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Order Execution Quality in Equity Options Markets

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ABSTRACT

In Part 1, we examine the effects of an order cancellation fee on limit order behavior and execution quality on the NASDAQ OMX PHLX. We find that the cancellation fee is effective in reducing the rate at which limit orders are submitted and subsequently deleted. Order volume declines, however, the remaining displayed orders appear to constitute more genuine liquidity, as the duration of canceled orders lengthens. The reduction in order cancellation activity is associated with lower effective spreads and higher order fill rates. We also find that differences in trading venues and option characteristics are important determinants of order cancellations in options markets. Overall, our results suggest that reducing excessive order cancellation activity may improve the quality of liquidity provision and, consequently, enhance order execution quality. In Part 2, we examine if the priority rules, such as price-time or pro-rata, which govern the order matching process on an exchange, affect limit order quality and transaction outcomes. Our multivariate tests show that the probability of execution is higher in the price-time model, while time-to-execution is significantly shorter in the pro-rata model. We also provide evidence that traders risk overtrading in the pro-rata model by submitting large order sizes to achieve a desire fill amount and then cancel the remaining contracts. In Part 3, we examine the impact of option quote stuffing and trading spikes on market quality. We find that quote stuffing and trading spikes in U.S. equity options are more frequently observed on exchanges using price-time priority, relative to exchanges using pro-rata priority. Our multivariate analysis shows that quote stuffing reduces the probability of execution and lengthens the time-to-execution on option orders. We also find that both quote stuffing and trading spikes are associated with transitory frictions in option order execution prices. In addition, we find that bid-ask spreads in the underlying securities increase, with a one-minute lag, around option quote stuffing episodes. Overall, our analysis provides evidence that quote stuffing and trade spikes reduce both liquidity and order execution quality in securities markets.

DEDICATION

This dissertation is dedicated to my wife and two children, who encouraged and supported me through this process.

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PART 1

INTRODUCTION

Limit orders play a pivotal role in both equities and options markets (Berkman, 1996 and Chung, Van Ness, and Van Ness, 1999). The traditional view is that limit order traders patiently supply liquidity (Seppi, 1997 and Foucault, Kadan, and Kandel, 2005). This perspective often characterizes limit order traders as functional equivalents to dealers, who are modeled as risk-neutral liquidity providers, and are indifferent as to whether or not their orders execute.[1] Hasbrouck and Saar (2009) question this view of limit order traders as patient providers of liquidity, as they find that nearly one-third of all nonmarketable limit orders in equity securities on NASDAQ are canceled within two seconds of submission.[2] Excessive order cancellation activity also occurs in options markets, as the quotes for SPY options exceeded one billion on June 5, 2013, nearly 15 times greater than on the day of the flash crash, with a quote-to-trade ratio of 11,254.[3]

Technology has changed financial markets, altering the behavior of limit order traders.[4] High-speed computerized trading strategies, and electronic order-driven trading platforms, enable limit order traders to better monitor their orders and make faster, more accurate decisions.[5]

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[1] See Copeland and Galai (1983), Glosten and Milgrom (1985), and Easley and O'Hara (1987) for the modeling of dealers as risk-neutral traders subject to adverse selection. Glosten (1994) and Sandas (2001) model limit order books in a similar fashion.

[2] The U.S. Securities and Exchange Commission (SEC) documents that over 96 percent of orders placed in the equities market in the second quarter of 2013 are canceled (See "Trade to Order Volume Ratios" market structure research from the U.S. SEC released on October 9, 2013).

[3] See the research analysis posted by Nanex, LLC at http://www.nanex.net/aqck2/4308.html

[4] See O'Hara (2015) for a discussion on how technology has changed financial markets and Boehmer, Saar, and Yu (2005) for a review of the literature on the evolution of limit order trading strategies.

[5] See Goldstein, Kumar, and Graves (2014) for a brief overview of the evolution of computerized trading.

Trading in financial markets has entered the nanosecond age, where liquidity is added and subtracted in billionths of a second. The increase in trading speed coincides with an explosion in order cancellation activity (Hasbrouck and Saar, 2009, 2013).[6] Therefore, technology and computerized trading has ultimately changed the way liquidity is supplied and demanded, raising concerns about the effect of excessive order cancellations on the trading welfare of market participants.

The issue of traders who cancel a lot of their orders has drawn significant attention from the popular press, regulators, and exchange officials, each of whom propose potential solutions. For instance, former U.S. Democratic presidential candidate Hillary Clinton proposes a tax on high-frequency trading (HFT), targeting securities transactions with excessive levels of order cancellations, under the presumption that such trading strategies are abusive and detrimental to financial markets.[7] In response to the flash crash on May 6, 2010, the Commodity Futures Trading Commission (CFTC) and the U.S. SEC recommend a uniform fee across all exchanges to fairly allocate the costs imposed by high levels of order cancellations.[8] Exchange officials also believe that curbing excessive order cancellations will improve trading for their market participants. For example, The NASDAQ proposed a "minimum life" order type on the NASDAQ OMX PSX (PSX) equities exchange, with the intent on encouraging longer-lived limit orders (Jones, 2013). In the purpose section of the proposed rule change (see SEC Release No. 34-65610), the exchange states:

[6] Wall Street's Need for Trading Speed: The Nanosecond Age. *The Wall Street Journal*, June 14, 2011.
[7] The HFT-specific aspects of the broad proposals for the financial system provided by Hillary Clinton in an op-ed piece in The New York Times on December 7, 2015 entitled, "How I'd Rein in Wall Street."
[8] Recommendations Regarding Regulatory Responses to the Market Events of May 6, 2010: Summary Report of the Joint CFTC-SEC Advisory Committee on Emerging Regulatory Issues, page 11.

"Today's cash equities markets are characterized by high levels of automation and speed… In such an environment, the degree to which displayed orders reflect committed trading sentiment has become less predictable, because many entered orders are rapidly canceled. Market participants that seek to interact with orders that are canceled before they can execute may ultimately achieve less favorable executions than would have been the case if the order had not canceled."

The primary purpose of this study is to examine the effect of an order cancellation fee on the NASDAQ OMX PHLX (PHLX) on limit order trading and execution quality. Since the PHLX is one of few U.S. exchanges to enforce an order cancellation fee, our analysis has important policy implications. To the extent the rule change improves execution quality, then competing options exchanges with similar market structures may consider enforcing an order cancellation fee. However, if the rule change is associated with deteriorating execution quality, then our results might discourage trading venues from adopting a cancellation fee. Since trading in options is shown to contribute to price discovery in the underlying equities markets, the results of this paper may also apply to equities.[9]

On August 18, 2010, the PHLX filed a proposal with the U.S. SEC to assess a cancellation fee on electronically delivered all-or-none (AON) orders submitted by professional traders. The purpose and statutory section of the rule filing (see SEC Release No. 34-62744, page 2) states:

"The Exchange has observed that the number of canceled professional AON orders greatly exceeds the normal order cancellation activity on the Exchange for all other order types, and thus affects the automated order handling capacity of the Exchange's systems… The Exchange believes that the proposed amendments are reasonable because they will ease

[9] See Manaster and Rendleman (1982), Easley, O'Hara, and Srinivas (1998), and Chakravarty, Gulen, and Mayhew (2004) for a review of the finance literature on informed trading in stock and option markets.

system congestion and allow the Exchange to recover costs associated with excessive order cancellation activity."

The change in fee policy serves as a natural environment to test our research questions. First, we examine the overall effectiveness of an order cancellation fee in reducing the level of cancellation activity on the PHLX. In our difference-in-difference regressions, we find that that the average order cancellation rate declines by 26 percentage points more on the PHLX than on the NOM from the pre-fee period to the post-fee period. The cancellation fee is associated with decreased order volume on the PHLX, however, the displayed limit orders that remain on the book appear to constitute more genuine liquidity (Friedrich and Payne, 2015). For instance, we find that the order cancellation fee increases the duration, or time between order submission and cancellation, of resting limit orders. Therefore, market participants might be less concerned with "fake depth," as orders appear less likely to disappear before they are traded against (Angel, 2014). The increase in firm orders on the PHLX book seems to improve several aspects of execution quality.

The probability of order execution is 16.3 percentage points higher on the PHLX that on the Nasdaq Options Market (NOM) in the post-fee period, relative to the pre-fee period.[10] Therefore, limit order traders face less non-execution risk (Liu, 2009), which might increase their end-of-period wealth (Colliard and Foucault, 2012). Holding constant known determinants of trading costs, we find that effective spreads are 20 bps lower on the PHLX following the implementation of the cancellation fee, which suggests that reducing excessive order cancellation activity improves execution quality by lowering transaction costs. We also examine the relation

[10] In Table A.2 we separate order volume into marketable and nonmarketable. Consistent with Battalio, Corwin, and Jennings (2016), we find that the improvement in order fill rates is at least partially attributable to an increase in the arrival rate of marketable orders.

between cancellation activity and order fill speeds. In our difference in difference analysis, we do not find significant evidence that the change in cancellation fee significantly impacts order execution speeds.

In the last section of this paper, we attempt to identify the determinants of order cancellations in options markets. Specifically, we study how order cancellation activity varies by option type (call or put), option moneyness, time-to-expiration, and across trading venues. We find that order cancellation rates are 1.84 percentage points higher for put options, relative to call options. We also show that order cancellation rates increase as an option becomes more in-the-money. Order cancellation activity is significantly higher on option expiration days than on non-expiration days. Interestingly, the probability of an order cancellation is roughly 32 percentage points lower on the PHLX, relative to the NOM. This differential in order cancellations can be partially explained by the differences in order volume, order size, and order duration.

Policy-makers and exchange officials seem to believe that there must be something duplicitous in the submission of numerous orders that are almost immediately canceled (see Friederich and Payne, 2015). Since exchange officials in both options and equities markets are addressing the problems associated with excessive limit order cancellations, our study has important policy implications. The benefits of reducing excessive order cancellation activity on the PHLX seem to outweigh the costs, in terms of order execution quality.

PHLX ORDER CANCELLATION FEE POLICY

Effective August 18, 2010, the PHLX updated its cancellation fee policy to include a $1.10 per order charge on each canceled electronically delivered all-or-none (AON) order submitted by a professional trader, in excess of the total number of orders submitted and executed by the "professional" in a given month.[11] The order cancellation fee is only assessed in a month in which more than 500 electronically delivered orders are submitted and canceled by the same professional. The term professional refers to any person or entity that (1) is not a broker or dealer, and (2) submits more than 390 orders in listed options per day on average during a calendar month. An AON order is a limit order that executes in entirety or not at all. Electronic orders are delivered through the Exchange's options trading platform. The rule change applies to professional order flow only, however, the implications of such a fee change can affect all market participants on the exchange, as professionals both supply and demand liquidity in significant volume.

Since the majority of price changes on an exchange are made on monthly intervals, it is a rare occurrence for a fee change to publish and become effective mid-month. The data seems to suggest that the "true" effective date was closer to the end of August, 2010. It could be that firms simply assumed that the change would go into effect the following month, similar to other price changes. Alternatively, the exchange calculates the 500 order threshold in a particular calendar month and then assesses the per order fee. Therefore, the fees for August would not be calculated

[11] See the NASDAQ Options Trader Alert #2010 – 53 for a more detailed description of the updates to the cancellation fee assessment criteria effective August 18, 2010. See also the SEC Release No. 34-62744 for the notice of filing and immediate effectiveness of the proposed rule change relating to the cancellation fee.

until the end of the month, which could have possibly delayed the reaction of traders to the new pricing policy. We use August 30^{th}, 2010 as the effective date in our pre-versus-post analyses.

HYPOTHESIS DEVELOPMENT

Limit orders play an important role in establishing the national best bid and offer in financial markets. Chung, Van Ness, and Van Ness (1999) examine the role of limit orders in equities on the NYSE in the 1990's when the market had both specialists and limit-order traders establishing prices, and find that a majority of the quotes that make up the NBBO originate from the limit order book. The conventional view of limit order traders, is that they patiently supply liquidity (see Seppi, 1997 and Foucault, Kadan, and Kandel, 2005). Foucault, Kadan, and Kandel develop a dynamic model of a limit order market, and show that in equilibrium, patient traders submit limit orders while impatient traders submit marketable orders.

However, a feature of modern equity markets is that submitting orders and quickly canceling those orders is common and frequent. For instance, Hasbrouck and Saar (2009) investigate trading of 100 NASDAQ-listed equity securities on its INET platform, an electronic communications network organized as a limit order book, and find that over 35% of limit orders are canceled within two seconds of submission. Hasbrouck and Saar find that traders implement "fleeting order" strategies to chase market prices or to search for latent liquidity.[12] Ellul, Holden, Jain, and Jennings (2007) analyze a sample of NYSE securities during January of 2001, and document that over one-third of all order submissions are eventually canceled prior to execution. Van Ness, Van Ness, and Watson (2015) provide a time-trend analysis of cancellation activity in

[12] Baruch and Glosten (2013) also examine fleeting orders, orders that are submitted and canceled within two seconds, and find that traders manage the risk of getting undercut while sitting on the limit order book by quickly canceling their limit orders.

the equity markets and find that order cancellation rates are increasing over time, starting at 35% in 2001, and reaching around 90% in 2010.

Liu (2009) contends that advancements in technology, and the transition of exchanges to electronic trading venues are convenient explanations for the high level of cancellation rates in the current marketplace (see also Goldstein, Kumar, and Graves, 2014). In fact, Boehmer, Saar and Yu (2005) show that cancellation activity increases following the introduction of NYSE OpenBook, which lowered trading latency. There are also more nefarious explanations for the excessive order cancellation rates observed in financial markets. For example, there is evidence of order spoofing, in which large limit orders are entered far away from the bid-ask to create an illusion of demand, and are subsequently canceled.[13] Lee, Eom, and Park (2013) show that traders in the Korea Exchange (KRX) strategically place orders with little chance of execution with the intent on misleading other market participants into thinking an order book imbalance exists, and capitalizing on subsequent price movements.

Order execution quality is important for all market participants. Since limit orders impact both the supply of and demand for liquidity (see Chung, Van Ness, and Van Ness, 1999), it is important to understand the effect of order cancellation activity on execution quality.

Canceling limit orders does not necessarily have adverse effects on order execution quality. In fact, limit order traders mitigate non-execution risk by quickly canceling their orders and resubmitting new orders at prevailing bid and ask quotes (Liu, 2009). In addition, market makers must continuously offer to buy and sell securities, which requires close monitoring of their inventory positions. In current high-speed markets, high cancellation rates might simply be a result

[13] Navinder Singh Sarao was imprisoned in 2010 for creating a spoofing algorithm trading E-mini S&P 500 future contracts, suspiciously close to the May 6, 2010 flash crash. The day-trader allegedly canceled more than 99 percent of orders being submitted. In addition, on October 8, 2015 the Securities Exchange Commission (Sec) settled spoofing charges with Briargate Trading for over $1 million.

of the way the liquidity provision game is played (Baruch and Glosten, 2013). Suppose that a market maker places an order to buy 100 shares for ACME common stock for $49.99, and contemporaneously places a sell order for 100 shares for the same stock at $50.01. If someone decides to buy 100 shares at $50.01, then the market maker will cancel the sell order at $49.99 and enter a new buy order at $50.00 and a new sell order at $50.02. Again, if someone decides to buy 100 shares at $50.02, then the market maker will cancel the sell order at $50.00 and adjust it upward. This simple example generates an order strategy whereby 50% of the orders are canceled without ever executing. However, since limit orders are being canceled and resubmitted in response to shifts in supply and demand, there is no reason to believe that this strategy is harmful to execution quality.

If, however, order cancellations reduce the supply of liquidity, as is the case when orders are canceled and not resubmitted, then cancellation activity may have a negative impact on execution quality. Market participants who seek to interact with orders that are canceled before their order arrives, may achieve less favorable executions. Yeo (2005) examines the set of actions available to limit order traders following an order cancellation: complete withdrawal, resubmission of a marketable order, or resubmission of a more aggressive limit order. Yeo (2005) finds that in most cases, limit order traders completely withdraw from trading after canceling a limit order, thereby reducing liquidity provisions. Thus, it is not surprising that the issue of traders who cancel a lot of their orders has received significant attention and debate. Regulatory agencies, such as the U.S. SEC, recommend a minimum duration on limit orders and/or fees on order cancellations.[14]

[14] See page 47 of the January 14, 2010 SEC CFTC Concept Release on Equity Market Structure. SEC and CFTC report on February 18, 2011, a discussion about a uniform cancellation fee across all exchange markets. See also SEC May Ticket Speeding Traders: High-Frequency Firms Face Fees on Canceled Transactions. *The Wall Street Journal*, February 23, 2012.

For example, former U.S. SEC Chairwoman Mary Schapiro in an address given on September 7, 2010, states:

> *"A type of trading practice that has received recent attention involves submitting large volumes of orders into the markets, most of which are canceled… There may, of course, be justifiable explanations for many canceled orders to reflect changing market conditions… But we also must understand the impact this activity has on price discovery, capital formation and the capital markets more generally, and consider whether additional steps such as registration and trading requirements are needed to foster – not undermine – fair and orderly markets."* [15]

Exchange officials on the PHLX acknowledge the costs associated with excessive order cancellations. Consequently, the exchange enforces an order cancellation fee to help monitor trading practices with high levels of order submissions and cancellations.[16] The primary purpose of the cancellation fee is to reduce the number of canceled orders and improve the trading environment for all market participants. A cancellation fee might discourage traders from implementing aggressive price-chasing order strategies that require numerous order revisions (see Hasbrouck and Saar, 2009). If so, the rate at which orders are canceled might decline and displayed limit orders might remain standing on the order book for a longer period of time. We begin by examining whether the enforcement of a cancellation fee reduces order cancellation activity on the PHLX exchange.

Hypothesis 1a: The probability of order cancellation is lower with the enforcement of a cancellation fee policy on the PHLX.

[15] Speech by SEC Chairman: "Strengthening Our Equity Market Structure" by Mary L. Schapiro on September 7, 2010.

[16] On the CHX, a $0.01 per order cancellation fee is assessed if a trader surpasses set criteria laid out in the fee schedule.

Traders can be made better off ex ante if the order cancellation fee increases the probability of completing a trade, as the welfare of traders depends on the non-execution risk faced by liquidity suppliers (Colliard and Foucault, 2012). Since limit orders are stored in the order book and do not demand immediacy, the execution of a limit order is not guaranteed (Hollifield, Miller, and Sandas, 1996; Foucault, 1999; and Peterson and Sirri, 2002). The probability that an order is filled may depend on a number of factors including prevailing market conditions, stock characteristics, and exchange fee structures (see Colliard and Foucault, 2012 and Brolley and Malinova, 2013). Battalio, Corwin, and Jennings (2016) document that take fees, which are assessed on marketable orders accessing liquidity, can reduce the arrival rate of marketable orders and, consequently, negatively affect order execution quality. In contrast, a cancellation fee might induce liquidity suppliers to post 'firm' orders (Angel, 2014), giving traders more confidence in the displayed depth, which can increase marketable order arrival rates. Since order fill rates depend on the arrival of marketable orders and the stock of standing limit orders, and we anticipate, a priori, an increase in marketable orders and an increase in 'firm' limit orders post cancellation fee, we expect the following hypothesis to hold.

Hypothesis 1b: The probability of order execution is higher with the enforcement of a cancellation fee policy on the PHLX.

Limit orders are not only exposed to the risk of non-execution, but also to the uncertainty in time-to-execution. Speed of order execution has grown in importance since the proliferation of automated and computerized trading (see Boehmer, 2005). In fact, Boehmer, Jennings, and Wei (2007) show that exchanges receive more order flow when execution speeds increase. Time-to-execution is a random function of several variables including order price, order size, and market conditions (Lo, MacKinlay, and Zhang, 2002).

We examine if a cancellation fee impacts time-to-completion. Prior to the fee change, traders could cancel innumerous orders without penalty. Hence, many submitted orders may lack committed trading sentiment. In fact, traders have been shown to intentionally flood markets with order submissions and cancellations in an attempt to create arbitrage opportunities (Egginton, Van Ness, and Van Ness, 2015; and Biais and Woolley, 2011). For example, the NASDAQ disciplined Citadel Securities LLC on June 16, 2014 for sending millions of orders to the exchange with few or no executions.[17]

A cancellation fee might encourage traders to display orders that reflect committed trading sentiment, because there is a potential cost associated with submitting frivolous orders. Consequently, traders may be more willing to submit marketable orders, quickening the speed with which a liquidity-supplying trader finds a ready counterparty (Battalio, Corwin, and Jennings, 2016), which motivates our second testable hypothesis.

Hypothesis 2: Order fill speeds are faster following the enforcement of the cancellation fee policy.

Features unique to the options market give rise to several interesting questions with regards to order cancellations. First, options are negotiable contracts in which investors have the right, but not the obligation, to trade securities at a predetermined price, within a certain period of time. A call option gives the buyer the option to purchase, while a put option gives the buyer the option to sell. In this study, we examine if cancellation activity differs between puts and calls.

Trading volume for equity options is generally higher for calls, relative to puts (see Pan and Poteshman, 2006). In fact, the average put/call ratio for equity options volume on the PHLX

[17] See the letter of acceptance, waiver and consent no. 20100223345-02 posted on June 16, 2014, page 6. On February 13, 2014 between 13:32:53:029 and 13:33:00:998 Citadel transmitted over 65,000 orders for 100 shares per order to buy Penn National Gaming, Inc. with zero executions.

has historically remained below one.[18] Biais and Weill (2009) develop a model showing that as the market approaches continuous trading, order cancellations increase monotonically. Therefore, as trading volume increases, so does order cancellation activity. Since trading volume is typically higher for calls than for puts, we might expect cancellation rates to be higher for calls compared to puts.

On the contrary, research also shows that trading costs, approximated by bid-ask spreads, are higher for call options than for put options. For instance, Battalio, Shkilko, and Van Ness (2016) find that effective spreads are higher for call options than for put options, in an analysis of eight option exchanges. Liu (2009) develops a model that predicts a negative relation between cancellation activity and spreads. Liu argues that as spreads widen, the marginal benefit of monitoring limit orders declines, thereby decreasing cancellation activity. To the extent that spreads are higher for calls than for puts, and spreads are inversely related with cancellation activity, we expect order cancellation rates to be higher for puts than for calls. This leads to our third testable hypothesis.

Hypothesis 3: Cancellation rates are higher for put options, relative to call options.

Second, the value of an option contract if it were exercised immediately (i.e. intrinsic value) is often determined by the difference between the underlying stock price and the option strike price. Option contracts are often separated into moneyness categories: at-the-money, in-the-money, and out-of-the-money. If the strike price for a call option is less (greater) than the underlying stock price, then the option is in-the-money (out-of-the-money). The opposite is true for put options. If the strike price is equal to the underlying stock price, then the option is at-the-money. In this study, we examine how cancellation activity differs by option moneyness.

[18] Historical options data, including put-call ratios, for each option exchange are available at the following website: http://www.optionsclearing.com/webapps/put-call-ratio

Lakonishok, Lee, Pearson, and Poteshman (2007) show that open volume in equity options, for both puts and calls, is concentrated in near-the-money options. In addition, volatility is shown to increase as options becomes more in-the-money (Rubinstein, 1994 and Jackwerth and Rubinstein, 1996). Since both trading volume and volatility are shown to have positive relations with order cancellation activity (see Biais and Weill, 2009 and Van Ness, Van Ness, and Watson, 2015), and option volume and volatility are greater for in-the-money options, we expect order cancellation rates to be higher for in-the-money options, relative to out-of-the-money options. This leads to our fourth testable hypothesis.

Hypothesis 4: Order cancellation rates are higher for options in-the-money, relative to options out-of-the-money.

Third, equity option contracts expire on the third Friday of every month. Research shows that both trading volume and volatility increase on and around option expiration days (see Stoll and Whaley, 1987 and Stephan and Whaley, 1990). For example, Day and Lewis (1988) provide evidence that market volatility is increasing around expiration days in index futures contracts. Large (2004) predicts a positive relation between order cancellation activity and market uncertainty. Since market volatility is increasing, it seems reasonable to assume that market uncertainty is also increasing. Therefore, we might expect to find an influx of canceled orders on option expiration days, as traders are less certain about the committed trading sentiment of displayed orders.

In addition, arbitrageurs and market makers often unwind positions around expiration days, forcing them to submit and cancel a large amount of orders as they move in and out of positions (see Ni, Pearson, and Poteshman, 2005). As option traders attempt to rebalance, a natural consequence might be an increase in both limit order submissions and cancellations. Therefore, we expect the following hypothesis to hold.

Hypothesis 5: Order cancellation rates are higher on expiration days, relative to non-expiration days.

DATA DESCRIPTION

The NASDAQ OMX PHLX market data feed provides the current state of simple and complex orders on the PHLX book. This includes nanosecond information on orders added and changes made to orders to option series on the PHLX limit order book.[19] The PHLX reports a simple order message when a single order is received or any change is made to an order. "Simple order" messages include the following fields: nanosecond time stamp, day-unique order id, market side (buy or sell), underlying security symbol, expiration date, explicit strike price, option type (call or put), original order volume, executable order volume (can increase or decrease as the size available for trading changes due to away exchange routing), order status (open, filled, or canceled), limit price, time in force (day order or good till canceled), and customer/firm identifier (customer, firm, market maker, broker/dealer, or professional). We eliminate orders reported before 9:45 a.m. and after 3:50 p.m. from our sample because the opening and closing rotations impede option series from trading freely. Complex orders, such as spreads and straddles, are priced as a package, so we remove them from the sample.

In an attempt to control for unobserved macroeconomic trends that might affect order behavior and execution quality, we obtain order level data for a competing exchange, the NASDAQ Options Market (NOM). The NASDAQ Historical TotalView-ITCH to Trade Options (ITTO) is a direct data feed that provides millisecond view of simple equity options on the NASDAQ Options Exchange (NOM). This includes orders added and changes made to orders

[19] An option series is defined as a particular underlying stock, call or put, strike price, and expiration date.

resting on the NOM limit order book. We download several different types of messages that are linked by a unique order reference number. “Add order” messages are time stamped records for new orders added to the book, including order time (stamped to the millisecond), market side (buy or sell), order size (# of contracts), option type (call or put), expiration date, explicit strike price, and order price. “Executed order” modification messages are time stamped records generated by (partial) executions and report executed contracts and execution price (when the execution price differs from the add order price).[20] “Order cancel” messages are time stamped records generated by partial cancellations and report the number of contracts canceled. “Replace” messages are time stamped records that report the new order reference number, new order price, and new order size. “Delete” messages are time stamped records that report when an order is deleted from the NOM order book.

We focus on a 56-day sample period from July 26, 2010 to October 15, 2010. The initial sample consists of 2,249 option classes and 139,525 option series.[21] To concentrate on the most active options, we exclude classes with less than one filled order each day, which reduces the sample to 296 option classes and 53,495 option series. We then exclude option series with fewer than five orders in a day, which reduces the sample to 25,727 option series on 296 underlying assets. We merge these data with closing prices and shares outstanding from the Center for Research in Security Prices (CRSP), and retain options on common stocks and ETFs. To ensure accurate comparisons among exchanges, we conduct a daily match between options series originating on the PHLX with those originating on the NOM by option series.

[20] Since the analysis involves examining execution quality around extreme quote stuffing episodes and trade spikes, we ignore “trade” messages that report executions involving non-displayed order types.

[21] A single underlying stock will have both puts and calls with perhaps ten or more strike prices and five expiration dates, giving a total of 100 option series per stock.

As part of the analysis investigates how an order cancellation fee affects execution quality, we obtain price and volume information on trades and on current bids and offers from a data technology company LiveVol. Options exchanges report both trade and quote data to the Options Price Reporting Authority (OPRA) and LiveVol creates historical data files that include trade price and size, the exchange (eight trading venues during our sample period) where the trade prints, the NBBO quote and depth, the underlying bid and ask, implied volatility, and calculated delta. We follow Battalio, Hatch, and Jennings (2004) and combine multiple executions in the same option series, executing on the same exchange at the same price at the same time with the same trade condition identifier into a single trade. We also eliminate NBBOs that are either locked or crossed (see Battalio, Shkilko, and Van Ness, 2016). After merging our order data with the OPRA files we are left with 8,908 unique option series on 133 underlying assets. Due to data corruption issues in the OPRA feed, we drop August 13th, August 19th, and September 2nd. We find that our final sample accounts for around 50% of total order volume on the PHLX over our sample time period.

Table 2 shows the distribution of trading activity among the eight option trading venues. The Chicago Board Options Exchange (CBOE) is the most dominant exchange, executing 23.5% of trades for 25.7% of trade volume. The PHLX has the second highest market share, accounting for 25% of volume. The sample exchanges, PHLX and NOM, execute roughly a quarter of all trades for just under 30% of trade volume. In addition, we find that the 113 option classes (8,908 option series) examined in this study account for 40% of all trade volume across the eight option exchanges during our sample period.

