final robustness test, pseudo treatment, focuses on estimating the effect of a treatment known not to have an effect. Pseudo treatment is one approach in causal inference for assessing the assumption of unconfoundedness (see Heckman, Ichimura, and Todd, 1998). We estimate a "pseudo" average treatment effect by analyzing two control groups as if one of them were the treatment group. In particular, we construct a sample of pseudo events drawn from the non-flash period, two months pre- and post-flash period. We use a longer sample period than in the main analysis, because we want to have more observations for our statistical inference and to ensure non-overlap with the event study in Section VI. We test for the null hypothesis that the treatment effect of the pseudo event studies on our variables of interest, V, is not different from the event (flash) study. As in the event study in the earlier section, our variables of interest, V, are quoted and relative spread, ILR, and return volatility. We consider each day, from February 6 to May 8, 2009, and from September 29 to December 31, 2009, as a pseudo event date, for the pre- and post-flash period, respectively.

For each pseudo event date, we construct the mean and the median of our variables of interest for 5 days before and after the pseudo event date. As with the event study we carried out for the flash period, we then create the difference in the pre- and post-period for these pseudo events. For the pre-flash pseudo events from February 6 to May 8, 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 to December 31, 2009, and calculate the percentage change in means and medians, and call this change $Removal_j^{pseudo}$. Panel A of Table A13 in the Appendix shows the

[32] Results are not presented to conserve space but are available from the authors upon request.

mean and median change across the pre- and post-event periods, as for the flash period in Table VI. Differently from the flash period, all means and medians are statistically not different from zero, with the exception of the relative spread mean in the introduction period.

We test for the difference of the treatment effect of the pseudo events from the actual event by taking the difference between *Introduction* for the flash and pseudo event for each pseudo event day i ($Introduction^{flash} - Introduction_i^{pseudo}$). We do the same for *Removal* and test whether 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, 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.

VIII Conclusions and Discussion

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. The signaling 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 is 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.. Both our analysis and our results help explain the impact and implications of similar competition-enhancing mechanisms that might also be used by dark pools, such as Getco and Knight Link, which are establishing new trading venues in Europe and Asia. Nonetheless, further research in the U.S. option market, where flash orders are still widely used, would be useful. Furthermore, our results inform future decisions on market design and transparency.

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; 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 for 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 entire 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 CRSP and the Toronto Stock Exchange (TSE) 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 entire 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 CRSP and 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 CRSP and TSE stocks, *Volume Diff.* is the difference in volume between CRSP 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. All regressions include a constant, not reported to conserve space. *p*-values calculated using Thompson (2010) two-way clustered robust standard errors. *,**,*** 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	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. All regressions include a constant, not reported to conserve space. p-values calculated using Thompson (2010) two-way clustered robust standard errors. *,**,*** represent significance at the 10, 5, and 1% level, respectively.

	Spread	Rel. Spread	ILR	Volatility
Flash Dummy	-0.005***	-0.014***	-0.020***	-0.002***
Log Market Cap.	0.035***	-0.076***	-0.260***	-0.007***
Volume	-0.007	-0.006	0.118***	0.032***
VWAP	-0.003***	-0.070***	-0.080***	0.025***
Adj. R^2	0.52	0.44	0.20	0.28

Table A12
Cross-sectional Effect of 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-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 log price, and *lag DV* is the lagged dependent variable. The rest of the variables are defined in Table A2 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 57 periods and report the significance level based on Newey-West standard errors. All regressions include a constant, not reported to conserve space. *,**,*** 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 6-May 8, 2009 and the post-flash pseudo event period, from September 29-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 VI. 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 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 VI, $(Introduction^{flash} - Introduction_i^{pseudo})$. 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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