EMPIRICAL RESULTS

ORDER CANCELLATIONS AND EXECUTION QUALITY

The costs associated with excessive order cancellations has forced exchange officials to take corrective action. Hence, the primary purpose of the cancellation fee policy on the PHLX is to discourage traders from submitting frivolous orders that are immediately canceled. The exchange anticipates that the removal of excessive order cancellations will improve the trading process for all market participants (see SEC Release No. 34-62744). In this section, we examine the effectiveness of the cancellation fee policy in both deterring excessive order cancellations and improving execution quality for market participants. We focus on a 55-day event window, the 23 days before the adjusted effective date (August 30, 2010) and the 32 days after.

To determine if a cancellation fee deters traders from canceling orders, we estimate order cancel rates as the number of orders canceled divided by the total number of orders added to the book. Figure 1 provides a visual representation of how the order cancellation fee on the PHLX impacts cancellation activity. We plot average cancellation rates on the PHLX (solid dark line) and the NOM (dotted light line) in event time. We show that average order cancellation rates for options on the PHLX decline substantially around the fee change, and remain at a lower rate in the 32 days following the effective date.[22] In contrast, the average order cancellation rate on the NOM has no distinct pattern over the sample time period.

[22] Table A.1 reports average market quality measures in event time for the 10 days before and after the cancellation fee was introduced on the PHLX.

Table 3 shows that the average order cancellation rate on the PHLX prior to the fee is 73.64%, which decreases to 62.31% following the fee. The decrease in order cancellation rates is significant at the 0.01 level and economically meaningful as it represents a 15% decline. Over the same time period, the average order cancellation rate on the NOM remains constant at 99.7%. Therefore, the difference in average order cancellation rates between the PHLX and the NOM increases from 26.05% in the pre-event period to 37.38% in the post-event period. The order cancellation fee appears effective in removing a portion of limit orders that do not constitute genuine liquidity (see Angel, 2014) and provides support for our first hypothesis, which states that the probability of order cancellation is lower following the implementation of a cancellation fee on the PHLX.

Similar to Hasbrouck and Saar (2001) and Lo, MacKinlay, and Zhang (2002), we estimate the duration between when an order is submitted and subsequently canceled. Market participants complain about "phantom liquidity" in which liquidity disappears when they attempt to trade against it (Angel, 2014). Traders may be unable to distinguish between a "firm" quote that can be traded upon and a "fake" quote. An order cancellation fee should discourage traders from submitting frivolous orders and, therefore, increase the duration between order submission and cancellation. Figure 2 shows that order duration increases substantially around the enforcement of a cancellation fee on the PHLX. Specifically, Table 3 reports that the average number of seconds between order submission and cancellation on the PHLX increases from 683 in the pre-fee period to 891 in the post-fee period. This difference of 208 seconds is significant at the 0.01 level, and represents a 30.5% increase. In contrast, the duration of orders on the NOM increase by only 10.6% from the pre-fee period to the post-fee period. Thus, limit order traders appear to be more patient when supplying liquidity in the post-fee trading environment.

Next, we examine what happens to overall order flow following the enforcement of a cancellation fee by the PHLX. Table 3 shows that the average daily number of orders submitted for an option series decreases from 483 in the pre-fee period to 163 in the post-fee period, a decline of over 66%. We also find a significant decline in order volume on the NOM over the sample period. However, Figure 3 shows that the decline in order volume on the PHLX is more abrupt around the change in fee policy, whereas the decline in order volume on the NOM is more gradual over the sample period. We note that during the sample period, the NOM is a pure order-driven market, where all participants trade in limit orders. This includes quotations entered by market makers. In comparison, the PHLX is both quote driven and order driven. Therefore, it is not surprising that we find such a large difference in order volume, in terms of number of orders, between the two exchanges. We control for this difference in order volume between the two exchanges in our multivariate tests.

Order volume does not appear to move from the PHLX to the NOM following the cancellation fee change. In fact, there appears to be more of a contagion effect, likely due to the fact the two venues operate under the NASDAQ OMX Group. The change in cancellation fee might cause some market participants to route their order flow to exchanges away from the NASDAQ entirely.

Since the order cancellation fee on the PHLX appears to impact the behavior of limit order traders, it might also impact the execution quality of orders. Similar to Foucault (1999), we estimate the likelihood of complete execution using daily fill rates, or the ratio of the number of orders filled divided by the total number of orders submitted for an option series. Table 3 shows that the average order fill rate on the PHLX increases by 8.57 percentage points from the pre-fee period to the post-fee period. In comparison, the average fill rate for orders that execute on the

NOM does not significantly change over the sample period. Specifically, in the pre-fee period we find that the mean fill rate for orders on the PHLX is 16.6%, compared to 0.3% on the NOM. In the post-fee period, the average fill rate for orders on the PHLX is 25.16%, relative to 0.29% for orders on the NOM. We find that these differences are significant at the 0.01 level and suggest that the order cancellation fee is associated with a significant increase in the probability of execution on the PHLX.

Figure 4 plots average fill rates on the PHLX (solid dark line) and NOM (dotted light line) over the sample period. We show that order fill rates on the PHLX increase substantially around the introduction of the order cancellation fee and remain elevated in the 32 days after. This indicates that the cancellation fee has a positive long-term effect on order fill rates. Thus, the reduction in order cancellation activity leads to an improvement in one of the most important areas of execution quality (see Battalio, Corwin and Jennings, 2015), the probability of execution, which provides support our first hypothesis that the probability of order execution is higher with the enforcement of a cancellation fee on the PHLX.

We also examine how limit order fill speeds change around the introduction of the order cancellation fee on the PHLX. Figure 5 plots average order fill speeds in event time for orders that execute on the PHLX (solid dark line) and NOM (dotted light line). Unlike our previous measures, there does not appear to be a clear jump in fill speeds around the event date. In fact, Table 3 reports that the average order fill speed on the PHLX increases from 1,026 seconds in the pre-fee period to 1,016 seconds in the post-fee period. However, this difference of 10.2 seconds is not significant. Similar to the PHLX, we do not find a significant change in average order fill speeds on the NOM over the sample period. Therefore, our univariate tests lead us to reject our second hypothesis that fill speeds are faster post-cancellation fee.

An important aspect of execution quality is the estimated transaction cost of a trade, which we measure using percentage effective spreads, or twice the absolute difference between the trade price and the execution time NBBO midpoint divided by the midpoint (see Battalio, Shkilko, and Van Ness, 2016). Table 3 shows that the average percentage effective spread on the PHLX decreases from 0.043 in the pre-fee period to 0.039 in the post-fee period. This decline of 40 bps is significant at the 0.01 level. Our difference-in-difference shows a marginal decrease in transaction costs on the PHLX after the introduction of a cancellation fee. Liu (2009) argues that patient liquidity traders reduce the risk of being picked off by widening bid-ask spreads. Therefore, one interpretation of our results is that limit order traders' risk appears to be less in the post-fee trading environment.

We also examine average trading volume around the enforcement of a cancellation fee by the PHLX. Consistent with the notion that traders are more confident in the displayed limit orders post cancellation fee, we find a significant increase in the number of trades on the PHLX. Table 3 shows that the average daily number of trades for an option on the PHLX increases from 13.51 in the pre-fee period to 17.14 in the post-fee period. However, we find a similar increase in trading volume on the NOM. Therefore, we cannot rule out the possibility that trading volume is simply increasing across all exchanges over the sample period.[23]

Overall, the results from these univariate tests suggest that the enforcement of a cancellation fee is effective in reducing cancellation rates and lengthening the amount of time a displayed order rests on the book. In addition, the cancellation fee is associated with an increase in the probability of a complete order execution and a decrease in average trading costs. Our results show that order volume is declining over the sample period, while trading volume is

[23] In unreported tests, we use OPRA data and find that trading volume is in fact increasing for all exchanges over the sample period.

increasing. Therefore, it appears that the order cancellation fee is effective in reducing the number of "noise" orders submitted to the PHLX.

We use Ordinary Least Squares (OLS) to control for other macroeconomic and firm-specific factors that could affect order behavior and execution quality. We analyze three order behavior dependent variables (*order cancel rates*, *order duration*, and *# of orders)* and four execution quality dependent variables (*order fill rates*, *order fill speeds*, *% effective spreads*, and *# of trades*). We contend that the relevant regressors are option and stock attributes, order characteristics, and venue traits (see Battalio, Corwin, and Jennings, 2015; and Battalio, Shkilko, and Van Ness, 2016). The unit of measurement is option series/day and the general specification for our models is outlined as follows:

$$\begin{aligned} DepVariable_{i,t} = \alpha + \tau_j + \beta_1 Post_t + \beta_2 Penny_i + \beta_3 ETF_i + \beta_4 Expiration_t + \beta_5 Price_{i,t} \\ + \beta_6 IVOL_{i,t} + \beta_7 Order\ Size_{i,t} + \beta_8 S/X_{i,t} + \beta_9 Call_i \\ + \beta_{10} UNBBO\ Midpoint_{i,t} + \beta_{11} Log(Underlying\ Volume)_{i,t} \\ + \beta_{12} Underlying\ MCAP_{\ i,t} + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

where *Post* equals one during the 33-day post cancellation fee period and zero otherwise; *Penny* equals one if the option is traded and quoted in pennies and zero otherwise; *ETF* equals one if the option class is an ETF and zero if it is a common stock; *Expiration* equals one if the order is submitted on an expiration Friday (August 20, September 17, and October 15) and zero otherwise; *Price* is the average NBBO midpoint; *IVOL* equals the option's implied volatility at the time of the trade; *Order Size* equals the average order size; *S/X* equals the underlying stock price divided by the strike price; *Call* equals one for call options and zero for put options; *UNBBO Midpoint* equals the prevailing underlying asset's NBBO midpoint at the time of the trade; *Underlying Volume* equals the underlying asset's average daily share volume; and *Underlying MCAP* is the underlying asset's average daily market capitalization, measured in $billions. We also include option class fixed effects, τ_j, that control for unobservable asset characteristics. We exclude the event date in our regression analysis and, therefore, we do not include a pre-event categorical variable as to avoid violating the full column rank assumption for consistent estimation. We report t-statistics in parentheses obtained from standard errors clustered at the option class level.

Table 4 reports the results of estimating eq. (1). Column [1] of Panel A shows that the average order cancellation rate for options on the PHLX is 10.9 percentage points (t-value = -2.789) lower following the cancellation fee, other factors held constant. When we estimate the model including option class fixed effects, we find that our results continue to hold. For instance, the average order cancellation rate for an option on the PHLX decreases by 9.1 percentage points from the pre-fee period to the post-fee period. These results are consistent with our univariate tests and support Hypothesis 1a, which states that an order cancellation fee will reduce cancellation rates.

Traders allow their orders to sit on the PHLX book for longer period of time before canceling them following the cancellation fee. Columns [3] and [4] of Panel A show that the duration of canceled limit orders is between 163 and 192 seconds longer following the cancellation fee. Therefore, the displayed limit orders in the post-fee period appear to be more static and less fleeting.

We also analyze the impact of the cancellation fee on order flow. We find that the PHLX loses order volume around the enforcement of a cancellation fee. The average number of orders for an option series decreases by at least 247 from the pre-fee period to the post-fee period, other factors held constant. This decline is both significant and economically meaningful, as it represents approximately 50% of the pre-fee period average number of orders on the PHLX. Although we find a decrease in the number of orders added to the PHLX book following the enforcement of a cancellation fee, it does not translate into fewer executions. In fact, we find a significant increase in the number of trades on the PHLX post cancellation fee. The average number of trades for an option series on the PHLX is between 3.4 and 3.9 higher in the post-fee period than the pre-fee period.

The reduction in order cancellation activity on the PHLX has a direct impact on the probability of completing an order. Columns [1] and [2] of Panel B show that the average order fill rate on the PHLX is between 6.6 and 8.4 percentage point higher in the post-fee period, relative to the pre-fee period. Thus, reducing order cancellations coincides with a significant improvement in execution probability. To the extent that trader welfare depends on the non-execution risk faced by liquidity suppliers (Colliard and Foucault, 2012), our results suggest that reducing order cancellations makes limit order traders on the PHLX better off ex ante. These results provide support for our first hypothesis, which states that order fill rates increase following the change in cancellation fee policy.

Next, we examine the impact of the cancellation fee on order fill speeds and trading costs. We fail to find support for Hypothesis 2, as average order fill speeds are not significantly different in the post-fee period, relative to the pre-fee period. When we control for potential trading cost determinants, we find that effective spreads are between 20 and 30 bps lower on the PHLX in the post-fee period, relative to the pre-fee period. The narrowing of effective spreads indicates that the order cancellation fee on the PHLX lowers execution costs for limit order traders.

To more accurately control for option characteristics and unobservable macroeconomic factors, we perform a daily match of option series between the PHLX and the NOM. We then estimate a series of OLS regressions using a difference-in-difference approach. The dependent variables are the same as those used in eq. (1). We estimate the following general model using the sample of option series trading on both the PHLX and the NOM.

$$\begin{aligned} DepVariable_{i,t} = {} & \alpha + \tau_j + \beta_1 Phlx_i + \beta_2 Post_t + \beta_3 Phlx \times Post_{i,t} + \beta_4 Penny_i + \beta_5 ETF_i \\ & + \beta_6 Expiration_t + \beta_7 Price_{i,t} + \beta_8 IVOL_{i,t} + \beta_9 Order\ Size_{i,t} + \beta_{10} S/X_{i,t} \\ & + \beta_{11} Call_i + \beta_{12} UNBBO\ Midpoint_{i,t} + \beta_{13} Log(Underlying\ Volume)_{i,t} \\ & + \beta_{14} Underlying\ MCAP_{\ i,t} + \varepsilon_{i,t}, \end{aligned} \tag{2}$$

where *Phlx* equals one if the order originated on the PHLX and zero for an order on the NOM. *Post* equals one if the order is submitted in the post-fee period and zero otherwise. We exclude the event date in the analysis and, therefore, we do not include a pre-event dummy variable as to avoid violating the full column rank assumption for consistent OLS estimation. The interaction term between *Phlx* and *Post* is our difference-in-difference test, which captures the marginal impact of the cancellation fee on order behavior and execution quality. We include option class fixed effects and cluster standard errors by underlying asset.

Table 5 reports the results of estimating eq. (2). Panel A shows that the average order cancellation rate declines by 26 percentage points more on the PHLX than on the NOM from the pre-fee period to the post-fee period. After controlling for firm-specific factors and other macroeconomic trends, we continue to find support for Hypothesis 1a, which states that the probability of cancellation is lower on the PHLX following the implementation of a cancellation fee.

The cancellation fee has a strong marginal impact on order duration. For instance, the time between order submission and cancellation is 600 seconds longer on the PHLX than on the NOM in the post-fee period, relative to the pre-fee period. This decrease in average order cancellation speed provides support for the conjecture that limit orders are more "firm" post cancellation fee (Angel, 2014). Even though the average number of orders submitted to the PHLX is significantly lower post-fee, the remaining limit orders seem to better reflect committed trading sentiment. The decline in professional order cancellations increases the likelihood of a complete order fill (16.3%) and decreases trading costs (20 bps). Since we fail to find evidence of a marginal impact of declining order cancellations on fill speeds, we reject Hypothesis 2, which states the time-to-complete fill is faster after the implementation of the cancellation fee on the PHLX.

The implications of our results are broad, as they suggest that the PHLX was able to improve order execution quality for its liquidity demanders by enforcing a fee on excessive order cancellations by professional traders. Fewer limit orders are canceled, and displayed orders remain on the PHLX book for longer durations following the cancellation fee, which seems to improve the probability of execution and reduce trading costs. The probability of completing a trade and the cost to transact are both in the SEC's definition of order execution quality (see Battalio, Corwin, and Jennings, 2016). Exchanges with similar market structures to that of the PHLX, might consider adopting an order cancellation fee.

ORDER CANCELLATIONS AND OPTION CHARACTERISTICS

A noted feature of today's equity markets, is that orders are submitted and then quickly canceled (see Hasbrouck and Saar, 2009 and Baruch and Glosten, 2013). However, much less is known about order behavior in options markets, particularly order cancellation activity. Therefore, in the following section we provide a more in-depth analysis of limit order cancellation activity in two equity options markets, the PHLX and the NOM. To ensure that the following results are not biased due the structural change on the PHLX discussed above, we perform our tests using the time period, September 15, 2010 and October 15, 2010, to avoid the initial effects of the cancellation fee on the PHLX. We can see from Figure 1 that the initial effects of the cancellation fee stabilize by mid-September.

An important decision traders make each time they submit a limit order, is how long they allow that order to remain on the order book. Hasbrouck and Saar (2009) show that nearly one third of limit orders on INET are canceled within two seconds of submission. We examine the pattern of cancellation rates by the time elapsed between order submission and deletion. Figure 6 plots order cancellation rates on both the PHLX and the NOM against the time from order submission to cancellation. For options on both exchanges, as more time passes following the submission of a limit order, the probability of cancellation declines. We find a near monotonic decrease in cancellation rates as the time between order submission and cancellation lengthens. For instance, the probability of an order being canceled is highest, 86.69% (99.93%), when an order is sitting on the PHLX (NOM) order book for less than ten seconds. The average cancellation rate for an option on the PHLX (NOM) reaches a minimum of 47.43% (94.91%) when the order sits on the book for more than 1,000 seconds, or 16½ minutes.

Table 6 reports mean order cancellation rates for options submitted to both the PHLX and the NOM disaggregated by time to cancellation. In unreported results, we find similar patterns in the standard deviations of cancellation rates between the two exchanges. There appears to be more dispersion in cancellation rates for options that sit on the book longer. We find that as the time-to-cancellation lengthens, the difference between order cancellation rates between the PHLX and the NOM increases. Specifically, for orders that sit on the book for more than 1,000 seconds, we find that that the average cancellation rate is 47.49 percentage points lower on the PHLX, relative to the NOM. This difference is significant at the 0.01 level. In contrast, when an order is on the book for less than a second, the difference in cancellation rates between the two exchanges is only 13.24 percentage points.

Prior research highlights important differences between call options and put options, such as trading costs (Battalio, Shkilko, and Van Ness, 2016), open interest (Lakonishok et al. 2007), and trading volume (Roll, Schwartz, and Subrahmanyam, 2010). In this section, we examine how order cancellation activity differs between calls and puts. Panel A of Table 7 reports the results of our univariate tests on order cancellation rates between call options and put options. The average order cancellation rate for call options on the PHLX is 60.23%, which is 5.6 percentage points less than for put options. Similarly on the NOM, average order cancellation rates are higher for put options (99.75%), relative to call options (99.65%). We find that the average cancellation rate for PHLX call options is significantly less than that for NOM call options (difference = 39.42%). We also report that the average cancellation rate for PHLX put options is 33.92 percentage points less than that for NOM put options.

In unreported results, we find that the put-to-call ratio on the PHLX exchange is 0.97, suggesting that order volume is slightly greater for call options, relative to put options. Similarly, the put/call ratio on the NOM is 0.68, which is consistent with the average sentiment in the market being more bullish than bearish. To the extent that order volume is a key driver behind order cancellation activity, our results suggest that the difference in cancellation rates between puts and calls is at least partially attributable to order flow. Overall, the results from these simple univariate tests support our third hypothesis, in which cancellation rates appear higher for put options, relative to call options.

Option contracts are often sorted into moneyness categories, based on the difference between the underlying stock price and option strike price. This value represents the profit that the option holder would receive if he or she exercised the option immediately. Lakonishok et al. (2007) show that open volume is concentrated in options that are near-the-money. Since order volume and cancellation rates are positively related, we expect cancellations to be increasing with option moneyness.

We separate observations by option type (put or call) and option moneyness. Similar to Lakonishok et al. (2007), we focus on three different ranges of option moneyness. For call (put) options, an S/X ratio of less than 0.9 represents options out-of-the-money (in-the-money). An S/X range between 0.9 and 1.1 represents options near-the-money for both puts and calls. For call (put) options, an S/X ratio of greater than 1.1 identifies options in-the-money (out-of-the-money).

For both exchanges, we find that orders for options in-the-money are canceled more frequently than any other option series. Specifically, Panel B of Table 7 shows that the average order cancellation rate for in-the-money call (put) options on the PHLX is 2.53 (9.19) percentage points higher than the average cancellation rate for out-of-the-money call (put) options. Although smaller in magnitude, we find similar results for option orders submitted to the NOM. Our results suggest that the probability of order cancellation is highest for options in-the-money than for those out-of-the-money. Therefore, market participants are more likely to observe flickering orders in the more valuable options.

In Figure 7, we plot order cancellation rates on both exchanges by option moneyness categories. Cancellation rates are on the primary and secondary vertical axes, while S/X ranges for moneyness are on the horizontal axis. We find that the plots are consistent with the findings in Panel B of Table 7. The results from this analysis provide support for Hypothesis 4, at least for call options, as order cancellation activity is highest for options in-the-money, relative to options out-of-the-money. Thus, limit order traders are less likely to remain at a position on the order book when the option is increasing in value.

Prior research shows differences in trading behavior on, and around expiration days, relative to non-expiration days (see Stoll and Whaley, 1987 and Stephan and Whaley, 1990). In this section, we test our fifth hypothesis that order cancellation rates are higher on option expiration days than non-expiration days. Panel C of Table 7 reports the results of our univariate analysis on mean cancellation rates on option expiration Fridays, relative to non-expiration days. Order cancellation rates on the PHLX and NOM are neither higher nor lower on option expiration days, relative to non-expiration days. The results in Table 7 lead us to reject Hypothesis 5, which states that order cancellation rates are higher on option expiration days, relative to non-expiration days.

Figure 8 plots mean cancellation rates on the vertical axes and days-to-expiration on the horizontal axis. The dark solid line illustrates average order cancellation rates for options on the PHLX, whereas the light dotted line represents cancellation rates for options on the NOM. We find that order cancellation rates are highest when the option is between 25 to 50 days to expiration and lowest when the option has over 125 days to expiration. As we expect, order cancellation rates continue to decline as the number of days to expiration increase.

We test the relation between order cancellation rates and option characteristics further in a multivariate setting, where we control for other factors that may affect the probability of cancellation. The sample consists of 113 option classes during the period September 15, 2010 to October 15, 2010. We use OLS to estimate the following regression equation:

$$
\begin{aligned}
Order\ Cancel\ Rate_{i,t} \\
&= \alpha + \delta_t + \tau_j + \beta_1 Phlx_i + \beta_2 Order\ Duration_{i,t} + \beta_3 Call_t \\
&+ \beta_4 In - the - money_{i,t} + \beta_5 Expiration_t + \beta_6 Price_{i,t} + \beta_7 IVOL_{i,t} \\
&+ \beta_8 Order\ Size_{i,t} + \beta_9 UNBBO\ Midpoint_{i,t} \\
&+ \beta_{10} Log(Underlying\ Volume)_{i,t} + \beta_{11} Underlying\ MCAP_{\ i,t} + \varepsilon_{i,t},
\end{aligned} \tag{3}
$$

where *In-the-Money* equals one if the option is in-the-money and zero if the option is out-of-the-money. The remaining independent variables have all been defined previously. Since we are no longer performing an event study, it is important to control for time fixed effects, δ_t, and option class fixed effects, τ_j. We cluster the standard errors by underlying asset. The results of estimating eq. (3) are found in Table 8.

Consistent with our univariate tests, we find that order cancellation rates are inversely related with the speed of cancellation. Columns [2] and [4] of Table 8 show that the average order cancellation rate is roughly 31.8 percentage points higher on the PHLX than on the NOM. We find a negative and significant relation between the probability of order cancellation and the time-to-cancellation (cancel speed). Specifically, the coefficient on *Cancel Speed* is equal to a negative 0.0001 in each of the regression specifications. Since order cancellation speeds are measured in seconds, a one-minute increase in the speed of cancellation decreases the probability of order cancellation by 0.6 percentage points, other factors held constant.

In support of Hypothesis 3, we find that order cancellation rates are significantly higher for put options, relative to call options. Columns [2] of Table 8 shows that the average order on a call option has a cancellation rate that is about 1.82 percentage points lower than the average order on a put option. Therefore, marketable order traders are less (more) likely to receive a favorable execution when interacting with limit orders on put (call) options, as the displayed orders with which they seek to interact are more (less) likely to cancel before the arrival of their marketable order.

In addition, we find support for Hypotheses 4 and 5 in which order cancellation rates are significantly higher for in-the-money options and on option expiration days. In the full model, which includes day-fixed effects, we show that order cancellation rates are 1.26 percentage points higher on expiration days, relative to non-expiration days. Order cancellation rates are 1.11 percentage points higher for options in-the-money than for options out-of-the-money, which holds even after controlling for order/stock characteristics and exchange differences. Option market makers unwind, or move in and out of position, on expiration days (see Ni, Pearson, and Poteshman, 2005), which might help explain the higher probability of order cancellation observed on option expiration days.

In an attempt to explain the difference in order cancellation rates between the PHLX and the NOM observed in the analysis above, we run the following regression model using data for our paired sample option series.

$$\begin{aligned} &Order\ Cancellation\ Rate^{PHLX} - Order\ Cancellation\ Rate^{NOM} \\ &\quad = \alpha_0 + \sum \alpha_i\left(Y_i^{PHLX} - Y_i^{NOM}\right) + \sum \beta_j X_j + \varepsilon \end{aligned} \tag{4}$$

The dependent variable is the difference in daily order cancellation rates between the PHLX and the NOM. Y_i (i = 1 to 5) represents one of five limit order characteristics: *order duration*, *implied volatility*, *order size*, *# of trades* and *% effective spreads*. We include controls for option and underlying attributes. We also include day fixed effects and option class fixed effects to control for time-series and cross-sectional variation. Test-statistics are reported in parentheses and are obtained from standard errors clustered by underlying asset.

The results of estimating eq. (4) are reported in Table 9. We find that the differential in order cancellation rates, which is substantially higher on the NOM than on the PHLX, is significantly and negatively related to the difference in order duration, order size, and trade volume. This result suggests that the higher trade volume and order sizes on the PHLX at least partially explains the difference in order cancellation rates between the two exchanges. Since the NOM is an all-electronic options market, it might attract more algorithmic-type traders that are shown to cancel a substantial amount of their orders (see Hasbrouck and Saar, 2009), which can help explain the differential in cancellation activity between the two exchanges. Table 3 shows that orders submitted to the NOM are canceled, on average, 802 seconds faster than those submitted to the PHLX. Therefore, the results from Table 9 suggest that the speed with which limit orders are canceled on the NOM helps explain the higher probability of order cancellation.

ROBUSTNESS

In this section we report the results of a series of robustness tests that help validate our findings. Since order cancellation rates, fill rates, and execution speeds remain constant for the sample of NOM orders, we are less concerned that our event study is biased due to the sample time period. However, it is still possible that order execution quality changed significantly during our particular sample period. Therefore, we perform a pseudo-event study, where we examine order execution quality for options on the PHLX around an alternative event date. We select the calendar year immediately following the event date, August 18, 2011.

We estimate eq. (1) for each order execution quality measure for orders submitted to the PHLX. Similar to our event study, we use a 50-day event window, the 25 days before the pseudo-event date and the 25 days after. We find that the coefficient on the categorical variable *Post*, is insignificant in each of the regressions, providing support for our main analysis. Since we do not observe any significant change around the pseudo-event date, we are confident that the fee change had a causal impact on order execution quality.

In our final set of tests, we separate order flow on the PHLX into marketable and nonmarketable. We approximate a marketable order as a limit order that fills within 500 milliseconds of submission.[24] Table A.2 reports the results of estimating eq. (1) on the partitioned sample. We believe it is important to distinguish between marketable and nonmarketable orders when considering order fill speeds, as limit order traders submitting marketable orders are more

[24] Our results are robust to different millisecond cutoff levels 50, 100, and 200.

concerned with fast executions, relative to those placing more passive nonmarketable orders. Consistent with our Hypothesis 2, we find that the speed of execution for marketable order flow is substantially faster in the post-fee period than in the pre-fee period. The average marketable order executes roughly 5,000 microseconds (one millionth of a second) faster following the introduction of the cancellation fee. In a trading environment where orders are submitted and revised in nanoseconds, 5,000 microseconds is an economically significant difference.

We find that the observed increase in order fill rates on the PHLX around the cancellation fee is at least partially attributable to the increase in marketable order flow. Table A.2 shows that both raw marketable order flow and the arrival rate of marketable orders (marketable orders divided by total orders) increase in the post-fee period, relative to the pre-fee period, which is consistent with the notion that order fill rates depend on the arrival rate of marketable orders (Battalio, Corwin, and Jennings, 2016).

CONCLUDING REMARKS

Limit orders play a pivotal role in options markets (see Berkman, 1996). The canceling of these limit orders has captured significant attention from exchange officials, the popular press, and regulators. For instance, some trading venues believe that curbing excessive order cancellations might improve the overall trading environment for all market participants (see SEC Release No. 34-62744, page 2). In this study, we examine the effect of an order cancellation fee on limit order behavior and execution quality. On August 18, 2010, the PHLX introduced a cancellation fee on professional orders.

We find that the cancellation fee causes a significant decline in average order cancellation rates. In our difference-in-difference regression analysis, we find that the probability of cancellation is 26 percentage points lower on the PHLX than on the NOM in the post-fee period, relative to the pre-fee period. Since we observe a shock to order cancellation rates, it allows us to test the relation between cancellation activity and other aspects of order behavior.

Some market participants are concerned with “phantom liquidity”, or quotes that disappear when they attempt to trade against them (see Angel, 2014). We find that the order cancellation fee on the PHLX increases the duration of resting limit orders. The increase in firm quotes seems to improve several aspects of execution quality. For instance, we find that the probability of order execution is 16.3 percentage points higher on the PHLX that on the NOM in the post-fee period, relative to the pre-fee period. In addition, the cancellation fee is associated with a decrease in effective spreads by roughly 20 bps. We also find a decrease in what appears to be noisy nonmarketable order volume, and an increase in trading volume. To the extent that limit order traders are better off when facing less non-execution risk (Colliard and Foucault, 2012), lower cancellation activity seems to have a positive impact on overall trader welfare.

Our analysis also contributes to our understanding of limit order trading behavior in equity options markets. We find that the probability of order cancellation is approximately 1.82 percentage points higher for put options, relative to call options. Orders submitted on option expiration days are 1.26 percentage points more likely to cancel than those submitted on non-expiration days, other things held constant. We also note that the probability of an order cancellation is roughly 32 percentage points lower on the PHLX, relative to the NOM. This differential in order cancellations is partially explained by differences in trading volume, order size, and order duration.

Overall, the fee structure change on the PHLX significantly affects limit order behavior, which improves several aspects of execution quality. Our results suggest that the benefits of reducing order cancellation rates seem to outweigh the perceived costs. Limit order traders on the PHLX appear better off following the cancellation fee, as they face less non-execution risk (Liu, 2009) and trade at lower costs. Market participants criticize trading strategies that result in excessive order cancellations, as displayed liquidity might not reflect committed trading sentiment (Friederich and Payne, 2015). The implications of our analysis are broad, as exchange officials in the equity options market might be encouraged to consider enforcing an order cancellation fee.

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APPENDIX

APPENDIX 1: SAMPLE SELECTION

Table 1
Sample Selection

The table summarizes the sample selection process and reports the distribution of trading activity across the remaining option class contracts. The sample period is the 56 trading days between July 26, 2010 and October 15, 2010. Due to data corruption issues, we drop August 13, August 19, and September 2 trading days.

Panel A. Sample filters

	# of remaining option classes	*# of remaining option series*	*% of initial PHLX order volume*
Initial sample	2,249	139,525	100.00%
Exclude option classes that have fewer than 1 order fill per day	296	53,495	85.80%
Exclude option series with fewer than 5 orders in a day	296	25,727	83.87%
Exclude option classes that are not on common stocks or on ETFs	231	20,788	68.85%
Match PHLX with NOM by option series and merge with OPRA	133	8,908	48.33%
Final Sample	133	8,908	48.33%

Panel B. Distribution of option classes

	# of option classes	*# of remaining option series*	*% of sample orders*
Option classes on common stock that trade in pennies	70	5,433	72.74%
Option classes on common stock that do not trade in pennies	47	1,695	7.20%
Option classes on ETFs that trade in pennies	14	1,531	14.93%
Option classes on ETFs that do not trade in pennies	2	249	5.14%
Final Sample	133	8,908	100.00%

APPENDIX 2: DISTRIBUTION OF TRADING ACTIVITY ACROSS OPTION EXCHANGES

Table 2

Distribution of Trading Activity across Option Exchanges

We obtain historical Option Price Reporting Authority (OPRA) trade and quote data from a technology company LiveVol for the period June 26, 2010 to October 15, 2010. Option exchanges report volume information on trades and on current bid and offers in eligible securities to OPRA. We report the distribution of trading activity across eight option exchanges, in terms of volume and number of trades, for all eligible option classes and for our final sample of option classes. We find that the 113 option classes observed in this study account for over 43% of trades and just under 40% of market volume during the sample period.

	All Option Classes Classes = 3,417		Sample Option Classes Classes = 113	
	% of volume	% of trades	% of volume	% of trades
NOM	4.14%	9.06%	5.86%	12.36%
AMEX	12.44%	12.94%	14.28%	12.34%
CBOE	25.69%	23.51%	19.80%	20.60%
ISE	17.85%	20.60%	20.22%	20.79%
NYSE ARCA	11.79%	13.49%	11.79%	13.39%
PHLX	24.98%	14.18%	24.28%	13.47%
BX	2.62%	5.00%	3.14%	5.42%
BATS	0.49%	1.23%	0.63%	1.62%

APPENDIX 3: ORDER EXECUTION QUALITY AROUND INTRODUCITON OF PHLX ORDER CANCELLATION FEE

Table 3

Order Execution Quality around Introduction of PHLX Order Cancellation Fee

The sample consists of orders in 113 option classes during the period July 26, 2010 to October 15, 2010. We conduct univariate tests around the introduction of an order cancellation fee on the PHLX in August of 2010. We use a 55-day event window, the 23 trading days before the adjusted effective date (August 30, 2010) and the 32 trading days after. We exclude the event date in the analysis. Simple t-tests are used to calculate differences in means. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Event Window [-23, 32] 07/26/2010 - 10/15/2010								
	Pre		Post		Difference PHLX	Difference NOM	Pre Difference	Post Difference
	PHLX	NOM	PHLX	NOM	(Post - Pre)	(Post - Pre)	(PHLX - NOM)	(PHLX - NOM)
Order Cancel Rate	73.64%	99.70%	62.31%	99.69%	-11.33%***	-0.01%	-26.05%***	-37.38%***
Order Duration (seconds)	683.0	80.8	891.4	89.4	208.3***	8.5994***	602.2***	802***
# of Orders	483	17,490	163	14,262	-321***	-3228***	-17,007***	-14,099***
Order Fill Rate	16.60%	0.30%	25.16%	0.29%	8.57%***	-0.02%	16.29%***	24.87%***
Order Fill Speed (seconds)	1026.6	793.5	1016.4	806.0	-10.2	12.5	233.1***	210.4***
% Effective Spreads	0.0430	0.0349	0.0390	0.0322	-0.0040***	-0.0027***	0.0081***	0.0068***
# of Trades	13.51	14.00	17.14	16.95	3.63***	2.9498***	-0.49	0.20

APPENDIX 4: IMPACT OF PHLX ORDER CANCELLATION FEE ON ORDER EXECUTION QUALITY

Table 4
Impact of PHLX Order Cancellation Fee on Order Execution Quality

The sample consists of orders in 113 equity and ETF option classes during July 26, 2010 to October 15, 2010. We use Ordinary Least Squares to examine the impact of an order cancellation fee on order behavior. *Order Cancel Rate* equals the number of canceled orders divided by the total number of order submitted. *Order Duration* equals the number of seconds between order submission and cancellation. *# of Orders* equals the total number of orders added to the book. *Post* equals one during the period of August 13, 2010 to October 15, 2010 and zero otherwise. We examine four measures of execution quality: *Order Fill Rate*, *Order Fill Speed*, *% Effective Spreads*, and *# of Trades*. *Order Fill Rate* equals the average number of orders completely filled. *Order Fill Speed* equals the number of seconds between order submission and a complete fill. *# of Trades* equals the total number of trades reported to OPRA. *Penny* equals one if the option is traded and quoted in pennies and zero otherwise. *ETF* equals one if the option class is an ETF and zero if it is a common stock. *Expiration* equals one on option expiration Fridays and zero otherwise. Price is the average option NBBO midpoint. *IVOL* is an option's average daily implied volatility as computed by OPRA. *Order Size* is the average number of contracts attached to a particular order. *S/X* equals the underlying stock price divided by the strike price. *Call* equals one if the order is for a call option and zero for a put option. *Underlying NBBO Midpoint* is the underling stock's NBBO midpoint as reported by OPRA. *Underlying Volume* equal the underlying stock's average daily share volume. *Underlying MCAP* is the underlying stock's average daily market capitalization, measured in $billions. We include option class fixed effects. T-statistics are reported in parentheses obtained from standard errors clustered by option class. ***, **, and * denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

Panel A. Order Behavior – Event Window [-23, 32] 07/26/2010 - 10/15/2010

	Order Cancel Rate		**Order Duration (seconds)**		**# of Orders**	
	[1]	[2]	[3]	[4]	[5]	[6]
Post	-0.109***	-0.091**	191.558**	163.125**	-313.871***	-247.277***
	(-2.789)	(-2.567)	(2.249)	(2.203)	(-3.130)	(-3.495)
Penny	0.009		-173.838**		132.511	
	(0.307)		(-2.132)		(1.502)	
ETF	-0.008		-22.280		369.242	
	(-0.141)		(-0.133)		(1.347)	
Expiration	-0.001	-0.006	-5.405	-9.921	-47.500*	-61.644*
	(-0.152)	(-0.668)	(-0.134)	(-0.267)	(-1.797)	(-1.960)
Price	0.000	-0.000	-4.556	-0.752	5.140	0.749
	(0.280)	(-0.184)	(-0.883)	(-0.237)	(1.246)	(0.373)
IVOL	0.003	0.022***	130.403*	-61.778*	-66.523	-37.284
	(0.189)	(3.184)	(1.904)	(-1.661)	(-0.675)	(-0.773)
Order Size	-0.000	-0.000	1.288***	0.468***	-0.616*	-0.409
	(-1.566)	(-1.592)	(5.707)	(2.874)	(-1.764)	(-1.368)
S/X	0.043**	0.041*	-190.177*	-168.320	-249.387**	-260.572***
	(2.189)	(1.976)	(-1.701)	(-1.252)	(-2.279)	(-2.628)
Call	-0.071***	-0.045***	204.688***	121.379***	-144.859***	-55.129***
	(-8.661)	(-6.085)	(6.530)	(4.954)	(-3.737)	(-3.023)
Log(Underlying Volume)	-0.038***	-0.028***	182.227***	-84.034***	-0.684	9.205
	(-3.552)	(-3.392)	(5.029)	(-2.696)	(-0.018)	(0.534)
Underlying MCAP	-0.000	-0.004***	0.473	9.618***	1.259	-11.982***
	(-0.616)	(-4.309)	(0.862)	(4.774)	(1.503)	(-7.942)
Constant	1.370***	1.451***	-2200.724***	1533.908***	588.592	1,457.832***
	(8.088)	(9.427)	(-3.870)	(2.875)	(1.025)	(4.043)
Option Class FE	No	Yes	No	Yes	No	Yes
R^2	0.092	0.062	0.044	0.009	0.063	0.038
N	49,164	49,164	48,136	48,136	49,164	49,164

Panel B. Order Execution Quality – Event Window [-23, 32] 07/26/2010 - 10/15/2010								
	Order Fill Rate		**Order Fill Speed (seconds)**		**% Effective Spread**		**# of Trades**	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Post	0.084***	0.066**	-6.981	15.844	-0.003***	-0.002**	3.900**	3.399**
	(2.982)	(2.560)	(-0.227)	(0.562)	(-3.427)	(-2.002)	(2.184)	(2.495)
Penny	-0.004		-227.357***		-0.019***		4.636	
	(-0.235)		(-2.682)		(-12.589)		(1.099)	
ETF	0.036		-244.518**		-0.011***		4.288	
	(1.103)		(-2.223)		(-7.091)		(1.108)	
Expiration	0.000	0.007	-121.220***	-141.443***	-0.003	-0.004*	-1.217*	-0.425
	(0.053)	(0.952)	(-2.636)	(-3.041)	(-1.343)	(-1.754)	(-1.673)	(-0.832)
Price	0.001***	0.001	-12.227***	-6.670***	-0.002***	-0.002***	-0.604***	-0.891***
	(4.294)	(1.441)	(-2.663)	(-3.007)	(-30.702)	(-29.955)	(-3.310)	(-9.145)
IVOL	-0.009	-0.011	82.560**	-73.544	0.039***	0.037***	1.901	-0.779
	(-0.855)	(-1.585)	(2.444)	(-1.477)	(29.538)	(18.392)	(1.197)	(-0.209)
Order Size	0.000	0.000	1.362***	0.214	0.000***	0.000***	0.000	0.010***
	(0.152)	(1.013)	(3.140)	(0.980)	(18.954)	(16.039)	(0.053)	(3.130)
S/X	-0.010	-0.007	-224.195	-259.116	-0.016***	-0.015***	-7.445***	-7.611***
	(-0.603)	(-0.322)	(-1.217)	(-1.310)	(-4.013)	(-3.832)	(-2.958)	(-3.446)
Call	0.040***	0.030***	87.545***	25.257	0.001	0.001	2.835*	4.293***
	(9.597)	(7.125)	(3.581)	(1.063)	(1.323)	(0.648)	(1.749)	(2.870)
Underlying NBBO Midpoint	-0.000	0.000	-1.303**	-0.190	0.000***	0.000	0.062*	0.041
	(-0.853)	(0.249)	(-2.438)	(-0.159)	(15.106)	(0.812)	(1.796)	(0.519)
Log(Underlying Volume)	0.006	0.046***	160.387***	-177.010***	0.000	0.005***	2.088	7.358***
	(0.642)	(7.129)	(3.198)	(-5.673)	(0.093)	(4.012)	(1.592)	(8.225)
Underlying MCAP	0.000	0.003**	1.526*	1.874	0.000***	-0.000	0.057	0.298***
	(0.716)	(2.416)	(1.738)	(0.805)	(2.815)	(-1.357)	(1.356)	(3.509)
Constant	0.049	-0.802***	-1,217.726	4,135.199***	0.050***	-0.033	-28.609	-124.257***
	(0.323)	(-6.466)	(-1.513)	(6.960)	(4.883)	(-1.537)	(-1.438)	(-7.098)
Option Class FE	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.054	0.060	0.046	0.004	0.052	0.033	0.073	0.063
N	49,164	49,164	40,356	40,356	49,164	49,164	49,164	49,164

APPENDIX 5: MARGINAL IMPACT OF PHLX ORDER CANCELLATION FEE ON ORDER EXECUTION QUALITY

Table 5

Marginal Impact of PHLX Order Cancellation Fee on Order Execution Quality

The sample consists of orders in 113 equity and ETF option classes trading on the PHLX and NOM during July 26, 2010 to October 15, 2010. We use Ordinary Least Squares to examine the marginal impact of an order cancellation fee on order behavior and execution quality. We analyze four order behavior measures: *Order Cancel Rate, Order Duration*, and *# of Orders*. *Order Cancel Rate* equals the number of canceled orders divided by the total number of order submitted. *Order Duration* equals the number of seconds between order submission and cancellation. *# of Orders* equals the total number of orders added to the book. We examine four measures of execution quality: *Order Fill Rate, Order Fill Speed, % Effective Spreads,* and *# of Trades*. *Order Fill Rate* equals the average number of orders completely filled. *Order Fill Speed* equals the number of seconds between order submission and a complete fill. *# of Trades* equals the total number of trades reported to OPRA. *Phlx* is an indicator variable set equal to one if the order originated on the PHLX and zero for orders on the NOM. *Post* equals one during the period of August 13, 2010 to October 15, 2010 and zero otherwise. *Penny* equals one if the option is traded and quoted in pennies and zero otherwise. *ETF* equals one if the option class is an ETF and zero if it is a common stock. *Expiration* equals one on option expiration Fridays and zero otherwise. Price is the average option NBBO midpoint. *IVOL* is an option's average daily implied volatility as computed by OPRA. *Order Size* is the average number of contracts attached to a particular order. *S/X* equals the underlying stock price divided by the strike price. *Call* equals one if the order is for a call option and zero for a put option. *Underlying NBBO Mid* is the underling stock's NBBO midpoint as reported by OPRA. *Underlying Volume* equal the underlying stock's average daily share volume. *Underlying MCAP* is the underlying stock's average daily market capitalization, measured in $billions. We include option class fixed effects. T-statistics are reported in parentheses obtained from standard errors clustered by option class. ***, **, and * denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

Panel A. Order Behavior – Event Window [-23, 32] 07/26/2010 - 10/15/2010

	Order Cancel Rate		**Order Duration**		**# of Orders**	
	[1]	[2]	[3]	[4]	[5]	[6]
Phlx	-0.260***	-0.260***	600.041***	604.084***	-16,970.127***	-16,991.114***
	(-7.561)	(-7.577)	(6.392)	(6.486)	(-7.247)	(-7.249)
Post	0.002	0.011**	2.026	-13.134	-3,179.022***	-2,452.424***
	(0.969)	(2.170)	(0.217)	(-0.705)	(-3.728)	(-3.580)
Phlx * Post	-0.113***	-0.113***	196.642**	198.473**	2,943.654***	2,923.000***
	(-2.721)	(-2.724)	(2.080)	(2.104)	(3.590)	(3.560)
Penny	0.004		-100.815**		2421.950	
	(0.285)		(-2.339)		(1.600)	
ETF	-0.004		-23.827		4,078.841**	
	(-0.143)		(-0.277)		(2.129)	
Expiration	-0.001	-0.003	5.620	1.016	-2,232.912***	-1,954.556***
	(-0.145)	(-0.657)	(0.281)	(0.055)	(-4.359)	(-4.208)
Price	0.000	-0.000	-3.082	-0.888	256.490***	148.002***
	(0.293)	(-0.150)	(-1.120)	(-0.548)	(3.135)	(3.803)
IVOL	0.000	0.014***	100.866***	-39.488	-1024.485	-617.356
	(0.004)	(3.198)	(3.044)	(-0.977)	(-1.311)	(-0.933)
Order Size	-0.000	-0.000	1.052***	0.236	-13.178***	-5.564*
	(-1.296)	(-1.287)	(5.072)	(1.488)	(-3.453)	(-1.898)
S/X	0.022**	0.019*	-93.854	-77.023	-4247.603*	-4,898.065**
	(2.233)	(1.882)	(-1.365)	(-0.896)	(-1.899)	(-2.319)
Call	-0.036***	-0.023***	114.026***	63.922***	-1,589.722***	-275.388
	(-8.849)	(-6.233)	(6.924)	(4.869)	(-5.755)	(-0.924)
Log(Underlying Volume)	-0.019***	-0.015***	90.469***	-46.112***	-696.200	1,387.278***
	(-3.259)	(-3.578)	(4.560)	(-3.001)	(-1.421)	(5.435)
Underlying MCAP	-0.000	-0.002***	0.222	4.598***	30.446**	-40.789*
	(-0.615)	(-4.345)	(0.766)	(4.772)	(2.211)	(-1.702)
Constant	1.305***	1.373***	-1,363.933***	583.980**	29,106.617***	2,042.590
	(14.674)	(16.533)	(-4.344)	(2.127)	(3.402)	(0.530)
Option Class FE	No	Yes	No	Yes	No	Yes
R^2	0.412	0.428	0.117	0.103	0.207	0.185
N	98,328	98,328	97,300	97,300	98,328	98,328

Panel B. Order Execution Quality – Event Window [-23, 32] 07/26/2010 - 10/15/2010

	Order Fill Rate		**Order Fill Speed (seconds)**		**% Effective Spread**		**# of Trades**	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Phlx	0.163***	0.163***	204.383***	194.110***	0.008***	0.008***	-0.446	-0.491
	(7.888)	(7.869)	(7.851)	(7.369)	(8.127)	(8.204)	(-0.222)	(-0.242)
Post	-0.001	-0.010**	9.848	44.053**	-0.002**	-0.001	3.279**	3.236***
	(-1.381)	(-2.411)	(0.496)	(1.982)	(-2.005)	(-0.780)	(2.188)	(2.642)
Phlx * Post	0.086***	0.086***	-18.778	-8.086	-0.002**	-0.002**	0.728	0.678
	(2.953)	(2.946)	(-0.697)	(-0.308)	(-2.404)	(-2.381)	(1.316)	(1.249)
Penny	-0.003		-143.836**		-0.018***		7.412	
	(-0.313)		(-2.312)		(-18.745)		(1.567)	
ETF	0.018		-180.084*		-0.009***		3.700	
	(1.096)		(-1.720)		(-9.473)		(0.872)	
Expiration	0.000	0.003	-107.108***	-114.923***	-0.004***	-0.005***	-1.972***	-0.973*
	(0.098)	(0.956)	(-3.103)	(-3.294)	(-2.723)	(-3.114)	(-2.717)	(-1.811)
Price	0.001***	0.000	-9.657**	-5.183**	-0.002***	-0.002***	-0.652***	-1.011***
	(4.385)	(1.448)	(-2.430)	(-2.447)	(-45.767)	(-44.403)	(-2.670)	(-7.892)
IVOL	-0.004	-0.008*	51.984	-7.447	0.036***	0.042***	2.471***	-2.007
	(-0.621)	(-1.901)	(1.208)	(-0.199)	(42.474)	(30.999)	(2.935)	(-0.465)
Order Size	0.000	0.000	2.675***	0.815***	0.000***	0.000***	-0.017*	0.001
	(0.080)	(1.089)	(4.959)	(4.007)	(27.991)	(22.720)	(-1.873)	(0.271)
S/X	-0.005	-0.002	-93.204	-147.183	-0.011***	-0.014***	-7.897**	-7.783***
	(-0.632)	(-0.204)	(-0.613)	(-0.958)	(-4.736)	(-5.510)	(-2.391)	(-2.771)
Call	0.020***	0.016***	102.276***	47.166**	0.001**	0.000	3.101	4.672**
	(9.822)	(7.416)	(4.210)	(2.608)	(2.173)	(0.709)	(1.560)	(2.463)
Underlying NBBO Midpoint	-0.000	0.000	-1.445***	-0.142	0.000***	0.000*	0.076*	0.063
	(-0.886)	(0.242)	(-3.182)	(-0.106)	(22.167)	(1.793)	(1.741)	(0.625)
Log(Underlying Volume)	0.003	0.024***	136.859***	-176.416***	-0.000	0.003***	1.759	8.038***
	(0.645)	(7.251)	(3.172)	(-6.280)	(-0.812)	(4.185)	(1.109)	(6.845)
Underlying MCAP	0.000	0.001**	1.480**	0.156	0.000***	-0.000**	0.074	0.239**
	(0.712)	(2.433)	(1.995)	(0.068)	(5.155)	(-2.150)	(1.351)	(2.307)
Constant	-0.055	-0.499***	-1,273.306*	3,840.092***	0.043***	-0.018	-26.855	-132.173***
	(-0.710)	(-7.346)	(-1.767)	(7.140)	(6.709)	(-1.339)	(-1.090)	(-6.437)
Option Class FE	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.339	0.354	0.063	0.008	0.057	0.038	0.082	0.058
N	98,328	98,328	88,056	88,056	98,328	98,328	98,328	98,328

APPENDIX 6: DESCRIPTIVE STATISTICS OF ORDER CANCELLATION RATES BY ORDER DURATION

Table 6
Descriptive Statistics of Order Cancellation Rates by Order Duration

This table provides the distribution of order cancellation rates on both the PHLX and the NOM by order duration, or the time between submission and cancellation. The sample time period is taken after the structural change on the PHLX, i.e. September 15, 2010 to October 15, 2010. We report mean cancellation rates for different order duration time buckets. We test for differences in means using simple t-tests and find that all differences are significant at the 0.01 level.

Order Duration	*Panel A. PHLX*	*Panel B. NOM*	*Panel C. Difference*
(seconds)	PHLX	NOM	(PHLX - NOM)
0-1	83.24%	99.98%	-16.74%
2-10	86.69%	99.93%	-13.24%
11-40	81.15%	99.88%	-18.73%
41-70	70.06%	99.79%	-29.73%
71-100	64.23%	99.68%	-35.45%
101-200	58.56%	99.52%	-40.96%
201-300	56.67%	99.18%	-42.51%
301-400	54.22%	98.77%	-44.55%
401-500	54.66%	98.41%	-43.75%
501-600	54.78%	98.07%	-43.29%
601-700	52.65%	98.44%	-45.79%
701-800	51.14%	97.62%	-46.48%
801-900	52.90%	95.88%	-42.98%
901-1000	53.33%	95.88%	-42.55%
>1000	47.43%	94.91%	-47.49%

APPENDIX 7: DESCRIPTIVE STATISTICS OF ORDER CANCELLATION RATES BY OPTION CHARACTERISTICS

Table 7

Descriptive Statistics of Order Cancellation Rates by Option Characteristics

This table provides mean and median order cancellation rates disaggregated by option type, calls versus puts. The sample time period is taken after the structural break on the PHLX, i.e. September 15, 2010 through October 15, 2010. Panel A shows average daily order cancellation rates for options on both the PHLX and NOM. Panel B shows order cancellation rates for three ranges of option moneyness, in-the-money, near-the-money, and out-of-the-money. We define moneyness using the S/X ratio, which is the underlying stock price divided by the option strike price. A call (put) option is said to be in-the-money (out-of-the-money) if the S/X ratio is greater (less) than one. An option is said to be near-the-money if the S/X ratio is between 0.9 and 1.1. Panel C reports differences in means for order cancellation rates on option expiration days, relative to those on non-expiration days. Simple t-tests are used to calculate the difference in means. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Panel A. Order Cancellation Rates by Option Type

	Call Options	Put Options	Difference (Call - Put)
PHLX	60.23%	65.83%	-5.60%***
NOM	99.65%	99.75%	-0.09%***
Difference (PHLX - NOM)	-39.42%***	-33.92%***	

Panel B. Order Cancellation Rates by Option Moneyness

	Call Options			Put Options		
	PHLX	NOM	Difference (PHLX – NOM)	PHLX	NOM	Difference (PHLX – NOM)
[1] S/X < 0.9	56.55%	99.30%	-42.75%	75.61%	99.67%	-24.06%***
[2] 0.9 <= S/X <= 1.1	60.93%	99.71%	-38.78%	65.36%	99.82%	-34.46%***
[3] S/X > 1.1	59.08%	99.66%	-40.57%	66.42%	99.48%	-33.06%***
Difference [1] - [2]	-4.38%***	-0.40%***		10.26%***	-0.15%***	
Difference [1] - [3]	-2.53%***	-0.35%***		9.19%***	0.19%***	
Difference [2] - [3]	1.85%***	0.05%***		-1.06%***	0.34%***	

Panel C. Order Cancellation Rates by Expiration Days and Non-Expiration Days			
	PHLX	NOM	Difference (PHLX - NOM)
Expiration Days	63.120%	99.690%	-36.570%***
Non-Expiration Days	62.295%	99.689%	-37.394%***
Difference (Expiration - Non-Expiration)	0.825%	0.001%	

APPENDIX 8: ORDER CANCELLATION RATES – OPTION CHARACTERISTICS

Table 8
Order Cancellation Rates – Option Characteristics

The sample consists of orders in 113 equity and ETF option classes trading on the PHLX and NOM during September 15, 2010 to October 15, 2010. We use Ordinary Least Squares to examine the relations between order cancellation activity and various option characteristics. The dependent variable is the average order cancellation rate, or number of orders canceled divided by total orders submitted. In-the-Money equals one if the underlying stock price is greater (less) than the strike price for call (put) options and zero otherwise. The control variables are defined in Table 4. We include day fixed effects and option class fixed effects. Test-statistics are reported in parentheses obtained from standard errors clustered by option class. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	[1]	[2]
Phlx	-0.3177***	-0.3178***
	(-16.169)	(-16.200)
Order Duration	-0.0001***	-0.0001***
	(-15.581)	(-15.721)
Call	-0.0184***	-0.0182***
	(-5.607)	(-5.528)
In-the-Money	0.0111**	0.0114**
	(2.372)	(2.500)
Expiration	0.0126**	0.0052
	(2.045)	(0.892)
Price	0.0000	0.0000
	(0.257)	(0.253)
IVOL	0.0086	0.0084
	(1.630)	(1.579)
Order Size	-0.0001*	-0.0001*
	(-1.751)	(-1.756)
UNBBO Midpoint	0.0009**	0.0010***
	(2.370)	(2.897)
Log(Underlying Volume)	-0.0150**	-0.0135**
	(-2.485)	(-2.269)
Underlying MCAP	0.0032***	0.0037***
	(3.588)	(4.581)
Constant	0.9257***	0.8683***
	(8.681)	(8.845)
Day FE	No	Yes
Option Class FE	Yes	Yes
R^2	0.5520	0.5531
N	40,771	40,771

APPENDIX 9: ORDER CANCELLATION RATES – PHLX VS. NOM

Table 9
Order Cancellation Rates – PHLX vs. NOM

The sample consists of orders in 113 equity and ETF option classes trading on the PHLX and NOM during September 15, 2010 to October 15, 2010. We use Ordinary Least Squares to examine the difference in cancellation activity between the PHLX and the NOM. The dependent variable is the difference in average cancellation rates, calculated as the ratio of number of orders canceled to orders submitted. We include as regressors, the differences in order duration, implied volatility, order size, number of trades, and percent effective spreads between the PHLX and NOM in the same option series on the same day. The control variables are defined in Table 4. We include day fixed effects and option class fixed effects. Test-statistics are reported in parentheses that are obtained from standard errors clustered by option class. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	[1]	[2]
D(Order Duration)	-0.00004***	-0.00004***
	(-13.670)	(-13.757)
D(IVOL)	0.0072	0.0070
	(0.830)	(0.857)
D(Order Size)	-0.0001***	-0.0001***
	(-2.850)	(-2.719)
D(# of Trades)	-0.0004**	-0.0004**
	(-2.129)	(-2.169)
D(% Effective Spread)	0.0073	0.0077
	(0.086)	(0.094)
Call	-0.0313***	-0.0307***
	(-4.526)	(-4.363)
S/X	0.0445*	0.0467*
	(1.725)	(1.784)
Expiration	0.0255**	0.0151
	(1.989)	(1.257)
Underlying NBBO Mid	0.0017**	0.0018***
	(2.193)	(2.679)
Log(Underlying Volume)	-0.0239*	-0.0212*
	(-1.956)	(-1.775)
Underlying MCAP	0.0069***	0.0078***
	(3.993)	(4.713)
Day FE	No	Yes
Option Class FE	Yes	Yes
R^2	0.1105	0.1155
N	20,142	20,142

APPENDIX 10: EVENT STATISTICS

Table A.1
Event Statistics

This table provides order statistics in event time for matched options series on the PHLX and the NOM. We use August 30, 2010 as the event date as this seems to be the actual effective date of the fee policy. We match option series (underlying symbol, option type, strike, expiration date) on the PHLX by day with the same option series on the NOM. We examine the 10 days prior to the fee change and the 10 days following the rule change.

Day	Order Cancel Rate		Order Duration		# of Orders		Order Fill Rate		Order Fill Speed	
	PHLX	***NOM***	***PHLX***	***NOM***	***PHLX***	***NOM***	***PHLX***	***NOM***	***PHLX***	***NOM***
-10	73.92%	99.73%	597.4	75.1	621	17714	16.85%	0.27%	902.3	820.2
-9	75.32%	99.74%	743.4	88.8	499	15681	14.74%	0.27%	1014.2	1136.6
-8	72.06%	99.66%	709.3	93.0	333	12233	17.85%	0.35%	991.6	967.0
-7	72.92%	99.67%	672.9	91.8	431	16825	16.78%	0.33%	933.2	841.9
-6	72.18%	99.60%	752.1	99.1	349	10022	16.92%	0.40%	856.7	681.2
-5	67.66%	99.75%	846.3	104.0	325	13347	18.76%	0.25%	1353.0	961.5
-4	71.47%	99.75%	660.5	90.5	408	19819	17.83%	0.25%	924.1	774.9
-3	73.80%	99.80%	696.9	66.5	429	18030	16.62%	0.20%	1038.3	694.5
-2	75.65%	99.74%	699.0	78.7	443	18224	14.69%	0.26%	1007.1	784.2
-1	71.40%	99.79%	684.4	66.2	467	19531	18.54%	0.21%	912.3	710.7
1	59.04%	99.78%	1092.5	65.2	229	20145	26.12%	0.22%	1135.2	975.4
2	59.39%	99.64%	976.9	87.3	143	14592	27.42%	0.36%	1044.8	974.8
3	61.22%	99.66%	1088.0	90.8	70	13039	24.52%	0.34%	1192.0	822.2
4	63.94%	99.79%	923.1	77.1	132	13558	22.62%	0.21%	1001.4	920.5
5	61.29%	99.62%	853.2	102.8	150	14211	25.46%	0.38%	1008.8	714.5
6	67.19%	99.80%	734.6	90.2	165	13406	19.71%	0.20%	998.7	756.7
7	65.69%	99.73%	926.4	105.2	174	13119	20.92%	0.27%	1212.5	776.0
8	58.04%	99.58%	1087.8	133.6	116	10362	26.42%	0.42%	916.0	1088.3
9	64.25%	99.61%	784.7	88.2	120	12329	23.25%	0.39%	916.0	729.9
10	63.69%	99.71%	868.1	98.9	146	12072	24.43%	0.29%	1011.0	754.0

APPENDIX 11: ORDER EXECUTION QUALITY – MARKETABLE VS. NONMARKETABLE

Table A.2

Order Execution Quality – Marketable vs. Nonmarketable

This table reports the results of estimating eq. (1) separately for marketable orders and nonmarketable orders. The event window is the 55 trading days between July 26, 2010 and October 14, 2010. The variable of interest, *Post*, is a categorical variable set equal to one if the observation is in the post-event period, and zero for the pre-event period. We exclude orders on the event date. All remaining independent variables are defined in Table 4. Test-statistics are reported in parentheses obtained from standard errors clustered by underlying stock. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Event Period [-23, 32] 07/26/2010 - 10/15/2010					
	Marketable	Nonmarketable	Fill Speed (seconds)		# Orders	
	Arrival Rate	Fill Rate	Marketable	Nonmarketable	Marketable	Nonmarketable
	[1]	[2]	[3]	[4]	[5]	[6]
Post	0.017***	0.055**	-0.005**	45.652	0.205**	-252.257***
	(2.846)	(2.466)	(-2.514)	(1.461)	(2.349)	(-3.375)
Expiration	0.005**	0.003	-0.002	-138.100**	-0.011	-60.465**
	(2.336)	(0.429)	(-0.650)	(-2.303)	(-0.343)	(-1.983)
Price	0.001***	0.000	-0.000***	-6.627**	-0.026***	0.736
	(6.648)	(0.551)	(-5.348)	(-2.228)	(-13.546)	(0.371)
IVOL	0.001	-0.013*	-0.000	-87.307	-0.089	-37.775
	(0.535)	(-1.754)	(-0.317)	(-1.325)	(-0.535)	(-0.782)
Order Size	0.000***	0.000	-0.000	0.242	0.000**	-0.408
	(2.628)	(0.413)	(-1.197)	(1.006)	(1.990)	(-1.367)
S/X	0.002	-0.008	-0.012***	-206.309	-0.090	-260.132***
	(0.306)	(-0.432)	(-3.318)	(-0.926)	(-0.411)	(-2.634)
Call	0.003***	0.028***	-0.003**	31.083	0.319**	-55.219***
	(3.149)	(7.017)	(-2.128)	(1.095)	(2.397)	(-3.049)
Underlying NBBO Mid	0.000	0.000	-0.000	1.504	-0.001	1.244
	(1.240)	(0.056)	(-0.142)	(1.172)	(-0.249)	(0.520)
Log(Underlying Volume)	0.012***	0.039***	0.002	-208.123***	0.523***	6.459
	(5.851)	(7.172)	(1.445)	(-5.288)	(7.225)	(0.440)
Underlying MCAP	0.000	0.002**	-0.000	0.273	0.017***	-13.343***
	(1.456)	(2.484)	(-1.055)	(0.116)	(3.314)	(-4.978)
Constant	-0.230***	-0.668***	0.023	4,760.737***	-8.914***	1,475.172***
	(-6.071)	(-6.369)	(0.992)	(6.781)	(-8.531)	(4.431)
Option Class FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.026	0.048	0.004	0.003	0.016	0.038
N	49,164	49,164	19,153	37,349	49,164	49,164

FIGURES

FIGURE 1: ORDER CANCELLATION FEE AND ORDER CANCELLATION RATES

Figure 1
Order Cancellation Fee and Order Cancellation Rates

Figure 1 plots average order cancellation rates, measured as the number of orders canceled divided by the total number of orders submitted for a particular options series, over a 56-day event window [-23, 32] around the introduction of an order cancellation fee on the PHLX. The solid dark line represents orders on the PHLX, while the dotted light line represents orders on the NOM. We perform a daily match between the PHLX and NOM by option series.

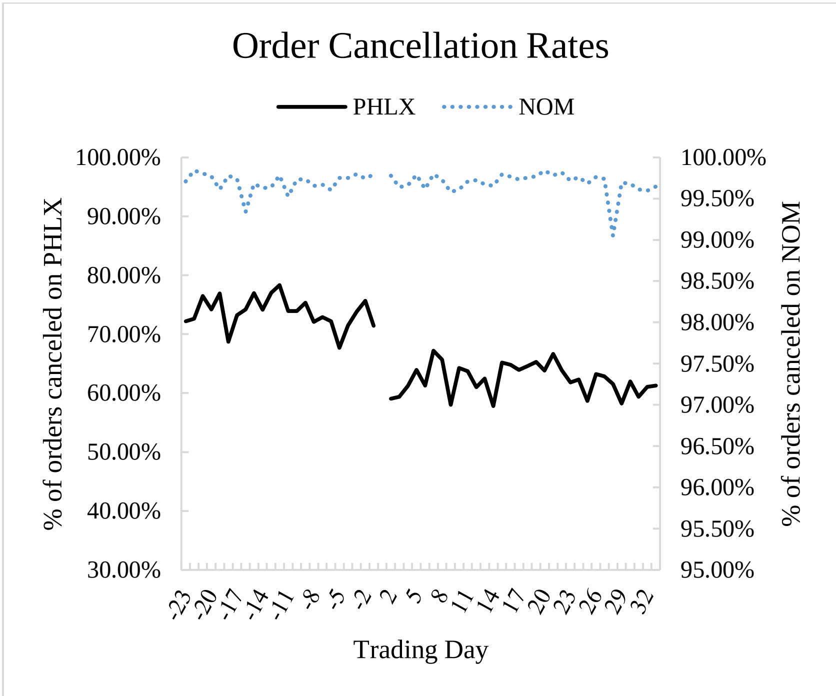


FIGURE 2: ORDER CANCELLATION FEE AND ORDER DURATION

Figure 2
Order Cancellation Fee and Order Duration

Figure 2 plots average order duration, defined as the number of seconds between order submission and deletion, over a 56-day event window [-23, 32] around the introduction of an order cancellation fee on the PHLX. The solid dark line represents orders on the PHLX, while the dotted light line represents orders on the NOM. We perform a daily match between the PHLX and NOM by option series.

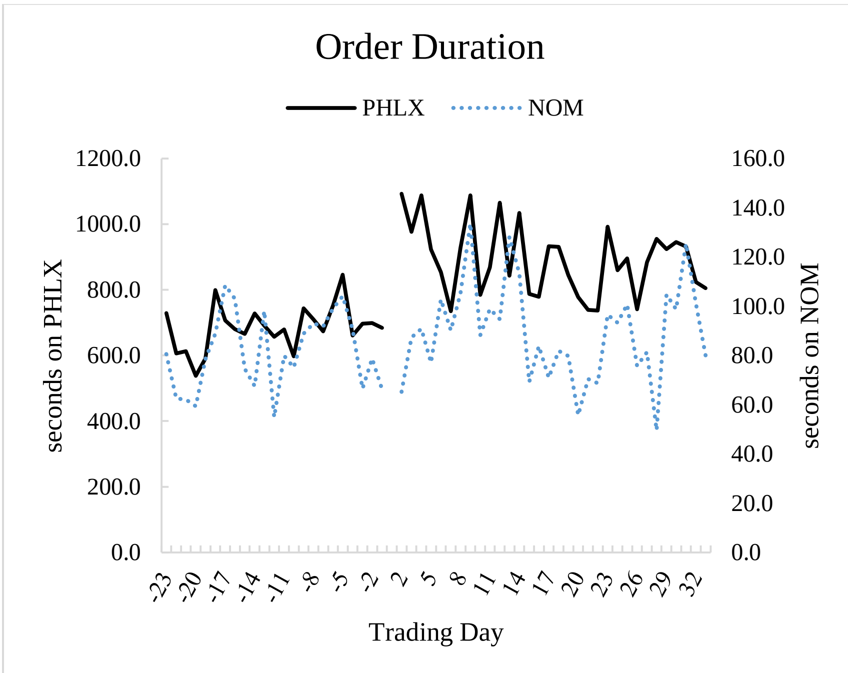


FIGURE 3: ORDER CANCELLATION FEE AND NUMBER OF ORDERS

Figure 3
Order Cancellation Fee and Number of Orders

Figure 3 plots average # of orders submitted to the PHLX and NOM over a 56-day event window [-23, 32] around the introduction of an order cancellation fee on the PHLX. The solid dark line represents orders on the PHLX, while the dotted light line represents orders on the NOM. We perform a daily match between the PHLX and NOM by option series.

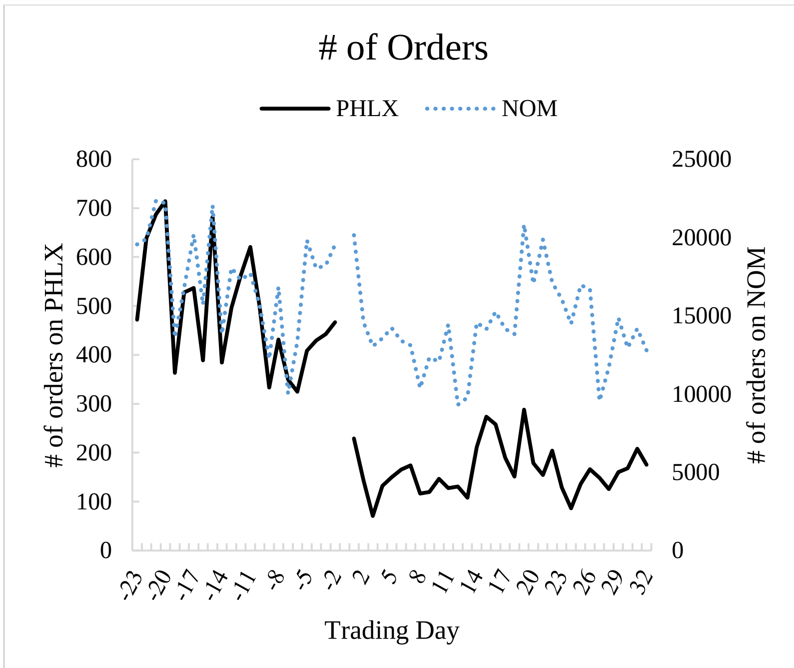


FIGURE 4: ORDER CANCELLATION FEE AND ORDER FILL RATES

Figure 4
Order Cancellation Fee and Order Fill Rates

Figure 4 plots average order fill rates on the PHLX and the NOM over a 56-day event window [-23, 32] around the introduction of an order cancellation fee on the PHLX. The solid dark line represents orders on the PHLX, while the dotted light line represents orders on the NOM. We perform a daily match between the PHLX and NOM by option series.

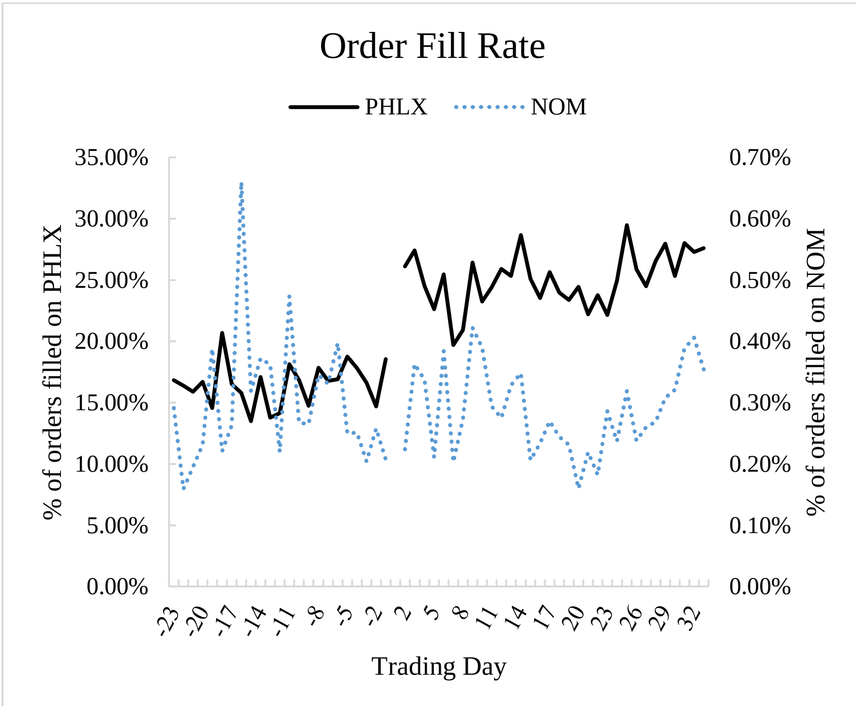


FIGURE 5: ORDER CANCELLATION FEE AND ORDER FILL SPEED

Figure 5
Order Cancellation Fee and Order Fill Speed

Figure 5 plots average order fill speeds, or the number of seconds between order submission and execution, over a 56-day event window [-23, 32] around the introduction of an order cancellation fee on the PHLX. The solid dark line represents orders on the PHLX, while the dotted light line represents orders on the NOM. We perform a daily match between the PHLX and NOM by option series.

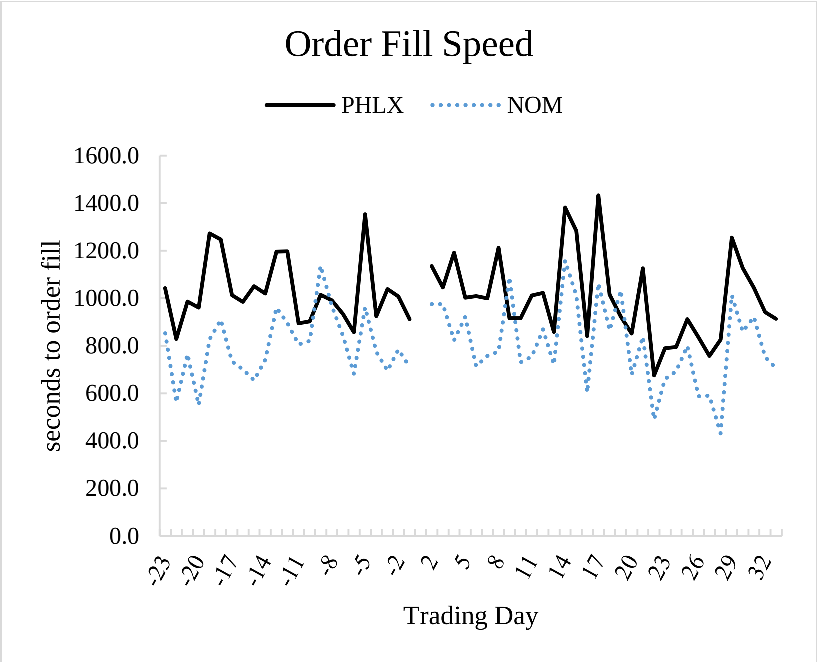


FIGURE 6: ORDER CANCELLATION RATES – ORDER DURATION

Figure 6
Order Cancellation Rates – Order Duration

Figure 2 plots daily average order cancellation rates for options on both the PHLX and the NOM, disaggregated by the passage of clocktime from order submission to cancellation. The time-to-cancellation is measured in seconds. The sample time period ranges from September 15, 2010 to October 15, 2010, as to avoid biasing the results due to the cancellation fee policy on the PHLX. The solid dark line represents cancellation rates for orders submitted to the PHLX, while the light dotted line represents cancellation rates for orders submitted to the NOM. We perform a daily match between the PHLX and NOM by option series.

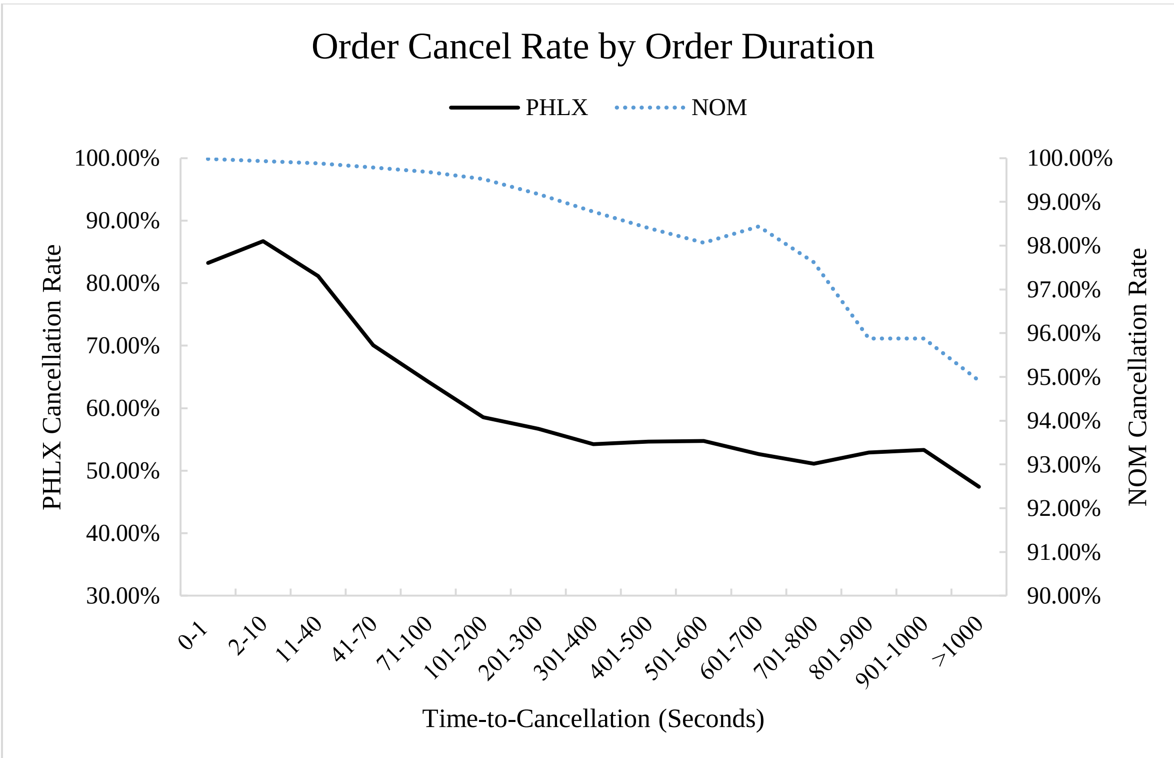
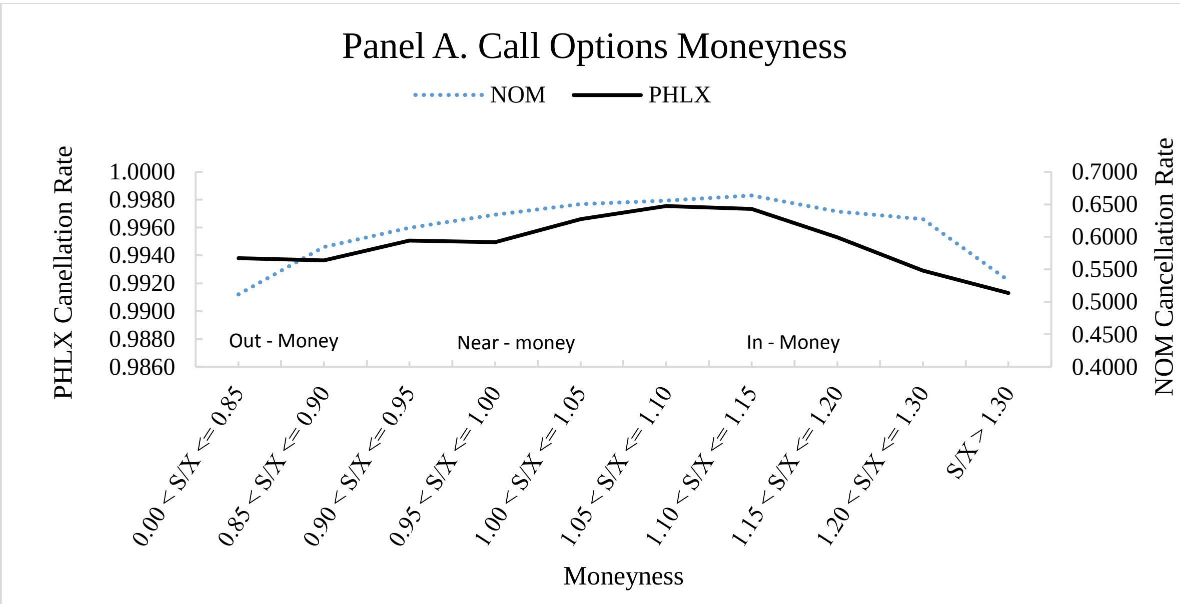


FIGURE 7: ORDER CANCELLATION RATES – OPTION MONEYNESS

Figure 7

Order Cancellation Rates – Option Moneyness

Figure 3 plots daily average order cancellation rates for options on both the PHLX and the NOM, disaggregated by option type (call or put) and option moneyness. Option moneyness is valued as the ratio of the underlying stock price to the option strike price, S/X. A call (put) option is said to be in-the-money (out-of-the-money) if the S/X ratio is greater (less) than one. An option is said to be near-the-money if the S/X ratio is between 0.9 and 1.1. The sample time period ranges from September 15, 2010 to October 15, 2010. The solid dark line represents cancellation rates for orders submitted to the PHLX, while the dotted light line represents cancellation rates for orders submitted to the NOM. We perform a daily match between the PHLX and NOM by option series.



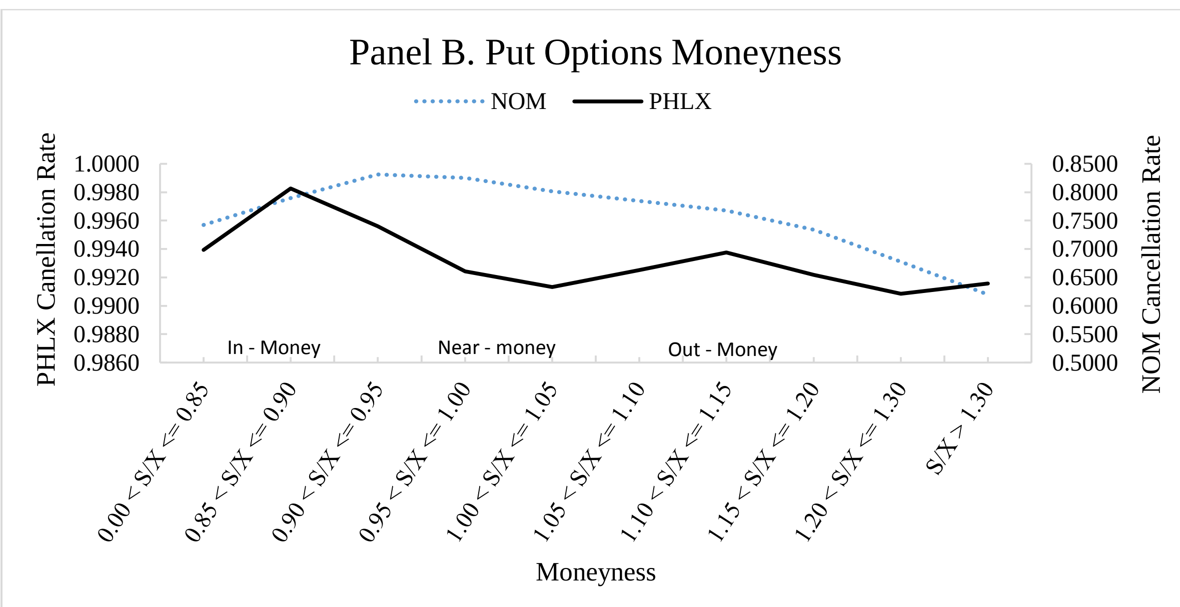
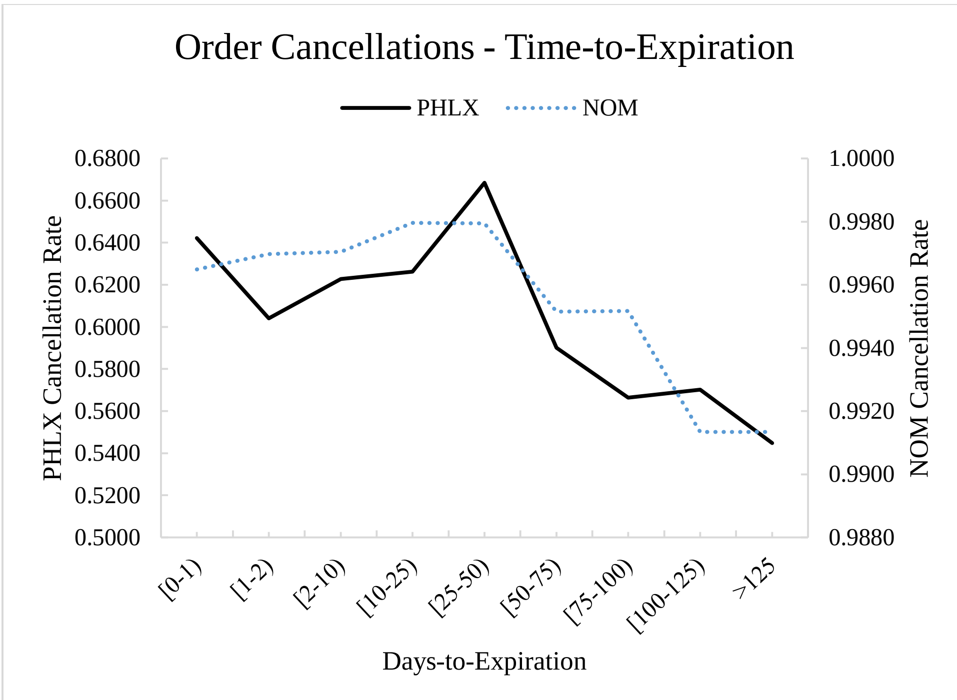


FIGURE 8: ORDER CANCELLATION RATES – TIME TO EXPIRATION

Figure 8
Order Cancellation Rates – Time to Expiration

Figure 4 plots daily average order cancellation rates on the vertical axes and the days to option expiration on the horizontal axis. Order cancellation rates are calculated as the total number of orders canceled divided by the number of orders submitted. The number of days until expiration are calculated as the total number of weekdays from the date of order submission to the expiration date. The sample time period ranges from September 15, 2010 to October 15, 2010. The solid dark line represents cancellation rates for orders submitted to the PHLX, while the dotted light line represents cancellation rates for orders submitted to the NOM. We perform a daily match between the PHLX and NOM by option series.



PART 2: MARKET STRUCTURE RULES IN U.S. EQUITY OPTIONS

PART 2

INTRODUCTION

Market structures are tailored to meet the particular needs of traders, which can impact order flow, trading strategies, and liquidity (see Parlour and Seppi, 2003 and O'Hara, 2015).[25] An important market design affecting competition for order flow between trading venues, is the priority rules that govern the order matching process. In a press release on April 16, 2015, BATS Global Markets states:

> *"The launch of the new EDGX Options market will enable Bats to compete for a new segment of order flow that does not trade on the price-time markets that BZX Options currently operates… We see a big opportunity to bring our innovative technology, operating efficiency, market leading pricing, and first-class customer service to help make markets better for participants in this segment of the market." (BATS to Launch Second U.S. Options Exchange – Targets November 2015 Launch for EDGX Options, page 1)*[26]

Exchanges employ various trade execution rules to prioritize orders in the matching process.[27] Most marketplaces grant price highest priority, but when two or more orders enter the limit order book at the same price, secondary priority rules, such as time or pro-rata, determine the

[25] For example, Ho and Stoll (1983) investigate competition between dealer and auction markets. Hendershott and Mendelson (2000) model competition between dealer and call markets. Santos and Scheinkman (2001) analyze competition in margin requirements. Foucault and Parlour (2000) examine competition in listing fees. Parlour and Seppi (2003) develop a model of competition between exchanges based on liquidity provision. Kwan, Masulis, and McInish (2014) examine the intermarket competition between dark trading venues and traditional stock exchanges.
[26] The press release can be found at http://www.bats.com/newsroom/press_releases/us_options/2015/
[27] Domowitz (1993) analyzes over 50 automated market structures in 16 different countries and discusses the different trade execution priority rules found in these markets.

ordering in the queue.[28] Limit order traders must balance the trade-off between the risks associated with delayed/non-execution with those of immediate execution (Harris and Hasbrouck, 1996; Handa and Schwartz, 1996; Parlour, 1998; Foucault, 1999). Marketable orders execute at posted prices in the limit order book, whereas nonmarketable orders have the potential to improve upon execution price, but at the risk of not executing.[29] Time priority allocates standing limit orders in sequence to marketable orders based on time of arrival in the book, whereas pro-rata priority allocates resting limit orders simultaneously to each countervailing marketable order in proportion to limit order size.[30] Since priority rules determine the mechanics of the order matching process, they may significantly impact equilibrium selection, order flow, order submission/cancellation decisions, and market liquidity (Parlour and Seppi, 2003; Angel and Weaver, 1998; Bessembinder, 2001; Field and Large, 2008; Lepone and Yang, 2012).[31]

In this paper, we investigate how order priority rules affect limit order quality and transaction outcomes in U.S. equity option markets. We focus on option markets for two reasons. First, the exchanges observed in this study have similar pricing schedules and overall market structures, with the exception of secondary priority rules, which is particularly true of the two Bats' exchanges. This makes for a natural laboratory to test our research questions, holding other structural differences constant. Second, and perhaps more importantly, both price-time and pro-

[28] Nonmarketable limit orders submitted to an exchange are stored in a queue in the order book and wait to execute against incoming marketable orders. See section 2 for a more detailed discussion of the secondary precedence rules analyzed in this study.

[29] Liu (2009) discusses two types of risk that limit order traders face when unanticipated information arrives in the marketplace: picking-off risk and non-execution risk. Picking-off risk is a result of limit orders providing others a free option to transact at a pre-specified limit price. Non-execution risk arises when the market price diverges from the limit order price.

[30] Size priority is different than pro rata priority in that an entire incoming marketable order may execute against a single limit order as opposed to being shared. The pro-rata percentage is calculated by dividing the marketable order size by the total quantity at a given price.

[31] Frino et al. (2000) examine Eurodollar futures on the Globex2 system for after-hours trading by the CME and find little evidence of changes in bid-ask spreads or volatility after the switch from price-time to pro-rata priority.

rata priority are successful models in U.S. option markets. With recent gains made by exchanges using price-time priority, slightly less than two-thirds of all trading volume executes on exchanges using pro-rata allocation.[32] In contrast to U.S. option markets, the pro-rata model has been unsuccessful in U.S. equity exchanges. For instance, the NASDAQ PSX was the first, and only, to attempt pro-rata allocation but failed to capture more than 1% market share in the first few years, resulting in the exchange relaunching in 2014 with a price-time model (see SEC Release No. 34-69452).

We first examine if priority rules affect the probability of execution. Price-time priority facilitates intense competition for queue position, as the first order to arrive at a particular price is given priority over all subsequent orders at the same price, even when the difference in arrival time is as short as a nanosecond (billionth of a second).[33] A better order position means less waiting time and a greater likelihood of a complete fill (Guo, Ruan, and Zhu, 2015). Pro-rata priority matches marketable orders at a price to all standing limit orders in proportion to order size, which might increase the likelihood of partial execution, but reduce the probability of a complete fill. We find that approximately 76% of the sample executions result in complete fills and average daily execution rates are between 2.09 and 2.22 percentage points higher in the price-time model, relative to the pro-rata model, other factors held constant.

Next, we analyze the effect of priority rules on the speed of order execution. We separate time-to-completion from time-to-first-fill, as it may require multiple marketable orders to completely fill a single nonmarketable limit order. For some traders, the uncertainty in time to

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[32] See statement from Bryan Harkins, executive vice president and head of U.S. markets at Bats in the Markets Media article entitled "*Bats to Launch Pro Rata Options Exchange*," published on April 30, 2015.
[33] See, for example, the comments made in section five of the SEC memorandum on April 30, 2015 addressing the problems with Rule 611 of Regulation NMS, also known as the "Order Protection Rule" or "Trade-through Rule." This is available at the web site https://www.sec.gov/spotlight/emsac/memo-rule-611-regulation-nms.pdf.

execution may not be important, but for others, the cost of waiting can be extremely high (see Lo, MacKinlay, and Zhang, 2002). Our multivariate analysis shows that the average time-to-first-fill is between 212 and 240 seconds shorter on the Bats EDGX Options Exchange (EDGX), which employs pro-rata priority, relative to the Bats BZX Options Exchange (BZX) and the NASDAQ Options Market (NOM), which employ price-time priority.

Our last set of tests examine how priority rules influence order cancellation decisions. The order strategy of submitting numerous orders, most of which are canceled, has received recent attention from policymakers, regulators, and exchange officials.[34] For example, to reduce excessive order cancellation activity and ensure fair and orderly markets, former SEC Chairwoman Mary Schapiro recommends a minimum time-in-force for quotations.[35]

We expect traders in the price-time model to closely monitor their orders as the probability of obtaining best position at a particular price is relatively low. In contrast, pro-rata priority gives traders less time to cancel orders before they face at least partial execution (Aldridge, 2013). Therefore, we expect order cancellation rates to be higher on exchanges using price-time priority, relative to exchanges using pro-rata priority, with one caveat. Field and Large (2008) develop a theoretical model where the pro-rata priority rule encourages traders to submit oversized orders and cancel any surplus, i.e. "pad-the-books," in attempt to realize a desired fill.[36] Consequently, the percentage of orders canceled with only a partial fill may actually be higher on exchanges using pro-rata allocation. We find that 88.72% of partial executions are subsequently canceled on the EDGX, relative to 61.63% on the BZX and 28.92% on the NOM. In addition, average order size

[34] Empirical research shows that a significant proportion of orders cancel prior to execution (Hasbrouck and Saar, 2009, 2013; Van Ness, Van Ness, and Watson, 2015).

[35] Speech by SEC Chairman: "*Strengthening Our Equity Market Structure*" by Mary L. Schapiro on September 7, 2010.

[36] See the Advantage Futures article, "*Is Pro Rata an Accident Waiting to Happen*," written by Ginger Szala in June of 2015. Also, see the Federal Reserve of Chicago 2014 paper, "*Recommendations for Equitable Allocation of Trades in High Frequency Trading Environments*," by John McPartland.

is 7.6 contracts larger on the EDGX than on the BZX, and 3.7 contracts larger on the EDGX than on the NOM. We argue that our results provide support for the notion that traders risk overtrading in the pro-rata model by submitting unrealistic quantities most of which are eventually canceled.

Overall, we document that neither price-time nor pro-rata priority dominate in all facets of execution quality. Based on this evidence, we conclude that priority rules matter, but they can be viewed as complements rather than substitutes. Thus, consistent with the argument of O'Hara (2015), market structures seem to meet the needs of different customers.

PRIORITY RULES: PRICE-TIME VS. PRO-RATA

Figure 1 illustrates the price-time and pro-rata matching processes in an example. For simplicity, we consider only the bid-side of the limit order book where the current highest price is $10.00, where there are four limit orders resting in the top of the book queue each for 1,000 contracts. If a market sell order for 2,000 contracts arrives, the price-time algorithm will allocate the contracts to the first two limit orders in the queue, which arrived earliest. The remaining two limit orders will remain on the book and must wait for the next incoming marketable order. In contrast, the pro-rata algorithm will distribute the shares proportionally among the limit orders at $10.00. In this example, the pro-rata percentage is 50% (2,000/4,000). Therefore, each limit order will execute against 500 contracts of the arriving market sell order, and the remaining contracts will be left on the book.

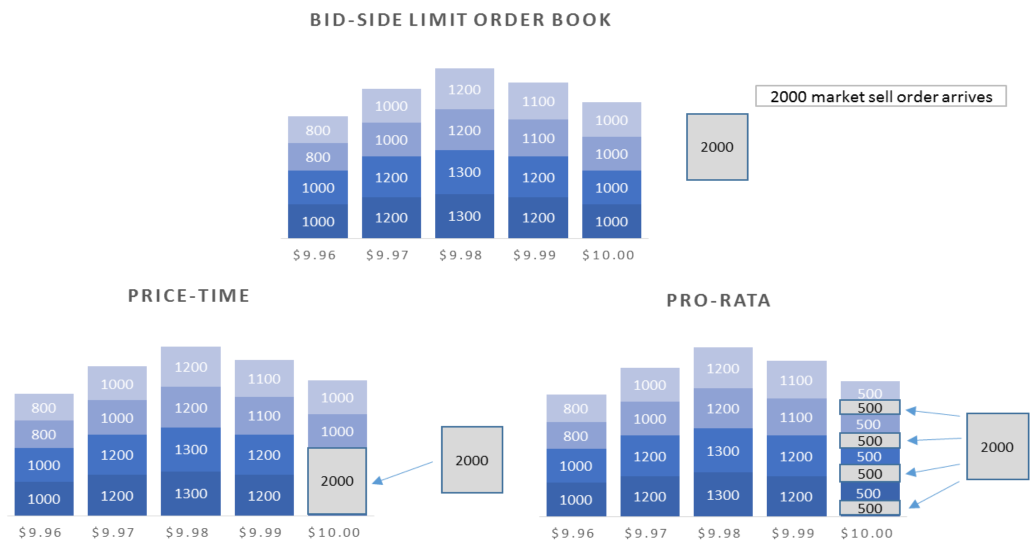

Figure 1. Price-Time and Pro-Rata matching algorithms, an illustration.

HYPOTHESIS DEVELOPMENT

The U.S. equity options exchanges analyzed in this study operate as electronic limit order books: the NASDAQ Options Market, Bats BZX Options Exchange, and Bats EDGX Options Exchange. There is substantial theoretical literature that considers the role of limit orders in the price discovery process (e.g. Glosten, 1994; Seppi, 1997; Parlour, 1998; Lo, MacKinlay, and Zhang, 2002; Parlour and Seppi, 2003; Foucault, Kadan, and Kandel, 2005). When a limit order is submitted to an exchange, it enters the order book or the queue. The queue then prioritizes the limit orders based upon the rules established by the exchange. In a competitive order-driven market, secondary priority rules, such as time and pro-rata, ultimately govern the mechanics of the matching process. Thus, priority rules can directly impact order placement strategies and, consequently, how liquidity is supplied on an exchange (Angel and Weaver, 1998; Bessembinder, 2001; Field and Large, 2008).

Cohen, Maier, Schwartz, and Whitcomb (1981) show that a trader's expected end-of-period wealth is an increasing function of order execution probability. Traders can achieve better execution prices by submitting more passive limit orders, but face the risk of non-execution (see Angel, 1994; Hollifield, Miller, and Sandas, 1996; Foucault, 1999; Peterson and Sirri, 2002). Non-execution risk increases as the market price moves further away from the order price (Liu, 2009). Nonmarketable orders are stored in the order book queue and must wait the arrival of marketable orders to execute. Therefore, the execution of a nonmarketable order is not guaranteed. Alternatively, traders have the option to achieve immediacy by submitting more aggressive marketable orders, but at the risk the market price will move in an unfavorable direction prior to execution.

Market structure rules that prioritize orders can directly impact the probability of order execution, a risk inherent in limit order placement. In the pro-rata model, a marketable order is distributed to all competitively-priced nonmarketable orders in proportion to order size. This may increase the probability of at least a partial execution. However, theory also predicts that traders will risk overtrading in the pro-rata model, and cancel any remaining contracts that go unexecuted (Angel and Weaver, 1998; Field and Large, 2008). Therefore, the probability of a complete fill might be relatively low on exchanges using pro-rata priority.

The price-time model, in contrast, matches marketable orders to the most competitively-priced nonmarketable order(s) that arrived in the queue first. Depending on the size of the marketable order, only one nonmarketable order may fill, while the remaining orders will sit on the book. As new information enters the market, standing limit orders face greater risk of being "picked off", as the value of the asset rises above (good news) or drops below (bad news) the current market price (see Stoll, 1992; Berkman, 1996; Handa and Schwartz, 1996; Foucault, 1999). Liu (2009) shows that limit order traders reduce the risk of being picked off by widening the limit order spread, which in turn, reduces the likelihood of an order filling.

To the extent that the pro-rata model increases the probability of partial executions, and the price-time model reduces the chance of an order filling, we expect the following hypothesis to hold.

Hypothesis 1: The probability of order execution is higher on exchanges with pro-rata priority, relative to exchanges with price-time priority.

Priority rules that govern the matching process between buyers and sellers can directly impact the time-to-execution. The uncertainty in execution time may not be important for all traders, but for some, the cost of waiting can be quite significant (see Lo, MacKinlay, and Zhang, 2002; Garvey and Wu, 2010). Exchanges that enforce price-time priority ultimately facilitate a race to the top of the order book queue, as orders execute on a first-come, first-serve basis. In price-time models, queue positioning is crucial, as a better order position means less waiting time and a higher probability of execution (Guo, Ruan, and Zhu, 2015). Hence, time priority encourages traders to place orders quickly to achieve faster execution at a desired price, which can shorten the time-to-completion, as long as those orders remain on the book.

In an article entitled "S*ize Matters"* in Marketview magazine, Brian Hyndman, Senior Vice President of NASDAQ OMX, explains:

> *"The price-time priority model benefits market participants who have the fastest technology, which allows their orders to rapidly reach the front of the line. With a price-size priority model, speed is de-emphasized with the objective of providing incentives for traders to send in sizable orders."*

Time, however, is not granted precedence on exchanges operating under a pro-rata model. Rather, all limit orders in the queue execute simultaneously against an incoming marketable order in proportion to size. Queue position is, therefore, less important in a pure pro-rata model. A limit order will not completely fill in this model, unless the arriving marketable order(s) is (are) sufficiently large to fill all limit orders at a particular price. For this reason, limit orders submitted to an exchange using pro-rata rules may sit longer in the queue before realizing a complete fill. Thus, we expect the following hypothesis to hold.

Hypothesis 2: Time-to-completion is shorter on exchanges using price-time priority, relative to exchanges using pro-rata priority.

Similar to Lo, MacKinlay, and Zhang (2002), we distinguish between the time-to-completion and time-to-first-fill, which is an important contrast when considering the effect of priority rules on order execution speed. In the pro-rata model, each order entered at a price is given priority based on size. Therefore, regardless of when the limit order entered the order book, it will at least partially execute when a marketable order arrives. In the price-time model, however, only the first nonmarketable order to arrive at a price may execute, while all remaining limit orders must wait for the next marketable order. Thus, we might expect the time-to-first fill to be shorter on exchanges using pro-rata priority than those using price-time priority.

Hypothesis 3: Time-to-first-fill is shorter on exchanges using pro-rata priority, relative to exchanges using price-time priority.

Advances in technology have changed financial markets by altering the trading behavior of limit order traders, who are now better able to monitor orders and make faster, more precise decisions (Goldstein, Kumar, and Graves, 2014).[37] The increase in high-speed computerized trading coincides with an increase in order cancelations (Hasbrouck and Saar, 2009). Van Ness, Van Ness, and Watson (2015) show that order cancellation rates in the U.S. equities markets are increasing over time, starting at 35% in 2001, and reaching above 90% in 2010. Hence, it is not surprising that order cancellation activity has drawn significant attention from the popular press, regulators, and exchange officials. For instance, in a policy proposal submitted by the NASDAQ to the SEC (see SEC Release No. 34-65610), the exchange states:

[37] See also Boehmer, Saar, and Yu (2005) for a review of the evolution of limit order trading strategies. O'Hara (2015) also discusses how high-frequency trading has changed financial markets.

"Today's cash equities markets are characterized by high levels of automation and speed… In such an environment, the degree to which displayed orders reflect committed trading sentiment has become less predictable, because many entered orders are rapidly canceled."

Thus, exchange operators are concerned with cancellation activity, and secondary precedence rules can have a direct impact on order cancellation rates.

Reducing low latency in trading and competing for order position are key drivers behind the technological race among high-speed trading firms (Hasbrouck and Saar, 2013 and Guo, Ruan, and Zhu, 2015). The price-time model favors speed, as faster traders receive the bids and offers first. Aït-Sahalia and Saglam (2013) model a trader who submits orders on both sides of the market and cancels one of the existing orders when the signal changes. Therefore, an order cancellation will occur when the signal received by the trader changes before a trade occurs. As the latency of the trader decreases, the cancellation rate increases monotonically. Since the price-time model prioritizes orders based on time of arrival, it might encourage higher cancellation rates as many of the orders submitted at a particular price will fall short of obtaining the best position and will subsequently be canceled.

Traders submitting orders to an exchange operating under the pro-rata model are likely to use a differing trading strategy, since jockeying for queue position is far less important. Every order submitted to a pro-rata exchange faces a positive probability of fractional execution, which discourages traders from submitting frivolous orders that almost immediately cancel. Since the pro-rata model gives priority to all orders at a particular price, it provides traders with less time to cancel orders prior to facing execution. By contrast, the price-time priority model gives traders more time to cancel orders before they face execution (Aldridge, 2013). We, therefore, expect the following hypothesis to hold:

Hypothesis 4: Order cancellation rates are higher in price-time exchanges than in pro-rata exchanges.

Although we expect order cancellation rates to be lower in pro-rata exchanges, relative to those in price-time exchanges, the percentage of orders canceled with only a partial fill might actually be larger in pro-rata exchanges. Since every order in a pro-rata model is executed in proportion to the total number of all orders in the top-of-the-book queue, to execute a desired order size in full, a trader must submit a larger-than-necessary order, and then cancel any surplus order once the desired execution size has been reached (Angel and Weaver, 1999 and Aldridge, 2013). Therefore, pro-rata priority incentivizes traders to inflate order size and cancel the remainder after a partial fill.

The public press has expressed concerns with the pro-rata model on this particular topic. A Federal Reserve of Chicago 2014 paper states:[38]

"If there is a criticism of the Pro Rata trade allocation logic, it is that many market participants are constantly bidding or offering unrealistically large quantities, often far greater than they could likely absorb."

Field and Large (2008) develop a theoretical model where the pro-rata priority rule forces traders to risk overtrading by submitting over-sized limit orders, most of which eventually cancel. In their model, the pro-rata algorithm matches limit orders to each countervailing marketable order in proportion to their sizes, which creates strategic 'complementarities' in the order-size decisions of traders. In equilibrium, traders over-inflate order sizes in attempt to achieve a desired fill amount.

[38] See the Federal Reserve of Chicago 2014 paper, "Recommendations for Equitable Allocation of Trades in High Frequency Trading Environments," authored by John McPartland.

Field and Large (2008) argue that this type of order-size competition is absent under the price-time rule. Thus, we expect the following hypothesis to hold.

Hypothesis 5: The percentage of partially filled orders canceled is higher in pro-rata exchanges, relative to that in price-time exchanges.

DATA DESCRIPTION

We use order-level data collected from three equity options exchanges: Bats BZX, Bats EDGX, and Nasdaq Options Market.[39] We receive depth of book quotations and execution information from the Bats historical Multicast PITCH. BATS uses a symbol mapping mechanism for the options Multicast PITCH to reduce the size of the feed. The day-specific mappings include unique identifiers and information on the option symbol, strike price, expiration date, and option type (call or put). The following messages are time stamped to the nanosecond and linked by a day-specific order id number. "Add order" message represents a new displayed order on the BATS book, which includes a side indicator (buy order or sell order), quantity (# of contracts), security mapping symbol, and limit order price. "Order executed" messages are sent when a visible order on the BATS book executes in whole or in part and includes the executed quantity and price (if different from the add order price). "Reduce size" messages are sent when a visible order is partially reduced. "Modify order" message is sent whenever an add order message is visibly (price and/or quantity) modified. "Delete order" message is sent when an open order is completely removed from the BATS book.

We combine the BATS information with order and trade data from the NASDAQ ITCH to Trade Options (ITTO) direct feed. We download several different message types that are linked by a unique order reference number. "Option directory" messages contain information for the

[39] These three exchanges are the only U.S. equity options markets for which we have both order and trade data. We do not view this as a limitation as these three venues operate under various priority models and capture one-quarter market share.

security symbol, expiration date, strike price, and option type (call or put). "Add order" messages are time stamped records for new orders added to the book, including order time (stamped to the nanosecond), market side (buy or sell), order price, and order size (# of contracts). "Executed order" modification messages are time stamped records generated by (partial) executions and report executed contracts and execution price (if the execution price differs from the add order price).[40] "Order cancel" messages are time stamped records generated by partial cancellations and report the number of contracts canceled. "Replace" messages are time stamped records that report the new order reference number, new order price, and new order size. "Delete" messages are time stamped records that report when an order is deleted from the NOM order book.

To supplement the order data, we obtain end-of-day market price and volume information on trades and quotes, as well as greek values, from the Options Price Reporting Authority (OPRA). In addition to options data, we acquire CRSP data to compute independent variables for the multivariate tests. We analyze the 21 trading days between October 3, 2016 and October 31, 2016. Using statistics from the Options Clearing Corporation, we find that these three exchanges account for nearly a quarter of all equity option trading volume.

Table 1 describes our sample selection process. The initial sample contains trade and matched order data for 3,232 option classes. We focus on orders during regular trading hours 9:30 a.m. to 4:00 pm and we remove complex orders, such as spreads and straddles, as they are priced as a package.[41] The initial sample consists of billions of orders submitted to the three options exchanges, of which 4.2 million execute for a total of 50.68 million option contracts. Since we are comparing execution quality across exchanges, we restrict the sample to options classes that

[40] Since the analysis involves examining limit order execution quality between order allocation models, we ignore "trade" messages that report executions involving non-displayed order types.

[41] For robustness, we exclude order messages transmitted before 9:45 am and after 3:50 pm to avoid the opening and closing rotations, and our results are qualitatively similar.

trade on all three exchanges, which reduces the sample to 2,476 option classes. These option classes account for 98.91% of trades and 98.97% of contract volume. Similar to Battalio, Shkilko, and Van Ness (2016) we eliminate option classes that have fewer than 10 trades per day. This screen reduces the sample to 472 option classes, which account for 87.56% of trades and 89.25% of contract volume. We next exclude options on foreign stocks, ADRs, and REITs. The final sample consists of 390 option classes of which 333 are on common stocks and 57 are on ETFs. We also report that 186 (41) of the 333 (57) option classes on common stocks (ETFs) trade in pennies, while 147 (16) do not trade in pennies. Out of the initial sample trades and volume, the 390 option classes account for 77% of trades and 79% of contract volume.

Next, we describe the distribution of sample trading activity across exchanges. Panel A of Table 2 shows that the BZX captures the largest sample market share, executing 60.12% of trades and 63.06% of trading volume across all option classes. The NOM executes 31.5% of trades and 31.43% of trading volume, while the EDGX executes 8.38% of trades and 5.51% of trading volume. The EDGX captures more sample market share in options on ETFs. Specifically, the EDGX accounts for 16.34% of trades and 9.08% of trading volume in options on ETFs.

On January 26th, 2007, the options exchanges commenced a pilot to quote and trade options in one-cent increments. The penny pilot program initially included options on 13 stocks and ETFs, but has expanded the program to options on 363 securities. Pilot stock and ETFs are quoted and traded in penny increments for options trading at less than \$3.00, and increments of five-cents for options trading at or above \$3.00.[42] Panel B of Table 2 shows that grouping option classes into penny-pilot and non-penny pilot yields slightly different sample market share results. For instance, the BZX executes 61.78% of trades in penny options, while only 49.98% of trades in non-penny

[42] Options on QQQ trade and quote in one-cent increments at all price levels.

options. The NOM executes only 29.22% of trades in penny options but 45.42% of trading in non-penny options. The EDGX executes the least amount of trades in penny options and non-penny options, 9% and 4.6%, respectively.

Panel A of Table 3 reports descriptive statistics for the 333 option classes on common stocks. The average option class has a strike price of $80.72, with a corresponding underlying closing price of $81.09. We estimate option moneyness, or value of an option contract, as the ratio of the underlying stock price to strike price. Since equity option open interest is concentrated in options near the money (Lakonishok, Lee, Pearson, and Poteshman, 2007), it is not unexpected to find a mean S/X ratio of 1.03. Since information is shown to flow from equity to options markets (Chen, Lung, and Tay, 2005), we observe underlying characteristics such as volume and market capitalization. The mean daily trading volume for an underlying common stock is 6.3 million shares and a market capitalization of $44.98 billion. Panel B of Table 3 displays option class statistics on the 57 ETFs in the sample. The average option class on an ETF has a strike price of $63.67, 54 days to expiration, and an S/X ratio of 1.024. The average trading volume on an ETF is 12.3 million shares.

Since the primary purpose of this study is to compare the difference in execution quality between the price-time and pro-rata priority models, we obtain information on the allocation models and fees for each exchange. Panel A of Table 4 shows that the BZX and the NOM use the price-time model, which allocates marketable orders to standing limit orders at a price in sequence based on time of arrival. The EDGX uses a pro-rata model that fills standing limit orders at a price in proportion to order size.

Each of the three exchanges use maker-taker pricing. A maker rebate is paid to standing limit orders when they provide liquidity to a marketable order, whereas a taker fee is paid by marketable orders when they access liquidity. Battalio et al. (2015) document a negative relation between take fees and several aspects of order execution quality. Panel B of Table 4 shows that the average take fee on the BZX is \$0.46, on the EDGX is \$0.32, and on the NOM is \$0.50. To the extent the relation between take fees and limit order execution quality holds in equity option markets, we might expect (a priori) fill rates to be lower on the BZX and NOM, relative to the EDGX.

EMPIRICAL RESULTS

To examine the differences, if any, in order execution quality between the price-time and pro-rata matching models, we estimate the following six measures: probability of order execution, time-to-complete fill, time-to-first fill, probability of order cancellation, proportion of partially executed orders canceled, and order size (see Lo, MacKinlay, and Zhang, 2002; and Battalio, Corwin, and Jennings, 2015).

To approximate the probability of order execution, we follow Foucault (1999) and estimate daily execution rates by option class as the ratio of the number of executed orders divided by the total number of orders submitted. Table 5 shows that the average execution rate is 2.98% on the BZX, 1.17% on the EDGX, and 4.98% on the NOM. We test for differences in mean execution rates between pro-rata and price-time priority using simple test-statistics. We find that the average execution rate is 1.8 percentage points lower on the EDGX, relative to the BZX. In addition, average execution rates are 3.8 percentage points lower on the EDGX than on the NOM. These results indicate that the probability of execution is significantly higher in the price-time model, relative to the pro-rata model, which leads us to reject our first hypothesis.

In an attempt to explain this result, we separate executions into complete fills and partial fills and report the statistics in the appendix (see Table A.1). We find that out of the 3.25 million orders that execute across the three exchanges during the sample period, 2.47 million are complete fills and only 0.78 million are partial fills. Since Field and Large (2008) predict that traders submit unrealistic quantities in the pro-rata model with the intention of cancelling unexecuted contracts, we might expect the proportion of partial fills to total executions to be relatively high in the pro-rata model, while the ratio of complete fills to total executions to be relatively low. We find as the percentage of partial orders to executions is highest on the EDGX, 35.9%, compared to 25.06% on the BZX and 19.38% on the NOM. The percentage of complete fills to total executions is, therefore, lowest on the EDGX, 64.15%, relative to 74.94% on the BZX and 80.62% on the NOM. Two-sample t-tests between proportions are performed to determine that there are significant differences in the percentage of partial/complete executions between the exchanges. The proportion of partial execution on the EDGX is significantly higher than on the BZX (difference = 10.80%; t-stat = 119.88) and the NOM (difference = 16.48%; t-stat = 182.19). Since the majority of executions are complete fills across all three exchanges, and we find a lower order completion rate in the pro-rata model, our finding that the probability of execution is lower on the EDGX is supported.

Our next measure of execution quality is limit order execution time. We follow Lo, MacKinlay, and Zhang (2002) and separate the time-to-completion from the time-to-first-fill. We estimate execution times using order data, which is time-stamped to the nanosecond (one billionth of a second). Time-to-complete fill is measured as the passage of time from initial order submission to complete execution. It is possible for the same limit order to execute in several parts, therefore, we estimate time-to-completion using the difference between the time of the initial display order message and the time of the last executed message that fills the original order. For ease of interpretation, we calculate execution times in seconds.

Table 5 shows that the average (median) time-to-completion for an order submitted to the EDGX is roughly 586 (333) seconds. In comparison, the average (median) time-to-completion on the BZX is 708 (644) seconds and 921 (819) seconds on the NOM. We find that the mean time-to-completion is approximately 122 seconds faster on the EDGX than on the BZX and 371 seconds faster on the EDGX than on the NOM. These differences are significant at the 0.01 level and economically meaningful. Our results suggest that the time-to-completion is faster on exchanges using pro-rata priority than price-time priority, and so we reject our second hypothesis.

We estimate the time-to-first-fill as the number of seconds between initial order submission and first execution. Table 5 shows that the average time-to-first-fill is 693 seconds on the BZX, 544 seconds on the EDGX, and 921 seconds on the NOM. The difference in mean time-to-first fill between the EDGX and BZX (NOM) is -148.398 (-377) seconds. Our univariate tests provide evidence to support our third hypothesis, which states that the time-to-first-fill is shorter on exchanges using pro-rata priority than exchanges using price-time priority.

To test our fourth hypothesis, which states that order cancellation activity is higher in price-time exchanges than in pro-rata exchanges, we estimate the probability of order cancellation for each option class as the ratio of the total number of orders canceled to the total number of orders submitted on a particular trading day. Table 5 reports that the average order cancellation rate on the BZX is 96.91%, relative to 96.9% on the EDGX. The difference in mean cancellation activity between the BZX and EDGX is insignificant. We do, however, find that the average probability of cancellation is significantly higher on the EDGX, relative to the NOM (difference = 0.0688, t-stat = 10.74). Thus, we find conflicting evidence for the difference in cancellation activity between exchanges using pro-rata and price-time priority.

Our last set of tests in this section examine if traders might risk overtrading, submit larger orders than they intend to execute, in the pro-rata model. A consequence of submitting oversized orders in hopes of achieving a desired fill amount, is that once a desired execution size is reached the remaining contracts will be canceled (Angel and Weaver, 1999 and Aldridge, 2013).[43] We

[43] We analyze only partial executions that are then canceled by a delete order message, and thus avoid day orders that cancel at the end of the trading session.

first measure the proportion of partially executed orders that are subsequently canceled. Table 5 shows that 88.72% of partially executed orders on the EDGX are canceled, whereas this ratio is only 61.63% on the BZX and 28.92% on the NOM. Our results indicate that the percentage of partially filled orders canceled is significantly higher on the exchange allocating orders on a pro-rata bases, relative to exchanges using price-time matching, which supports our last hypothesis that states the percentage of partially filled orders canceled is higher in pro-rata exchanges than in price-time exchanges.

We also analyze differences in mean order sizes across the sample exchanges. To the extent traders risk overtrading in the pro-rata model, we expect to find larger order sizes on the EDGX, relative to the BZX and NOM. Table 5 shows that the average order size on the EDGX is 23.84 contracts, relative to 16.22 contracts on the BZX and 20.14 contracts on the NOM. We find that average order size is significantly higher on the EDGX, relative to the BZX (difference = 7.6232; t-stat = 3.85) and NOM (difference = 3.7020; t-stat = 2.00). Therefore, average order size is significantly higher in the pro-rata model than in the price-time model, which provides further support for the notion that traders may submit unrealistic quantities in the pro-rata model to achieve a desired fill amount.

In this section, we examine if the differences in execution quality between the pro-rata and price-time matching models observed in the univariate tests hold in a multivariate setting. Presumably, a trader's limit order placement decisions and the quality of his/her executions are conditional on several factors including option and stock characteristics, market conditions, and priority rules. To address this concern, we conduct multivariate analyses to examine the determinants of execution quality.

We use OLS and quantile median regressions to analyze five dependent variables. First, *% execution rates*, defined as the ratio of executions (complete or partial) to total orders. Second, *time-to-completion*, calculated as the number of seconds between order time and a complete fill. Third, *time-to-first-fill,* measured as the number of seconds between order time and first fill time conditional on at least a partial fill. Fourth, *% order cancellation rates,* defined as the percentage of total orders canceled. Last, we examine the *% of partial executions canceled*. We contend that the relevant independent variables are option and stock attributes, order characteristics, venue traits, and trading day. The unit of measurement is option class/day and the general specification for our models is outlined as follows:

$$\begin{aligned} DepVariable_{i,t} = {} & \alpha + \delta_t + \gamma_i + \beta_1 BZX_{i,t} + \beta_2 NOM_{i,t} + \beta_3 EDGX_{i,t} + \beta_4 S/X_{i,t} \\ & + \beta_5 Days\ Expire_{i,t} + \beta_6 Call_{i,t} + \beta_7 IVOL_{i,t} + \beta_8 Spread_{i,t} + \beta_9 Order\ Size_{i,t} \\ & + \beta_{10} Cancel\ Speed_{i,t} + \beta_{11} Volume_{i,t} + \beta_{12} Price_{i,t} + \beta_{13} Pvolt_{i,t} \\ & + \beta_{14} UVolume_{i,t} + \beta_{15} UMCAP_{i,t} + \beta_{16} Penny_i + \beta_{17} ETF_i + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

where *BZX*, *NOM*, and *EDGX* are exchange-specific indicator variables equal to one if the order/execution occurs on that particular exchange and zero otherwise; *S/X* is the underlying stock price divided by the strike price; *Days Expire* is the number of days between order submission/update to option expiration; *Call* equals one if the option is a call option and zero for a put option; *IVOL* is an option's average daily implied volatility as computed by OPRA; *Spread* equals an option's average daily dollar quoted spread, or the difference between the ask price and bid price provided by OPRA; *Order Size* is the average number of contracts attached to a particular order; *Cancel Speed* is the number of seconds between order submission and cancellation conditional on a complete order deletion; *Volume* equals the option's average daily contract volume in 10,000s; *Price* equals the option's mean trade price; *Pvolt* equals the option's average daily standard deviation in trade prices; *UVolume* equal the underlying stock's average daily share volume in 10,000s; *UMCAP* is the underlying stock's average daily market capitalization, measured in $billions; *Penny* equals one if the option is traded and quoted in pennies and zero otherwise; and *ETF* equals one if the option class is an ETF and zero if it is a common stock.

We also include day dummy variables, δ_t. We estimate eq. (1) with and without option-class fixed effects, γ_i. The option class fixed effects prevent us from estimating the coefficients on the Penny and ETF indicator variables, as these measure do not have within-class variation. Most of the results are virtually identical between the two estimation approaches, with or without option-class fixed effects, and we therefore focus on the results without fixed effects. We do not include all exchange indicator variables in any of the model specifications as this would violate the full column rank assumption for consistent OLS estimation.

Table 6 reports the results of estimating eq. (1) inserting *execution rates* as the dependent variable. Our results show that call options are more likely to execute than put options. Also, we find a positive and significant coefficient on *Cancel Speed*, indicating that the probability of execution increases as the average order remains on the book for a longer period of time. The positive and significant coefficient on *UVolume* suggests that as the average daily shares traded in the underlying stock increases, so does the probability of execution in the related options.

We first compare order execution rates between the EDGX and the BZX, by removing observations on the NOM and omitting the NOM and EDGX indicator variables from eq. (1). Column [1] of Table 6 shows that an order submitted to the BZX is 1.12 percentage points more likely to fill than an order submitted to the EDGX, other factors held constant. We next compare execution rates between the EDGX and the NOM, by removing observations from the BZX and deleting the BZX and EDGX indicator variables from eq. (1). Columns [3] and [4] of Table 6 show that average daily execution rates are between 2.85 and 2.94 percentage points higher on the

NOM, relative to the EDGX. Since the EDGX operates using pro-rata priority and the BZX and NOM use price-time priority, our results do not support our first hypothesis that the probability of execution is higher in the pro-rata model than in the price-time model. In fact, we find the opposite, execution probability is higher in the price-time model, relative to the pro-rata model, which is consistent with our univariate tests.

Since execution time is uncertain when placing a limit order, traders must consider both the risk of non-execution and speed of execution. We separate execution times into time-to-first-fill and time-to-completion. To control for potential outliers, as the standard deviation in execution times are wide, we estimate eq. (1) for both *time-to-completion* and *time-to-first-fill* using quantile median regressions. Table 7 reports the results of estimating eq. (1) when *time-to-completion* is the dependent variable. The control variables generate several interesting results. As the underlying stock price increases relative to the option strike price, the time-to-completion lengthens. The positive and significant coefficients on *Days Expire* suggest that orders on options further from expiration take longer to fill. We also find that orders on call options take longer to fill than orders on put options, at both the mean and median. Similar to Battalio et al. (2015), time-to-execution is decreasing in trading volume and increasing in volatility. Last, orders submitted on options that trade in pennies fill faster than orders on options that do not trade in pennies.

To assess whether priority rules affect execution times, we focus on the exchange indicator variables. In Column [2] of Table 7, we find that the median time-to-completion is 156.55 seconds faster on the EDGX than on the BZX, other factors held constant. Column [4] of Table 7 shows that the time-to-completion is 412.18 seconds faster on the EDGX than on the NOM. Counter to our second hypothesis, our multivariate analysis shows that the time-to-completion is shorter in the pro-rata model, relative to the price-time model.

Table 8 reports the results of estimating eq. (1), inserting time-to-first-fill as the dependent variable. The coefficients on the BZX indicator variable in Columns [1] and [2] are positive and significant at the 1% level, indicating that the time-to-first-fill is shorter on the EDGX than on the BZX. In economic terms, the time-to-first-fill is between 97.8 and 149.6 seconds faster on the EDGX, relative to the BZX. We find even stronger results when we compare time-to-first-fill between the EDGX and NOM. For instance, the average (median) time-to-first-fill is 337 (384) seconds faster on the EDGX than on the NOM. The results in Table 8 support our third hypothesis that the time-to-first-fill is shorter on exchanges using pro-rata priority than on exchanges using price-time priority.

Next, we examine if order cancellation activity differs between the pro-rata and price-time models. We estimate eq. (1) using *% order cancellation rates* as the dependent variable and report the results in Panel A of Table 9. We suppress the control variables for brevity and concentrate on the exchange indicator variables. We find that, on average, the percentage of orders canceled is not significantly higher on the EDGX, relative to the BZX. However, the average number of orders canceled is between 3.49 and 4.11 percentage points higher on the EDGX than on the NOM. Therefore, we reject our fourth hypothesis, which states that order cancellation rates are higher in price-time than in pro-rata.

Interestingly, Panel B of Table 9 shows that the time-to-cancellation is significantly longer on the BZX and NOM, relative to the EDGX. Specifically, the average time-to-cancellation on the EDGX is 75.66 seconds faster than on the BZX and 363.74 seconds faster than on the NOM, other factors held constant, which suggests that the average limit order sits on the book for a shorter period of time on the EDGX than on the other two exchanges. Our finding are consistent with the conjecture that the price-time priority model gives traders more time to cancel orders before facing execution, relative to the pro-rata model (Aldridge, 2013), which might help explain why order cancellation activity is higher on the EDGX than on the NOM.

We also examine whether the percentage of partially filled orders canceled differs between the pro-rata and price-time models. To test this hypothesis, we estimate eq. (1) with the *% of partial executions canceled* as the dependent variable and report the results in Panel C of Table 9. We find that orders that receive a partial fill are more frequently canceled in the pro-rata model, relative to the price-time model. For instance, the percentage of executed orders canceled is 23.1 percentage point higher on the EDGX than on the BZX. Similarly, Panel C of Table 10 shows that the percentage of partial executions canceled is 64.21 percentage points higher on the EDGX than on the NOM. The results in Table 9 provide support for our final hypothesis that the percentage of partially filled orders canceled is higher in pro-rata exchanges than in price-time exchanges.

We interpret the results in Table 9 as support for our final hypothesis that the proportion of partially filled orders canceled is higher in the pro-rata model than in the price-time model, and contend that traders seem to risk overtrading in the pro-rata model. To further support this conclusion, we examine differences in order size across exchanges. The results of this analysis are reported in Table A.2 of the appendix. Consistent with our univariate tests, we find that average order size is significantly higher on the EDGX, relative to the BZX and NOM. However, this result is primarily driven by the difference in order size between the EDGX and BZX.

CONCLUDING REMARKS

Most non-option trading venues work on some variation of price-time priority, whereby the first order to be executed at a price is the one that arrived at the exchange first. But the needs of some customers, such as institutional traders who desire to submit large orders, might not be met by this one dominant model. In an attempt to accommodate such traders, some exchanges employ a price-size (or pro-rata) priority model, which allocates all limit orders at a price simultaneously to each countervailing marketable order in proportion to order size. U.S. option marketplaces compete for order flow by tailoring their priority rules to certain traders (Parlour and Seppi, 2003; and O'Hara, 2015). Therefore, a natural question is, do priority rules matter? If so, how do they impact order execution quality?

In this paper, we provide evidence that priority rules affect order execution quality in options markets. Our multivariate tests suggest that price-time priority facilitates higher execution rates and longer-lasting limit orders, relative to pro-rata priority. We do, however, show that pro-rata allocation shortens the time between order submission and first execution. Although price-time model emphasizes speed, this does not seem to translate into faster executions.

Our last set of tests examine if traders risk overtrading in the pro-rata model in order to achieve a desired fill amount (Field and Large, 2008). We find that the percentage of partially filled orders that are canceled is substantially higher in the pro-rata model, relative to the price-time model. In addition, average order size is significantly higher on exchanges using pro-rata matching than those using price-time. Our findings suggest that traders in the pro-rata model submit unrealistic quantities with little intention on executing the entire order.

To summarize, priority rules matter, but their impact on order execution quality is conditional on the measurement used. Neither model appears superior to the other in overall quality of execution. Thus as market structures evolve, the specific needs of customers may be better serviced by variation in priority models.

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APPENDIX

APPENDIX 1: SAMPLE SELECTION

Table 1
Sample Selection

The table summarizes the sample selection process and reports the distribution of trading activity across the remaining option class contracts. The sample period is the 21 trading days between October 3, 2016 and October 31, 2016.

Panel A. Sample filters

	# of remaining option classes	*% of initial trades*	*% of initial trade volume*
Initial sample	3,232	100.00%	100.00%
Exclude option classes that do not trade on each exchange	2,476	98.91%	98.97%
Exclude option classes that have fewer than 10 trades per day	472	87.56%	89.25%
Exclude option classes that are not on common stocks or on ETFs	390	77.08%	79.14%
Final Sample	390	77.08%	79.14%

Panel B. Distribution of option classes

	# of option classes	*% of sample trades*	*% of sample trade volume*
Option classes on common stock that trade in pennies	186	65.32%	53.10%
Option classes on common stock that do not trade in pennies	147	12.20%	6.30%
Option classes on ETFs that trade in pennies	41	20.62%	39.08%
Option classes on ETFs that do not trade in pennies	16	1.86%	1.51%
Final Sample	390	100.00%	100.00%

APPENDIX 2: DISTRIBUTION OF SAMPLE TRADING ACTIVITY ACROSS EXCHANGES

Table 2
Distribution of Sample Trading Activity across Exchanges

The table describes the distribution of trading activity for a sample of 390 option classes across three trading venues, the BZX, EDGX, and NOM. Trading activity is measures as either the total number of order executions or total execution volume, in terms of the number of option contracts. We separate the sample into options that trade on common stocks from those that trade on ETFs. We also separate options that trade in pennies from those that do not.

Panel A. Common stocks versus ETFs

	All Classes		Common Stock		ETF	
	% trades	% volume	% trades	% volume	% trades	% volume
Bats BZX	60.12%	63.06%	61.17%	59.70%	56.50%	67.97%
Bats EDGX	8.38%	5.51%	6.07%	3.08%	16.34%	9.08%
Nasdaq Options Market	31.50%	31.43%	32.75%	37.22%	27.16%	22.95%

Panel B. Penny pilot versus non-penny

	Penny		Non-Penny	
	% trades	% volume	% trades	% volume
Bats BZX	61.78%	64.42%	49.98%	46.98%
Bats EDGX	9.00%	5.76%	4.60%	2.63%
Nasdaq Options Market	29.22%	29.82%	45.42%	50.39%

APPENDIX 3: DESCRIPTIVE STATISTICS – OPTION AND UNDERLYING STOCK

Table 3
Descriptive Statistics – Option and Underlying Stock

The table summarizes the option and underlying stock characteristics for a sample of 390 option classes. Strike price is that average daily strike price for an option class. Days-to-expiration is the number of days between the date of order submission and option expiration. Underlying volume is the average daily number of shares traded in the underlying stock. Underlying size is the average daily market capitalization of the underlying stock. S/X equals the average daily underlying stock price divided by the average daily strike price.

Panel A. Common stocks

	N	Mean	Median	Std. Dev.
Strike price	333	80.7244	52.9002	126.2416
Days-to-expiration	333	58.5253	51.9416	23.9435
Underlying volume	333	6,339,138	3,620,175	8,291,559
Underlying close price	333	81.0852	52.2431	128.5050
Underlying size ($ billions)	333	44.9758	20.0771	72.4472
S/X	333	1.0304	0.9959	0.2505

Panel B. ETFs

		Mean	Median	Std. Dev.
Strike price	57	63.6695	47.0096	51.1750
Days-to-expiration	57	53.6170	53.0449	15.1803
Underlying volume	57	12,298,179	6,207,758	17,378,057
Underlying close price	57	63.3340	47.5377	51.3419
Underlying size ($ billions)	57	10.8930	2.1787	27.7349
S/X	57	1.0240	0.9981	0.0773

APPENDIX 4: PRIORITY RULES AND MAKER-TAKER FEES

Table 4
Priority Rules and Maker-Taker Fees

The table summarizes the priority models and the maker-taker fees enforced on each exchange. A maker rebate is paid to standing limit orders when they provide liquidity to a marketable order, whereas a taker fee is paid by marketable orders when they access liquidity.

Panel A. Exchange pricing and allocation models

Exchange	Pricing	Priority
Bats BZX Options	Maker-Taker	Price-Time
Bats EDGX Options	Maker-Taker	Pro-rata
Nasdaq Options Market	Maker-Taker	Price-Time

Panel B. Fees and rebates - penny pilot options

Exchange		Customer	Broker Dealer	Market Maker	Professional	Proprietary
BATS	Make	-0.30	-0.22	-0.25	-0.25	-0.25
	Take	0.45	0.45	0.47	0.47	0.47
EDGX	Make	-0.05	0.48	0.19	0.48	0.48
	Take	-0.05	0.48	0.19	0.48	0.48
NOM	Make	-0.26	-0.10	-0.20	-0.20	-0.10
	Take	0.50	0.50	0.50	0.50	0.50

APPENDIX 5: UNIVARIATE ANALYSIS – ORDER EXECUTION QUALITY

Table 5

Univariate Analysis – Order Execution Quality

The table summarizes order characteristics for a sample of over a billion orders for 390 option classes trading on the BZX, EDGX, and NOM during the month of October, 2016. We aggregate the order data to the daily level by option class. We test for differences in means between exchanges using simple t-tests and report the corresponding t-statistic in parentheses. ***, **, and * denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

	Pro-rata		Price-time				Difference in Means	
	Bats EDGX		Bats BZX		NOM		(pro-rata - price-time)	
	Mean	Median	Mean	Median	Mean	Median	EDGX - BZX	EDGX - NOM
Execution rate	0.0117	0.0056	0.0298	0.0203	0.0498	0.0253	-0.0180***	-0.0380***
							(-6.44)	(-10.61)
Time-to-complete fill (seconds)	586.1386	333.2610	707.9585	644.1755	956.6489	859.6861	-121.8199***	-370.5104***
							(-2.75)	(-8.24)
Time-to-first fill (seconds)	544.3850	340.6485	692.7830	630.3510	920.9167	818.7884	-148.3980***	-376.5317***
							(-3.72)	(-9.39)
Cancellation rate - all orders	0.9690	0.9699	0.9691	0.9698	0.9003	0.9444	-0.0001	0.0688***
							(-0.20)	(10.74)
Cancellation rate - partially executed orders	0.8872	0.9332	0.6163	0.6638	0.2892	0.2678	0.2709***	0.5980***
							(20.06)	(49.67)
Order size (# of contracts)	23.8383	13.5827	16.2151	10.8994	20.1362	16.9853	7.6232***	3.7020**
							(3.85)	(2.00)
# of trades	32.6500	17.6667	125.9462	46.9143	69.8376	34.2061	-93.2962***	-37.1876***
							(-5.07)	(-3.74)
Trade volume (# of contracts)	252.9408	87.5000	1606.8600	404.8810	858.2087	377.5054	-1,353.9192***	-605.2680***
							(-2.79)	(-3.66)

APPENDIX 6: MULTIVARIATE ANALYSIS ON THE PROBABILITY OF ORDER EXECUTION

Table 6

Multivariate Analysis on the Probability of Order Execution

The sample consists of orders in 390 equity and ETF option classes that average at least 10 executions per day during the month of October, 2016. We use Ordinary Least Squares to examine the relation between priority rules and the rate at which limit orders execute. We approximate the probability of execution using execution rates, or the number of executed orders to the total number of orders, expressed as a percentage. *BZX*, *NOM*, and *EDGX* equal one if the order/update message is sent to that particular exchange and zero otherwise. *S/X* equals the underlying stock price divided by the strike price. *Days Expire* is the number of days between order submission and option expiration. *Call* equals one if the order is for a call option and zero for a put option. *IVOL* is an option's average daily implied volatility as computed by OPRA. *Spread* equals an option's average daily dollar quoted spread, or the difference between the ask price and bid price provided by OPRA. *Order Size* is the average number of contracts attached to a particular order. *Cancel Speed* is the number of seconds between order submission and cancellation conditional on a complete order deletion. *Volume* equals the option's average daily contract volume in 10,000s. *Price* equals the option's mean trade price. *Pvolt* equals the option's average daily standard deviation in trade prices. *UVolume* equal the underlying stock's average daily share volume in 10,000s. *UMCAP* is the underlying stock's average daily market capitalization, measured in $billions. *Penny* equals one if the option is traded and quoted in pennies and zero otherwise. *ETF* equals one if the option class is an ETF and zero if it is a common stock. We include both day and option-class fixed effects. T-statistics are reported in parentheses obtained from standard errors clustered by option class. ***, **, and * denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

	EDGX vs. BZX		EDGX vs. NOM		EDGX vs. BZX and NOM	
	[1]	[2]	[3]	[4]	[5]	[6]
BZX	1.1227***	1.2388***				
	(4.62)	(8.69)				
NOM			2.8485***	2.9366***		
			(9.29)	(8.32)		
EDGX					-2.0921***	-2.2165***
					(-12.41)	(-11.58)
S/X	5.6625***	-7.5323**	-1.3883	-3.4427**	3.5002**	-4.5247**
	(5.45)	(-2.42)	(-1.50)	(-2.54)	(2.42)	(-2.21)
Days expire	0.0200***	0.0046	0.0011	-0.0015	0.0030	-0.0051**
	(3.21)	(1.07)	(0.50)	(-0.57)	(1.30)	(-1.99)
Call	0.7951***	-0.0952	0.0524	0.1070	0.3277***	0.1865**
	(6.99)	(-0.51)	(0.54)	(1.01)	(3.89)	(2.35)
IVOL	0.3923	1.3683**	3.3497***	0.4967	2.2005***	0.7981**
	(0.89)	(2.19)	(5.58)	(1.17)	(5.06)	(2.31)
Spread	-0.1505	0.6334***	4.1770***	0.8264**	2.1518***	0.8034***
	(-0.54)	(3.23)	(8.98)	(2.33)	(6.33)	(3.44)
Order size	-0.0156	-0.0225***	-0.0027	0.0003	-0.0031	0.0004
	(-1.37)	(-4.99)	(-1.50)	(0.11)	(-1.36)	(0.17)
Cancel speed	0.0050***	0.0045**	0.0029***	0.0028***	0.0032***	0.0030***
	(2.92)	(2.37)	(9.52)	(10.61)	(9.91)	(10.93)
Volume	0.3039	0.3959	0.4730	2.4131*	0.1911	0.4533
	(1.03)	(1.12)	(0.49)	(1.86)	(0.62)	(1.16)
Price	-0.0191	-0.0497***	0.0202	-0.0014	0.0471***	0.0317**
	(-0.40)	(-3.14)	(1.33)	(-0.12)	(2.93)	(2.44)
Pvolt	0.0087	0.0161**	-0.0020	-0.0002	-0.0020	-0.0005
	(0.67)	(2.49)	(-1.21)	(-0.16)	(-0.66)	(-0.17)
UVolume	0.0003***	0.0005***	-0.0000	0.0004***	0.0001*	0.0006***
	(3.84)	(4.40)	(-0.49)	(4.12)	(1.88)	(6.50)
UMCAP	0.0020*	-0.0243**	0.0053***	0.0129	0.0041***	0.0040
	(1.78)	(-1.98)	(2.90)	(0.44)	(3.69)	(0.20)
Penny	0.7150		-0.8015**		-0.5643**	
	(1.07)		(-2.32)		(-2.26)	
ETF	-0.9050***		3.5376***		1.3868***	
	(-4.11)		(6.28)		(4.05)	
Constant	-8.3885***	7.5161***	0.2687	3.6460*	-2.6956*	6.3611**
	(-3.93)	(2.70)	(0.28)	(1.73)	(-1.68)	(2.50)
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Option class FE	No	Yes	No	Yes	No	Yes
R^2	0.2336	0.1217	0.4525	0.3172	0.3169	0.2153
N	17,134	17,134	16,806	16,806	29,487	29,487

APPENDIX 7: MULTIVARIATE ANALYSIS ON THE TIME-TO-COMPLETE-FILL

Table 7

Multivariate Analysis on the Time-to-Complete-Fill

The sample consists of orders in 390 common stock and ETF option classes during the month of October, 2016. We use Ordinary Least Squares and Quantile Median regressions to analyze the relation between priority rules and the time-to-complete-fill, defined as the number of seconds between initial order submission and complete fill. *BZX*, *NOM*, and *EDGX* equal one if the order/update message is sent to that particular exchange and zero otherwise. The remaining control variables are defined in Table 6. T-statistics are reported in parentheses obtained from standard errors clustered by option class. ***, **, and * denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

	EDGX vs. BZX		EDGX vs. NOM		EDGX vs. BZX and NOM	
	[1] OLS	[2] Median	[3] OLS	[4] Median	[5] OLS	[6] Median
BZX	58.7544	156.5530***				
	(0.94)	(4.72)				
NOM			323.5339***	412.1783***		
			(5.05)	(12.00)		
EDGX					-182.3858***	-251.3029***
					(-2.97)	(-7.01)
S/X	182.8250***	168.7216***	419.7944***	178.4106	249.5901***	214.6552*
	(3.27)	(12.92)	(2.62)	(0.59)	(6.06)	(1.91)
Days Expire	1.7881***	1.1023***	1.1218***	0.6912**	1.1516***	0.7135***
	(2.91)	(2.60)	(3.89)	(2.37)	(4.03)	(2.97)
Call	78.2319***	60.3773***	91.5314***	62.7027***	99.7003***	78.6749***
	(5.86)	(6.88)	(6.18)	(5.28)	(8.28)	(8.63)
IVOL	78.5982	88.8899**	201.4485**	144.0347***	212.4906***	160.6979***
	(1.05)	(2.24)	(2.28)	(2.63)	(2.90)	(3.73)
Spread	-62.5537	-36.2868	-129.6381**	-98.9061***	-86.1747*	-48.5840*
	(-1.01)	(-1.35)	(-2.48)	(-3.18)	(-1.69)	(-1.65)
Order size	2.8722**	1.5330	0.0835	-0.1580	1.4864***	1.4130
	(2.17)	(0.81)	(0.29)	(-1.57)	(2.65)	(1.54)
Volume	-24.7601**	-11.9498*	-176.0000***	-81.1651**	-57.6079***	-32.7108**
	(-2.05)	(-1.65)	(-3.69)	(-2.05)	(-2.61)	(-2.16)
Price	-18.3914	-34.6966***	-6.4935**	-7.2657***	-4.7369*	-10.4139
	(-0.69)	(-3.34)	(-2.44)	(-5.80)	(-1.72)	(-1.52)
PVOLT	12.5396	17.4507***	0.4234	0.6266***	0.5557	3.0565
	(1.35)	(3.58)	(1.54)	(5.87)	(1.59)	(1.24)
UVolume	-0.0235	-0.0078	0.0137	0.0082	0.0046	0.0069
	(-1.30)	(-1.00)	(0.61)	(0.46)	(0.24)	(0.51)
UMCAP	-0.2308	0.1404	-0.0692	0.0613	-0.0178	0.1993*
	(-0.95)	(0.87)	(-0.35)	(0.58)	(-0.10)	(1.88)
Penny	-197.4571***	-267.3907***	-170.6690***	-172.1938***	-204.4049***	-222.8597***
	(-4.34)	(-9.13)	(-3.93)	(-5.17)	(-5.25)	(-8.06)
ETF	110.2442	51.7880	-28.6754	-70.0748	70.0300	30.1503
	(1.31)	(0.93)	(-0.42)	(-1.62)	(1.20)	(0.73)
Constant	422.3305***	216.7986***	239.0739	166.1251	527.2429***	345.7063***
	(3.82)	(4.10)	(1.33)	(0.54)	(7.92)	(2.87)
Day FE	Yes	No	Yes	No	Yes	No
R^2	0.0570	0.0372	0.0649	0.0501	0.0547	0.0360
N	17,080	17,080	16,753	16,753	29,433	29,433

APPENDIX 8: MULTIVARIATE ANALYSIS ON THE TIME-TO-FIRST-FILL

Table 8
Multivariate Analysis on the Time-to-First-Fill

The sample consists of orders in 390 common stock and ETF option classes during the month of October, 2016. We use Ordinary Least Squares and Quantile Median regressions to analyze the relation between priority rules and the time-to-first-fill, defined as the number of seconds between initial order submission and first fill, conditional on at least a partial execution. *BZX*, *NOM*, and *EDGX* equal one if the order/update message is sent to that particular exchange and zero otherwise. The remaining control variables are defined in Table 6. We report t-stats in parentheses obtained from standard errors clustered by option class. ***, **, and * denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

	EDGX vs BZX		EDGX vs. NOM		EDGX vs. BZX and NOM	
	[1] OLS	[2] Median	[3] OLS	[4] Median	[5] OLS	[6] Median
BZX	97.8123*	149.6190***				
	(1.65)	(4.78)				
NOM			337.0455***	384.3255***		
			(5.59)	(12.03)		
EDGX					-211.7493***	-239.6223***
					(-3.65)	(-7.68)
S/X	195.6309***	171.7132***	355.1159***	159.6500	233.8146***	176.1274***
	(3.88)	(12.41)	(2.72)	(0.58)	(6.13)	(3.53)
Days Expire	1.6125***	0.9078**	1.2037***	0.7179***	1.1375***	0.6566***
	(2.62)	(2.03)	(4.16)	(2.60)	(3.95)	(2.74)
Call	89.4316***	62.2166***	98.2944***	64.7190***	106.0220***	81.4350***
	(7.67)	(7.50)	(7.60)	(5.41)	(9.59)	(9.42)
IVOL	83.5256	75.5070*	206.1234**	135.7040**	216.4892***	152.0064***
	(1.15)	(1.73)	(2.45)	(2.27)	(2.97)	(3.39)
Spread	-60.1376	-34.2792	-112.5411**	-85.6803***	-77.6253	-50.2613*
	(-0.99)	(-1.16)	(-2.14)	(-2.89)	(-1.50)	(-1.80)
Order size	2.6509**	1.9016	-0.0162	-0.1359	1.3372**	1.5524**
	(2.34)	(1.12)	(-0.07)	(-1.34)	(2.55)	(2.05)
Volume	-28.8765***	-17.5483**	-168.0806***	-91.4352**	-61.4211***	-43.9731***
	(-2.82)	(-2.01)	(-4.23)	(-2.00)	(-2.90)	(-2.58)
Price	-17.0106	-33.6626***	-6.1890**	-7.3868***	-4.7299*	-10.4948*
	(-0.66)	(-2.83)	(-2.41)	(-5.81)	(-1.80)	(-1.67)
Pvolt	11.4446	17.1260**	0.4031	0.6321***	0.5387*	2.9664
	(1.24)	(2.37)	(1.47)	(5.86)	(1.69)	(1.26)
UVolume	-0.0218	-0.0044	0.0096	0.0081	0.0058	0.0115
	(-1.50)	(-0.36)	(0.57)	(0.37)	(0.36)	(0.77)
UMCAP	-0.2279	0.0798	-0.0384	0.0657	-0.0089	0.1832*
	(-1.05)	(0.57)	(-0.21)	(0.72)	(-0.05)	(1.84)
Penny	-179.0076***	-257.0193***	-164.9195***	-171.3598***	-187.6488***	-211.5867***
	(-3.95)	(-8.55)	(-3.86)	(-5.75)	(-4.78)	(-7.84)
ETF	112.2673	49.9071	-16.0051	-34.5265	78.9787	46.9507
	(1.44)	(0.85)	(-0.26)	(-0.73)	(1.43)	(1.12)
Constant	345.1868***	213.9578***	247.2629	181.4710	505.3233***	362.2541***
	(3.30)	(3.94)	(1.61)	(0.64)	(7.89)	(5.51)
Day FE	Yes	No	Yes	No	Yes	No
R^2	0.0642	0.0455	0.0747	0.0608	0.0610	0.0417
N	17,134	17,134	16,806	16,806	29,487	29,487

APPENDIX 9: MULTIVARIATE ANALYSIS ON CANCELLATION RATES AND TIME-TO-CANCELLATION

Table 9

Multivariate Analysis on Cancellation Rates and Time-to-Cancellation

The sample consists of orders in 390 common stock and ETF option classes during the month of October, 2016. We use Ordinary Least Squares to analyze the relations between priority rules and both cancellation probability and time-to-cancellation. Panel A reports average daily cancellation rates, or the number of orders canceled to total orders submitted. Panel B reports the percentage of executed orders that are subsequently canceled. Panel C reports time-to-cancellation, or the average number of seconds between order submission and deletion. *BZX*, *NOM*, and *EDGX* equal one if the order/update message is sent to that particular exchange and zero otherwise. We include as control variables: *S/X*, *Days Expire*, *Call*, *IVOL*, *Spread*, *Order Size*, *Volume*, *Price*, *Pvolt*, *UVolume*, *UMCAP*, *Penny*, and *ETF* whose definitions are found in Table 6. We also include both day and option-class fixed effects. We report t-stats in parentheses obtained from standard errors clustered by option class. ***, **, and * denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

Panel A. % Cancellation rate						
	EDGX vs. BZX		EDGX vs. NOM		EDGX vs. BZX and NOM	
	[1]	[2]	[3]	[4]	[5]	[6]
BZX	-0.0164	-0.0059				
	(-1.10)	(-0.58)				
NOM			-3.4931***	-4.1131***		
			(-8.52)	(-8.32)		
EDGX					1.2537***	1.7750***
					(5.46)	(6.16)
Constant	97.0462***	96.8523***	98.2195***	92.4550***	95.6376***	92.0236***
	(19.37)	(30.79)	(61.75)	(27.28)	(83.44)	(36.45)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Option class FE	No	Yes	No	Yes	No	Yes
R^2	0.1581	0.0372	0.5450	0.4069	0.4731	0.3984
N	17,134	17,134	16,806	16,806	29,487	29,487

Panel B. Time-to-cancellation						
	EDGX vs. BZX		EDGX vs. NOM		EDGX vs. BZX and NOM	
	[1]	[2]	[3]	[4]	[5]	[6]
BZX	155.2912***	75.6621***				
	(13.41)	(8.34)				
NOM			467.0636***	363.7356***		
			(7.99)	(6.04)		
EDGX					-302.2429***	-226.9183***
					(-9.79)	(-7.61)
Constant	-14.0061	359.8411***	-1089.5288***	-116.2980	-111.7310	505.9822*
	(-0.26)	(3.96)	(-4.44)	(-0.24)	(-1.11)	(1.67)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Option class FE	No	Yes	No	Yes	No	Yes
R^2	0.4523	0.1537	0.1400	0.0691	0.1043	0.0310
N	17,134	17,134	16,806	16,806	29,487	29,487

Panel C. % of partially filled orders canceled

	EDGX vs. BZX		EDGX vs. NOM		EDGX vs. BZX and NOM	
	[1]	[2]	[3]	[4]	[5]	[6]
BZX	-0.2280***	-0.2310***				
	(-19.23)	(-17.11)				
NOM			-0.6347***	-0.6421***		
			(-66.75)	(-60.69)		
EDGX					0.4181***	0.4300***
					(40.65)	(37.40)
Constant	0.9452***	0.9592***	1.0185***	0.8457***	0.5747***	0.4681***
	(32.88)	(16.88)	(41.57)	(11.83)	(22.12)	(6.18)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Option class FE	No	Yes	No	Yes	No	Yes
R^2	0.2531	0.1474	0.5099	0.4990	0.2455	0.2063
N	15,740	15,740	14,844	14,844	26,670	26,670

APPENDIX 10: DISTRIBUTION OF ORDER EXECUTIONS

Table A.1
Distribution of Order Executions

The table summarizes the distribution of over 3.2 million order executions in a sample of 390 options on equities and ETFs during October, 2016.

	Distribution of Executions				
Exchange	Total	Complete	Partial	% complete	% partial
BZX	1,956,682	1,466,411	490,271	74.94%	25.06%
EDGX	272,799	174,993	97,806	64.15%	35.85%
NOM	1,025,047	826,437	198,610	80.62%	19.38%
Total	3,254,528	2,467,841	786,687	75.83%	24.17%

APPENDIX 11: MULTIVARIATE ANALYSIS ON ORDER SIZE

Table A.2
Multivariate Analysis on Order Size

The sample consists of orders in 390 common stock and ETF option classes during the month of October, 2016. We use Ordinary Least Squares to analyze the relation between priority rules and order size decisions. *EDGX* equals one if the order/update message is sent to the Bats EDGX and zero otherwise. The remaining control variables are defined in Table 6. T-statistics are reported in parentheses obtained from standard errors clustered by option class. ***, **, and * denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

	EDGX vs. BZX and NOM	
	[1]	[2]
EDGX	4.3743***	5.2346***
	(3.38)	(3.92)
Constant	11.6704***	18.2004***
	(5.01)	(4.59)
Controls	Yes	Yes
Day FE	Yes	Yes
Option class FE	Yes	No
R^2	0.1447	0.0082
N	29,487	29,487

PART 3: QUOTE STUFFING AND TRADING SPIKES IN U.S. EQUITY OPTIONS

PART 3

INTRODUCTION

Financial markets are evolving to a more computer controlled environment, relying less on direct human interaction (O'Hara, 2015). Since computer trading algorithms are often triggered by a common signal (see Jarrow and Protter, 2012), the speed and simultaneity with which orders are submitted may cause temporary spikes in quotations, trades, and order cancellations.[44] Kirilenko, Kyle, Samadi, and Tuzun (2015) argue that high-speed algorithmic strategies remove the last few contracts at the best bid or ask levels, only to reestablish new best bids and asks at improved price levels. When there is an imbalance in the order book and prices move unilaterally, this trading strategy can exacerbate price moves and create additional volatility. Higher volatility further increases the speed at which the best bid and ask are removed from the order book, ultimately leading to a spike in quoting and/or trading. When an event as large as the Flash Crash on May 6, 2010 occurs, it captures national attention. What about smaller and less publicized liquidity events that occur daily, such as quote stuffing and trading spikes?[45] How do these events impact market quality?

Quote stuffing is a practice that involves the submission and almost immediate cancellation of a large number of orders, which can affect the supply of and demand for liquidity. Traders can be made worse off if the probability of completing a transaction declines (Colliard and Foucault,

[44] Gabaix, Gopikrishnan, Plerou, and Stanley (2007) build a theoretical model showing that spikes in trading volume are caused, in part, by very large trades in relatively illiquid markets. Kozhan and Wah Tham (2012) and Stein (2009) argue that the high correlation among algorithmic trades cause a crowding effect that push prices away from fundamental values.

[45] Easley, Lopez de Prado, and O'Hara (2014) state that "understanding the behavior of high frequency markets has taken on greater urgency in the wake of repeated liquidity events affecting futures and equity markets."

2012). Quote stuffing episodes can create confusion and congestion in the market, leading to potential arbitrage opportunities for certain market participants, such as high-speed traders.[46] Some market participants criticize quote stuffing, arguing that it creates an illusion of real trading sentiment. For example, on February 18, 2010, T3 Capital Management reported that orders to buy or sell stock on the NASDAQ exchange totaled 89.704 billion shares, but executed volume totaled only 1.247 billion shares. Therefore, only 1% of the orders submitted to the NASDAQ exchange executed. Sean Hendelman, chief executive officer at T3, says the practice creates an inaccurate picture of the true supply and demand for a stock.[47] Orders that are canceled within microseconds of submission do not constitute genuine liquidity and are often referred to as "fake depth" (Angel, 2014).

Policy-makers and exchange officials also criticize quote stuffing, as displayed orders might not reflect committed trading sentiment, which can shake the confidence of liquidity-seeking investors (see Friederich and Payne, 2015).[48] Baruch and Glosten (2013) note that some see quote stuffing as a manipulative practice by which traders create arbitrage opportunities by causing the reporting of quotes to lag behind the reporting of trades. In fact, the NASDAQ posted a disciplinary action against Citadel Securities LLC (CDRG) on June 16, 2014 for sending millions of orders to the exchanges with few or no executions.[49] The NASDAQ recounts the following trading behavior of CDRG on February 13, 2014 between 13:32:53:029 and 13:33:00:998:

[46] See NASDAQ's definition of quote stuffing at http://www.nasdaq.com/investing/glossary/q/quote-stuffing.
[47] Egginton, Van Ness, and Van Ness (2015) show that the majority of the quote stuffing episodes identified in their sample can be classified into a strategy the involves slowing down other traders in the same stock across exchanges. A large number of orders submitted to a particular exchange can cause the quotes on that exchange to lag other exchanges, creating arbitrage opportunities. See also *The Wall Street Journal's*, "SEC Probes Canceled Trades," updated on September 1, 2010.
[48] See the purpose section in SEC Release No. 34-65610
[49] The letter of acceptance, waiver and consent no. 20100223345-02 posted on June 16, 2014, page 6. The letter can be found at the following webpage http://www.nasdaqtrader.com/trader.aspx?id=ndisciplinaryactions.

"CDRG transmitted to NASDAQ approximately 8-9 orders to buy 100 shares of Penn National Gaming, Inc. (Penn) every microsecond for a total of 65,000 orders with zero executions. After receiving an inquiry from NASDAQ concerning an increase in order messaging activity in PENN, CDRG disabled the trading strategy."

Despite the documented instances of quote stuffing, and the abovementioned concerns regarding the practice, the trading strategy has not been extensively examined in the options market.

In this study, we investigate the market quality implications of both extreme quote stuffing episodes and trading spikes in U.S. equity options. We focus on the options market for the following reasons: First, the concern of spikes is not isolated to equities, as market participants document abnormal quoting and cancelling activity in options. For example, on June 5, 2013, the quotes for SPY options exceeded one billion, nearly 15 times greater than on the day of the May 2010 flash crash, and the quote-to-trade ratio increased to 11,254, which sparks the question, how prevalent are trading spikes and quote stuffing episodes in the options market?[50] Second, trading in options is shown to provide price discovery in the underlying equities (see Easley, O'Hara, and Srinivas, 1998 and Chakravarty, Gulen, and Mayhew, 2004).[51] Therefore, if there is an unexpected spike in trading or quoting activity in the options market, it may impact both the options and underlying equities.[52] Third, we are able to study how trading and quoting spikes differ between exchanges with various priority rules, such as price-time and pro-rata.

We focus on order-level data in three U.S. equity options exchanges, namely the NASDAQ Options Market (NOM), BATS BZX Options Market (BZX), and BATS EDGX Options Market

[50] See the research analysis posted by Nanex, LLC at http://www.nanex.net/aqck2/4308.html

[51] In a frictionless and complete market, options would be redundant securities and options and underlying securities move contemporaneously (Black and Scholes, 1973). However, in a dynamic economy, new information about stock prices may be reflected in option prices earlier. Hu (2014) explains that option market makers hedge using underlying securities, thereby transmitting information from the options market to the equities market.

[52] Bessembinder and Seguin (1992) find a positive relation between equity volatility and trading volumes in the equity futures and spot markets. Unexpected trading volume has a greater effect on volatility than expected trading volume.

(EDGX). These three exchanges make up nearly a quarter of all U.S. equity options trading volume during the sample period.[53] We find that quote stuffing episodes are frequently observed in equity options, particularly on exchanges using price-time priority (BZX and NOM). Over a 21 day sample period, we find that 319 unique option classes, which account for over 70% of the sample trade volume, experience at least one quote stuffing episode. We identify an extreme quote stuffing event as a one-minute period when the number of orders and cancellations exceed the daily average one-minute number of orders and cancellations by at least four standard deviations.

We examine if these option quote stuffing events affect order execution quality and liquidity in the options market. Our multivariate analysis shows that quote stuffing reduces the probability of execution, lengthens the time-time-to-execution and increases short-term volatility. Specifically, our multivariate tests show the order execution rates decrease between 8.95 and 9.11 percentage points from the pre-event window to the quote stuffing event. The average time between order submission and execution increases between 84 and 197 seconds from the pre-event window to the quote stuffing episode. Since the welfare of traders depends on the non-execution risk faced by liquidity suppliers (Colliard and Foucault, 2012), the results suggest that quote stuffing has a negative impact on order execution quality.

Next, we investigate whether extreme option quote stuffing events affect the liquidity in the underlying stocks. Our tests show that both quoted and effective bid-ask spreads increase, with a one-minute delay, following intense option quote stuffing episodes. The equal-weighted percent quoted spread in the underlying stock increases from 0.00071 in the minute prior to the event, to 0.0011 in the minute after the option quote stuffing event. The average percentage effective spread increases from 0.005 in the minute prior to the event, to 0.007 in the minute after the option quote

[53] As of January 27, 2016 according to the Options Price Reporting Authority (OPRA) available at NasdaqTrader.com.

stuffing episode, a 20 basis point increase. Consistent with Easley, O'Hara, and Srinivas (1998) and Chakravarty, Gulen, and Mayhew (2004), we provide evidence that option trading provides information to the underlying stock market.

We also analyze how option trading spikes affect execution quality and liquidity in the options market. Consistent with the theoretical predictions of Clark (1973) and Copeland (1976), we find a strong positive relation between short-term price volatility and trading spikes. Our results show that limit orders remain on the book for a longer period of time during extreme spikes in trading. For instance, the average number of seconds between order submission and cancellation increases by at least 67 seconds during extreme trading spikes, relative to the pre-event windows.

Overall, our empirical analysis reveals that quote stuffing episodes and trading spikes are pervasive in equity options markets. Quote stuffing harms order execution quality by reducing the probability of execution and lengthening the time-to-execution. Information contained in the option quote stuffing episodes carries over into the underlying securities, as bid-ask spreads increase with a one-minute delay. In addition, both quote stuffing episodes and trading spikes are associated with significant increases in short-term volatility, which suggests that frequent liquidity events might negatively impact overall market quality.

HYPOTHESIS DEVELOPMENT

Submitting orders and quickly canceling those orders is a common trading practice observed in financial markets. For instance, Hasbrouck and Saar (2013) show that only 6.8% of orders entered into the NASDAQ book eventually execute. The Securities and Exchange Commission document that only 3.2% of equity orders execute in the second quarter of 2013.[54] High levels of order cancellation activity might be a natural byproduct of evolving market structures (Liu, 2009) and/or improved trading technology (Gai, Yao, and Ye, 2012). However, policy-makers seem to believe that there must be something inappropriate in the submission of numerous orders that do not lead to executions (see Friederich and Payne, 2015). In fact, former SEC Chairwoman Mary Schapiro, in an address given on September 7, 2010, states:

"A type of trading practice that has received attention involves submitting large volumes of orders into the markets, most of which are cancelled… There may, of course, be justifiable explanations for many canceled orders to reflect changing market conditions… But we also must understand the impact this activity has on price discovery, capital formation and the capital markets more generally."[55]

Quote stuffing might temporarily disrupt the matching process between buyers and sellers, as it can create a false sense of liquidity in the market (Angel, 2014). Orders that are added and deleted in billionths of a second are not constituting genuine liquidity, or creating "fake depth."

[54] See the SEC market structure research "Trade to Order Volume Ratios" released on October 9, 2013. The data used detailed message feeds from 12 of 13 equity exchanges to compute the metrics.
[55] Speech by SEC Chairwoman: "Strengthening Our Equity Market Structure" by Mary L. Schapiro on September 7, 2010.

Order execution rates depend on the arrival rate of marketable orders and the posted depth on the limit order book (see Battalio et al. 2015). Since orders are deleted almost immediately after submission during quote stuffing episodes, the stock of standing limit orders is reduced. Market participants that seek to interact with orders that are canceled before they can execute may ultimately achieve less favorable executions, or no executions at all (see SEC Release No. 34-65610).

*Hypothesis 1a**:** Quote stuffing episodes are associated with a decrease in order execution rates.*

Limit orders are not only exposed to non-execution risk, but also to the risk associated with time-to-execution (Blume, 2001 and Boehmer, 2005). Boehmer, Jennings, and Wei (2007) show that trading venues attract more order flow when they shorten the time between order submission and execution, and time-to-execution is shown to be a random function of several variables including order and stock characteristics, exchange structures, and market conditions (see Lo, MacKinlay, and Zhang, 2002). If traders are less confident in the displayed depth during quote stuffing episodes, we might expect a decrease in the arrival rate of marketable orders as the perceived risk of achieving a less favorable execution is higher. A decrease in the arrival rate of marketable orders can lengthen the time it takes a limit order to find a countervailing marketable order, which leads to the following testable hypothesis.

*Hypothesis 1b**:** Quote stuffing episodes are associated with a lengthening of the time-to-execution.*

Quote stuffing, in certain cases, can be considered a manipulative trading strategy through which traders cause the reporting of quotes to fall behind the reporting of trades (Baruch and Glosten, 2013). In fact, in 2011, the NYSE adopted the text of FINRA (Financial Industry

Regulatory Authority) Rule 5210, which prohibits the publication of manipulative or deceptive quotations and transactions, and use quote stuffing as an example.[56]

Manipulation can take on various forms, including, but not limited to, insider trading, spoofing, and quote stuffing.[57] Egginton, Van Ness, and Van Ness (2016) empirically show that the most common quote stuffing strategy in a sample of equity securities, involves slowing down trading on one exchange to create arbitrage opportunities on another trading venue. Aggarwal and Wu (2006) develop a theoretical model in which market manipulation increases stock volatility.[58] To the extent that quote stuffing is an attempt to manipulate markets, we might expect volatility to increase during extreme quote stuffing episodes. If the order book is thin, less "firm" orders, during quote stuffing episodes, the noise may induce short-term volatility (Amihud and Mendelson, 1991).

Hypothesis 2: Quote stuffing episodes are associated with an increase in short-term price volatility.

We next examine the relation between trading spikes and both volatility and limit order execution quality. Several theoretical models predict a positive relation between price volatility and trading volume. For instance, Clark (1973) and Copeland (1976) contend that significant trading volume is produced by the sequential arrival of new information, which causes extreme movements in security prices. In addition, Epps and Epps (1976) develop a model in which traders

[56] See SEC Release No. 34-65954 for the proposed rule filing of the NYSE and SEC release No. 34-65955 for the rule filing of NYSE/Arca.

[57] Lee, Eom, and Park (2013) find that investors strategically place orders on the Korean Exchange with little chance of execution, in order to mislead other market participants into thinking that there is an imbalance in the order book. Spoofing orders are shown to be extremely profitable when the total quantity on each side of the order book is disclosed, but the price of each order is hidden. Such order-disclosure rules existed on the KRX, and to no surprise, have been subsequently changed.

[58] Aggarwal and Wu (2006) collect all SEC litigation releases from 1990 to 2001 that contain the key words "manipulation" and "9(a)" or "10(b)," which refer to the articles of the Securities and Exchange Act of 1934 that prohibit market manipulation.

elect to trade when markets are most active and indicate that volume and price movements are clustered in time. There are also several empirical studies that find a positive relation between price volatility and trading volume.[59] Therefore, we expect to find an increase in short-term price volatility around trading spikes.

Hypothesis 3: Trading spikes are associated with an increase in short-term price volatility.

The speed and volume of trading in high frequency markets creates concern about toxicity-induced volatility (Easley, Prado, and O'Hara, 2012). Order flow is considered toxic when it adversely selects market makers who might not be aware that they are supplying liquidity at a loss. Since extreme trading volume is often associated with large price moves, the uncertainty in the arrival rate of buy and sell orders may force liquidity providers away from their preferred inventory positions (see Stoll, 1979, Ho and Stoll, 1981, and O'Hara and Oldfield, 1986) and ultimately, they may choose to withdraw from trading. Large (2004) predicts a positive relation between order cancellation activity and market uncertainty. Thus, we expect to find an increase in order cancellation rates during intense short-term trading spikes.

Hypothesis 4: Trading spikes are associated with an increase in the probability of order cancellation.

Exchanges compete for order flow along many dimensions including, but not limited to, liquidity, payment structure, and execution speed.[60] Admati and Pfleiderer (1988), Pagano (1989), and Parlour and Seppi (2003) argue that liquidity is a fundamental variable driving competition among exchanges. Parlour and Seppi (2003) show that trading venues that attract more marketable

[59] Karpoff (1987) provides a review of 18 independent articles that examine the relation between price volatility and trading volume.
[60] For example, Foucault and Parlour (2000) examine exchange competition in listing fees. Biais (1993) find that spreads are less volatile in fragmented over-the-counter markets, relative to centralized markets. Bessembinder (2003) shows significant evidence of quote-based competition for order flow among seven markets.

orders also attract more limit orders. The increase in limit orders will then attract even more marketable orders, thus creating a liquid marketplace. If limit orders are constantly deleted before marketable orders arrive, then traders may choose to submit their marketable orders elsewhere. Therefore, frequent quote stuffing episodes on an exchange might encourage traders to route orders to a different trading venue.

Frequent quote stuffing episodes may deter traders from submitting orders to a particular venue.[61] This concern is evident in a rule change filed by the NASDAQ (SEC Release No. 34-65610), which states:

> *"The more often a market participant pursues displayed liquidity at a particular venue that is no longer available by the time its order arrives, the more likely it is that the market participant will pursue liquidity at another venue."*

Since trading venues are often designed to meet the specific needs of market participants (O'Hara, 2015), and certain traders are more inclined to engage in quote stuffing trading strategies, certain rules and fee structures can directly affect the frequency with which quote stuffing episodes are observed on that venue. For instance, option trading venues operate using one of two order priority allocation models, price-time or pro-rata.[62] BATS recently introduced the EDGX Options Market, which offers a pro rata allocation model, intended to attract more institutional order flow that is less concerned with speed.[63] Price-time priority ultimately facilitates a race to the top of

[61] Several articles examine order flow competition between exchanges, including Glosten (1994), Arnold, Hersch, Mulherin, and Netter (1999), Hendershott and Mendelson (2000), Santos and Scheinkman (2001), Foucault and Parlour (2004), and Foucault and Menkveld (2008).

[62] Time priority allocates limit orders in sequence to marketable orders based on time of arrival in the book, whereas pro-rata priority allocates limit orders simultaneously to each countervailing marketable order in proportion to order size.

[63] In an article entitled "S*ize Matters"* in Marketview magazine, Brian Hyndman, Senior Vice President of NASDAQ OMX, explains: "The price-time priority model benefits market participants who have the fastest technology, which allows their orders to rapidly reach the front of the line. With a price-size (pro-rate) priority model, speed is de-emphasized with the objective of providing incentives for traders to send in sizable orders."

the order book queue as it is a first come first serve model, which may attract high-speed algorithmic traders who are known for submitting short-lived orders that are canceled almost immediately (Jarrow and Protter, 2012; and Kirilenko et al., 2016). Therefore, we might expect trading venues using price-time to experience more frequent quote stuffing episodes than exchanges using pro-rata allocation.

Hypothesis 5: Quote stuffing episodes are more frequently observed on exchanges using price-time priority (BZX and NOM), relative to exchanges using pro-rata allocation (EDGX)

Option contracts generally expire on the third Friday of each month. Stoll and Whaley (1987) and Stephan and Whaley (1990) show that option trading volume and volatility are higher on expiration days, relative to non-expiration days. Expiration day effects are often attributed to the unwinding of arbitrage positions, where mispricing between stock options and underlying security prices is exploited (Chow, Yung, and Zhang, 2003). Initial long or short underlying market positions must reverse on the expiration day to close out the arbitrage position and realize any anticipated profits. Therefore, arbitrageurs are likely to submit a large amount of buy and sell orders on expiration days, which may increase the number of short-term trading spikes.

In addition, Egginton, Van Ness, and Van Ness (2015) show that a common quote stuffing strategy is to create a latency arbitrage opportunity in the same stock across exchanges. The sudden influx of quotes may cause the exchange receiving the quotes to lag other exchanges, as market participants are forced to process the onslaught of quotes. Proprietary traders, such as HFTs, might find option expiration days to be a perfect time to capitalize on potential arbitrage opportunities. Thus, we might expect to find more quote stuffing episodes on expiration days, relative to non-expiration days.

Hypothesis 6: Trading spikes and quote stuffing episodes are more frequently observed on option expiration days, relative to non-expiration days.

DATA DESCRIPTION

The NASDAQ ITCH to Trade Options (ITTO) is a direct data feed that provides a nanosecond view of simple equity options on the NASDAQ Options Exchange (NOM). This includes orders added and changes made to orders resting on the NOM limit order book. We download several different message types that are linked by a unique order reference number. "Option directory" messages contain information for the security symbol, expiration date, strike price, and option type (call or put). "Add order" messages are time stamped records for new orders added to the book, including order time (stamped to the nanosecond), market side (buy or sell), order price, and order size (# of contracts). "Executed order" modification messages are time stamped records generated by (partial) executions and report executed contracts and execution price (if the execution price differs from the add order price).[64] "Order cancel" messages are time stamped records generated by partial cancellations and report the number of contracts canceled. "Replace" messages are time stamped records that report the new order reference number, new order price, and new order size. "Delete" messages are time stamped records that report when an order is deleted from the NOM order book.

As the analysis involves examining quote stuffing episodes and trade spikes across exchanges, we obtain order data from multiple trading venues. BATS Multicast PITH provides nanosecond depth of book quotations and execution information for simple equity options on the BZX options exchange and EDGX options exchange. BATS uses a symbol mapping mechanism

[64] Since the analysis involves examining execution quality around extreme quote stuffing episodes and trade spikes, we ignore "trade" messages that report executions involving non-displayed order types.

for the options Multicast PITCH to reduce the size of the feed. The day-specific mappings include unique identifiers and information on the option symbol, strike price, expiration date, and option type (call or put). The following messages are time stamped to the nanosecond and linked by a day-specific order id number. "Add order" message represents a new displayed order on the BATS book, which includes a side indicator (buy order or sell order), quantity (# of contracts), security mapping symbol, and limit order price. "Order executed" messages are sent when a visible order on the BATS book is executed in whole or in part and includes the executed quantity and price (if different from the add order price). "Reduce size" messages are sent when a visible order is partially reduced. "Modify order" message is sent whenever an add order message is visibly (price and/or quantity) modified. "Delete order" message is sent when an open order is completely removed from the BATS book.

We focus on the 21 trading days from October 3, 2016 to October 31, 2016.[65] We eliminate orders reported before 9:40 a.m. and after 3:50 p.m. because opening and closing rotations impede equity options from trading freely. Complex orders, such as spreads and straddles, are priced as packages, so we remove them from our sample. Since we are attempting to understand the economic impact of quote stuffing and trade spikes, we aggregate the data by option class minute and exclude option/minutes with less than one trade. We merge these data with closing prices and shares outstanding from the Center for Research in Security Prices (CRSP). Part of the analysis seeks to examine the economic impact of option quote stuffing episodes and trade spikes on the liquidity in the underlying (equity) securities market. We obtain NYSE Trade and Quote (TAQ) data that includes information on all issues traded on the NYSE, NASDAQ, and Regionals.

[65] A single underlying stock will have both puts and calls with perhaps ten or more strike prices and five expiration dates, giving a total of 100 options per stock. It is not uncommon for the number of option series to far exceed 100. The average file size for a single day of uncompressed orders on the BZX is over 140 GB.

EMPIRICAL RESULTS

QUOTE STUFFING AND MARKET QUALITY

Quote stuffing is often referred to as a practice of placing an excessive number of buy or sell orders for a particular security and then immediately canceling them. Gai, Yao, and Ye (2012) argue that it is difficult to identify all potential quote stuffing events. Similar to Egginton, Van Ness, and Van Ness (2012), rather than identifying all events, we isolate extreme episodic spikes in quoting activity. However, we also require a contemporaneous spike in order cancellation activity. We divide the trading day into one-minute segments. We then calculate the intraday variation in quoting and cancelling activity by computing the average standard deviation of the number of quotes and cancellations in the one-minute segments over the trading day. We identify a quote stuffing episode when the number of orders submitted and canceled in a one-minute segment exceeds the daily one-minute average by more than four standard deviations.[66] We exclude events that experience above a two standard deviation increase in trading in the minutes leading up to the quote stuffing episode.

Table 1 provides summary statistics for the 2,585 unique quote stuffing events. Panel A shows that 280 option classes on common stocks experience at least one quote stuffing episode during the sample period, relative to only 39 option classes on ETFs. These 319 option classes account for over 70% of trading volume across the three exchanges during our sample period, suggesting that quote stuffing is pervasive in active option classes. The average time-to-expiration

[66] We also reduce the hurdle to three standard deviations and our results are robust.

is 58 days for options on common stocks and 55 days for options on ETFs. The median S/X ratio for options on both common stocks and ETFs is 1.0, indicating that the trading of options is concentrated in near-the-money options. We find that roughly 66% of option classes have a minimum price variation of one cent, while the remaining option classes trade in five-cent increments. The average market capitalization for an underlying stock is $47.06 billion, compared to $13.88 billion for an ETF. The average trade price on an underlying common stock is $79.57, relative to $64.58 for an ETF.

Panel B of Table 1 reports the order statistics during the one-minute quote stuffing episodes. The average number of orders submitted during a quote stuffing episode is 16,422 for 482,888 contracts. The average number of orders canceled during a quote stuffing event is 16,354, which implies a cancel-to-order ratio of 99.59%. Panel C of Table 1 displays the distribution of quote stuffing events as the number of standard deviations above the daily average. We find that 1,184 events, or 45.8% of the sample quote stuffing episodes, occur between five and six standard deviations above the mean. There are, however, 181 events that occur over eight standard deviations above the mean. Therefore, there is extreme variation in the severity of quote stuffing events. Panel D of Table 1 shows that 56.56% of sample quote stuffing events occur in call options and 82.75% occur in option classes trading in pennies. In support of our fifth hypothesis, we find that quote stuffing events are more frequently observed on the BZX and NOM, relative to the EDGX. Panel E of Table 1 shows that over 95% of the sample quote stuffing events occur on either the BZX or NOM.

Figure 1 provides several examples of the extreme quote stuffing episodes observed in this study. Panel A shows a quote stuffing event for IBM call options on the BZX at 11:39 a.m. on October 25th, 2016. The number of orders submitted to the BZX exchange during the time period

11:39:00 a.m. to 11:39:59 a.m. was 21,820. Panel B displays a quote stuffing event for American Airlines Group Inc. (AAL) call options on the EDGX at 12:07 p.m. on October 27th, 2016. The number of orders submitted to the EDGX between 12:07:00 p.m. to 12:07:59 p.m. exceeded 92,000. Panel C shows an extreme quote stuffing episode for Delta Air Lines, Inc. (DAL) call options on the NOM at 10:33 a.m. on October 13th, 2016. The number of orders submitted to the NOM between 10:33:00 a.m. and 10:33:59 a.m. was nearly 7,000. In each of these examples, the cancel-to-order ratio was well above 99% during the one-minute quote stuffing events.

When liquidity is supplied and removed from markets in nanoseconds, it is nearly impossible for market participants to identify displayed orders that reflect committed trading sentiment. To examine if order execution quality and/or liquidity deteriorate in option and equity markets around option quote stuffing episodes, we estimate three measures in the options market and three measures in the equities market. Similar to Battalio et al. (2015), we focus on the following three variables in the options market: order execution rates, time-to-execution, and short-term volatility.[67] We compute order execution rates as the daily ratio of orders executed to total number of orders added to the book (see Foucault, 1999). Time-to-execution is measured as the number of seconds between order submission and execution (see Battalio, Corwin, and Jennings, 2015). For a given minute, we estimate short-term volatility as the difference between the log of the high ask price and the log of the low bid price (Kwan et al., 2015). We also compute percent quoted spreads and percent effective spreads in the underlying equities by closely following Holden and Jacobsen (2014). The percent quoted spread is defined as

$$\%\ Quoted\ Spread = \frac{Ask - Bid}{Midpoint}, \tag{1}$$

[67] Similar measures of order execution quality are used in Battalio, Corwin, and Jennings (2015).

where Ask is the National Best Ask Price, Bid is the National Best Bid Price, and Midpoint is the average of the Bid and Ask Prices. For a given option class, the percent effective spread on the k^{th} trade is defined as

$$\%\, Effective\ Spread = \frac{2D_k(P_k - M_k)}{M_k}, \tag{2}$$

where D_k is an indicator variable that equals +1 if the k^{th} trade is a buy and -1 if the k^{th} trade is a sell, M_k is the midpoint of the NBBO quotes assigned to the k^{th} trade, and P_k is the trade price. As the TAQ data does not provide a buy/sell identifier, we following the Lee and Ready (1991) convention to assign trade direction, D_k. A trade is a buy when $P_k > M_k$, a sell when $P_k < M_k$, and the tick test, a trade is a buy (sell) if the most recent prior trade at a different price was a lower (higher) price than P_k, when $P_k = M_k$.

First, we examine the effect of quote stuffing on the probability of order execution. Panel A of Figure 2 plots average one-minute order execution rates for the 20-minutes before and after the quote stuffing episodes. The light dotted line is the average number of orders submitted for an option class during a given minute, while the solid dark line is the average number of orders executed. We show a substantial decline in average order fill rates during extreme quote stuffing episodes. However, there is an immediate rebound in order execution rates in the minutes after the events. Table 2 shows that order execution rates are lowest during the quote stuffing events, 1.43%, relative to 8.37% in the minute prior to the episodes.

Next, we examine if quote stuffing affects order execution speed. Panel B of Figure 2 shows a spike in the median time-to-execution during one-minute quote stuffing episodes. Table 2 shows that the median time-to-execution increases from roughly 172 seconds in the minute prior to the quote stuffing events, to roughly 331 seconds during the events. This increase in time-to-execution suggests that orders submitted during quote stuffing episodes take longer to execute, which is consistent with the second part of our first hypothesis that quote stuffing is associated with slower executions.

We also examine if quote stuffing affects short-term volatility in the options market. Panel C of Figure 2 shows that volatility in options increase substantially during quote stuffing episodes, and remains elevated for a short period after the events. In fact, Table 2 shows that volatility increases by over 37% during quote stuffing episodes, relative to the minute preceding the events. Therefore, we fail to reject our second hypothesis, which states that quote stuffing episodes are associated with an increase in volatility.

Since options trading is shown to provide price discovery in the underlying equities (see Easley, O'Hara, and Srinivas, 1998 and Chakravarty, Gulen, and Mayhew, 2004), we examine if option quote stuffing affects the underlying stocks' liquidity. Panel D of Figure 2 shows that volatility in the underlying equities peaks in the one-minute interval following the option quote stuffing episode. Table 2 shows that short-term volatility in the underlying stocks increases from 0.0420 in the minute prior to the option quote stuffing event, to 0.0559 in the minute following the episode. Spread measures follow patterns similar to that of volatility. Panel E of Figure 2 shows that average percent quoted spreads increase from 0.00071 in the minute before the option quote stuffing episode, to 0.00106 in the minute after the episode. Panel F of Figure 2 reports that percent effective spreads increase from 0.005 in the minute prior to the option quote stuffing event, to 0.007 in the minute after the event. Therefore, liquidity in the underlying stocks appears to deteriorate around option quote stuffing events, albeit with a slight lag, which suggests that options might provide valuable information to the underlying equities during extreme option events.[68]

[68] In an unreported analysis, we examine quoted depth around option quote stuffing events and find relatively little change during the event window. Therefore, it does not appear that the underlying stock is experiencing quote stuffing behavior during the identified events.

In this section, we examine if the effect of option quote stuffing on market quality survives in a multivariate setting. Presumably, a trader's limit order placement decisions and trading outcomes are conditional on option/stock characteristics and market conditions. To address this concern, we conduct multivariate analyses to estimate the determinants of options market quality.

We use Ordinary Least Squares (OLS) to analyze the impact of option quote stuffing on order execution quality in the options market. We analyze three dependent variables: *order execution rates*, *time-to-execution*, and *short-term volatility*. We contend that the relevant independent variables are option and stock attributes, order characteristics, venue traits, and trading day (see Battalio, Corwin, and Jennings, 2015; and Battalio, Shkilko, and Van Ness, 2016). The unit of measurement is option class/minute and the general specification for our models is outlined as follows:

$$\begin{aligned} DepVariable_{i,t} = {} & \alpha + \delta_t + \tau_j + \beta_1 Qstuffing_t + \beta_2 Post\ Qstuffing_t + \beta_3 BZX_i + \beta_4 EDGX_i \\ & + \beta_5 S/X_{i,t} + \beta_6 Days\ Expire_{i,t} + \beta_7 Call_{i,t} + \beta_8 Cancel\ Speed_{i,t} \\ & + \beta_9 Option\ Trade\ Size_{i,t} + \beta_{10} Option\ Volume_{i,t} \qquad (3) \\ & + \beta_{11} Option\ Trade\ Price_{i,t} + \beta_{12} Underlying\ Volume_{i,t} \\ & + \beta_{13} Underlying\ MCAP_{i,t} + \beta_{14} Penny_i + \beta_{15} ETF_i + \varepsilon_{i,t}, \end{aligned}$$

where *Qstuffing* equals one during the quote stuffing episode and zero otherwise; *Post Qstuffing* is equal to one for the period following the quote stuffing event and zero otherwise; *BZX* equals one if the option trades on the BZX and zero otherwise; *EDGX* equals one if the option trades on the EDGX and zero otherwise; *S/X* is the underlying stock price divided by the strike price; *Days Expire* is the number of days between order submission/update to option expiration; *Call* equals one if the option is a call option and zero for a put option; *Cancel Speed* is the number of seconds between order submission and cancellation conditional on a complete order deletion; *Option Trade Size* equals the average one-minute trade size; *Option Volume* equals the option's average one-minute contract volume; *Option Trade Price* equals the option's mean trade price; *Underlying Volume* equals the underlying stock's average one-minute share volume; *Underlying MCAP* is the underlying stock's average daily market capitalization, measured in $billions; *Penny* equals one if the option is traded and quoted in pennies and zero otherwise; and *ETF* equals one if the option class is an ETF and zero if it is a common stock. We also include either day dummy variables, δ_t, or event fixed effects, τ_j. The event fixed effects prevent us from estimating the coefficients on the trading venue indicator variables, *Underlying MCAP*, and the *Penny* and *ETF* dummies, as they do not have within-class variation. We report t-statistics in parentheses obtained from standard errors clustered at the option class level.

Columns [1] and [2] of Table 3 reports the results of estimating eq. (3) with *order execution rates* as the dependent variable. We find that order execution rates are between 8.95 and 9.11 percentage points lower during quote stuffing episodes, relative to the pre-event windows, other factors held constant. This decline is both significant and economically meaningful. The results in Table 3 provide support for the notion that quote stuffing impedes limit order traders from finding countervailing marketable orders, and so we fail to reject our first hypothesis that quote stuffing episodes are associated with a decrease in order execution rates. To the extent that limit order traders are worse off when the probability of their order executing declines (see Colliard and Foucault, 2012), our finding suggests that quote stuffing is detrimental to market quality.

Columns [3] and [4] of Table 3 report the results of estimating eq. (3) with *time-to-execution* as the dependent variable. Consistent with our univariate tests, we find that the time between order submission and execution is between 84 and 197 seconds slower during quote stuffing events, relative pre-event windows. Our findings support the conjecture that quote stuffing might discourage traders from submitting marketable orders, which in turn slows the speed of order execution (Battalio, Corwin, and Jennings, 2014). Again, we fail to reject the second part of our first hypothesis, which states that quote stuffing is associated with slower executions. If speed of order execution is important to limit order traders, our results suggest that quote stuffing harms order execution quality.

Next, we examine how option quote stuffing impacts short-term volatility. Columns [5] and [6] of Table 3 report the results of estimating eq. (3) with *short-term volatility* as the dependent variable. We find that volatility increases significantly during extreme quote stuffing episodes. For instance, short-term volatility is between 0.1512 and 0.4609 higher during quote stuffing events, relative to the pre-event windows, other things held constant. Our results support the argument that quote stuffing creates volatility in the marketplace (Egginton, Van Ness, and Van Ness, 2016). Therefore, we find support for our second hypothesis, which states that quote stuffing is associated with an increase in short-term price volatility.

We also analyze how option quote stuffing affects liquidity in the underlying stocks in a multivariate setting. We use OLS to examine the impact of option quote stuffing on liquidity in the underlying equities market. We analyze three dependent variables: *short-term volatility*, *percent quoted spreads*, and *percent effective spreads*. Similar to Egginton, Van Ness, and Van Ness (2015), we estimate the following regression model:

$$\begin{aligned} DepVar_{i,t} = \alpha + \tau_j + \beta_1 Qstuffing_t + \beta_2 Post\ Qstuffing_t + \beta_3 Underlying\ Price_{i,t} \\ + \beta_4 Underlying\ Volatility_{i,t} + \beta_5 \log(Underlying\ Trades)_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{4}$$

where *Qstuffing Event* equals one during the two one-minute segments during and after the option quote stuffing episodes and zero otherwise; *Post Qstuffing* equals one during the post event windows and zero otherwise; *Underlying Price* is the average one-minute stock price; *Underlying Volatility* is the average one-minute stock volatility, measured as the difference in the log of the high ask price and log of the low bid price; and *Underlying Trades* is the average number of trades for the stock during a given minute. We also include event fixed effects, τ_j, and report t-statistics in parentheses obtained from standard errors clustered at the stock level.

We report the results of estimating eq. (4) in Table 4. We find that short-term volatility is insignificantly different during option quote stuffing events, relative to pre-event windows. However, we find that both percent quoted spreads and percent effective spreads are significantly higher during option quote stuffing events than in pre-event windows.

The results in this section provide evidence that not only do option quote stuffing episodes negatively affect the quality of option markets but also negatively impact the liquidity in equity markets. Our results are robust to alternative model specifications and event identification strategies.

TRADING SPIKES AND MARKET QUALITY

In this section, we investigate if option trading spikes negatively affect market quality. To identify trade spikes, we calculate the intraday variation in trading activity as the average standard deviation of the number of trades in one-minute segments. Although order volume is high for options, executions are far less frequent. Therefore to be classified as a trading spike, we require that the number of trades in a given minute exceed the daily average number of trades by at least six standard deviations.[69]

Table 5 provides summary statistics on the 1,619 trading spikes on 217 unique option classes. Panel A of Table 5 shows that 184 of the 217 option classes are on common stocks, while 33 are on ETFs. The average S/X ratio is 1.00 for options on common stocks and 1.02 on ETFs, suggesting that the average order submitted is for an option near-the-money. We also show that

[69] The results hold if we reduce the cut-off to three standard deviations, although we are less confident that these are truly trading spikes, as less frequently trading options may only have a few trades in a given minute.

the average market capitalization for options on common stocks (ETFs) with at least one trading spike during the sample period is $64.91 ($15.8) billion. Panel B of Table 5 displays trade statistics during intense spikes in order executions. The mean number of orders executed during a trading spike is 27.87 with a maximum of 293. The average trade size during a spike is 12.77 contracts and a median price of $1.26. Panel C of Table 5 shows that 75% of the sample trading spikes fall between seven and eight standard deviations above the daily one-minute average number of trades. Similar to quote stuffing episodes, we find that trading spikes are more common in call options than put options, and in penny options than non-penny options. Consistent with our fifth hypothesis, we show that trading spikes are more frequently observed on the BZX and NOM, relative to the EDGX.

Figure 3 provides an example of a trading spike on each sample exchange. Panel A shows a trading spike for Caterpillar Inc. (CAT) call options at 11:22 a.m. on October 25, 2016 on the BZX. The number of executed orders increases to 38 during the event minute. Panel B shows an intense trading spike for Bank of America (BAC) call options at 12:00 p.m. on October 27, 2016 on the NOM. Last, Panel C shows a trading spike for Deutsche Bank (DB) put options at 3:38 p.m. on October 31, 2016 on the EDGX when the number of trades increases to 28. We examine these trading spikes in more detail in the following analysis.

To investigate the impact of trading spikes on market quality, we examine the 20 one-minute trading segments before and after the identified events. Consistent with the theory of Clark (1973) and Copeland (1976) we find a positive relation between volatility and trading volume. Panel A of Figure 4 shows a substantial increase in short-term volatility during extreme trading spikes. Specifically, volatility increases from 0.7485 in the minute before the event to 1.4572 during the one-minute spike in trading (see Table 6), which provides support for our third hypothesis that states trading spikes are associated with an increase in volatility.

We also examine the effect of option trading spikes on limit order trading decisions. Panel B of Figure 4 shows that average order cancellation activity decreases during extreme trading spikes, although it is relatively volatile over the sample period. This decline in order cancellation activity suggests that limit order traders are more willing to let their orders sit on the book when execution rates are increasing. However, Panel C of Figure 4 shows that the median time-to-cancellation increases sharply during trading spikes, but then immediately decreases in the minutes following the events. The time-to-cancellation remains relatively low for approximately 10 minutes after the events. Table 6 shows that the median time between order submission and cancellation increases from 98.62 seconds in the minute prior to the trade spike, to 181.33 seconds during the trade spike, and then to 67.14 second in the minute following the event.

Next, we analyze the effect of option trading spikes on liquidity in the underlying equities market. Figure 4 and Table 6 show no distinct patterns in volatility or effective spreads around option trading spikes. However, we find an increase in average quoted spreads in the two minutes around the trading spikes. In fact, average percent quoted spreads increase from 0.00051 to 0.00057 from the minute prior to the trading spike to the minute after the trading spike.

In our last set of tests in this section, we examine if the impact of trading spikes on market quality hold in a multivariate setting. We estimate specifications of the following regression equation:

$$DepVariable_{i,t} = \alpha + \delta_t + \tau_j + \beta_1 Tspike_t + \beta_2 Post\ Tspike_t + \boldsymbol{\gamma X} + \varepsilon_{i,t}, \qquad (5)$$

where the dependent variable is set to either *short-term volatility*, *order cancellation rates*, or *time-to-cancellation*; *Tspike* equals one during trading spikes and zero otherwise and *Post Tspike* equals one during the post-event windows and zero otherwise. We include the following as control variables: exchange identifiers, S/X ratio, days to expiration, call dummy variable, time-to-cancellation, option trade size, option volume, option trade price, underlying stock volume, underlying market capitalization, and dummy variables for penny options and ETFs. We also include either day dummy variables, δ_t, or event fixed effects, τ_j.

Table 7 reports the results of estimating eq. (5). We find that the BZX and EDGX have lower volatility, higher cancellation activity, and faster cancellation speeds than the NOM. We also find that option volume, option trade price, and underlying stock volume are all positively related to short-term volatility. Option classes that trade in pennies have significantly higher order cancellation rates and faster cancellation speeds than non-penny option classes.

Consistent with theory (Copeland, 1976) and in support of our third hypothesis, we find that short-term volatility is significantly higher during trading spikes than during the pre-event window, other factors held constant. In fact, volatility is between 0.5456 and 0.9005 higher during trading spikes than during the 20 minute pre-event window. Columns [3] and [4] report the results of estimating eq. (5) with *order cancellation rates* as the dependent variable. We reject our fourth hypothesis that trading spikes are associated with higher cancellation activity, as we do not find significant evidence that order cancellation rates differ during the identified trading spikes. Consistent with our univariate tests, we find that limit order traders are more reluctant to cancel their orders during trading spikes as the average time-to-cancellation lengthens between 66.82 to 110 seconds.

Next, we analyze if option trade spikes affect liquidity in the underlying equities, holding stock characteristics and market conditions constant. We use OLS to examine the impact of trading spikes on liquidity in the underlying equities. We analyze three dependent variables: *short-term* *volatility*, *percent quoted spreads*, and *percent effective spreads*. We estimate the following regression model:

$$DepVar_{i,t} = \alpha + \tau_j + \beta_1 Tspike_t + \beta_2 Post\ Tspike_t + \boldsymbol{\gamma X} + \varepsilon_{i,t}, \qquad (6)$$

where *Tspike* equals one for the minute during the option trading spike and the minute after the event and zero otherwise; *Post Tspike* equals one for the post-event window and zero otherwise. Similar to eq. (4) we include the underlying trade price, underlying volatility, and underlying number of trades as control variables. We also include event fixed effects and cluster the standard errors by stock.

Table 8 reports the results of estimating eq. (6). In Column [2], we find that the coefficient on the event dummy variable, *Tspike*, is positive and significant at the 0.01 level, which suggests that percent quoted spreads appear to increase during option trade spikes, other factors held constant. We do not find significant evidence that either short-term volatility or percent effective spreads change during option trading spikes. Thus, it does not seem that short-lived trading spikes in options significantly impact liquidity in the underlying stocks, with the exception of percent quoted spreads.

QUOTE STUFFING AND TRADING SPIKES ON OPTION EXPIRATION DAYS

In our last set of tests, we compare quote stuffing episodes and trading spikes on option expiration days and on other trading days. Figure 5 plots the distribution of quote stuffing episodes and trading spikes over the 21 trading days examined in this study. We show that the most quote stuffing events to occur on a single day is on October 26, 2016 (220 episodes). The number of trading spikes in a single day peaks on October, 28, 2016. In comparison, 142 (87) quote stuffing events (trading spikes) occur on option expiration, October 21, 2016.

To control for other factors that might influence the probabilities of quote stuffing episodes and trading spikes, we estimate the following logistic regression:

$$Qstuff\ or\ Tspike_i = \alpha + \beta_1 Option\ Expiration_t + \boldsymbol{\gamma X} + \varepsilon_{i,t}, \tag{7}$$

where the dependent variable are binary, *Qstuff* equals one during a quote stuffing event and zero otherwise; *Tspike* equals one during a trading spike and zero otherwise; and *Option Expiration* equals one on October 21, 2016 and zero otherwise. We include as control variables: a call dummy variable, S/X ratio, time-to-cancellation, option trade size, # of option trades, option trade price, # of underlying trades, and underlying market capitalization.

Panel A of Table 9 reports the results of estimating eq. (7) with *Qstuff* as the dependent variable. We find that the S/X ratio, option trade size, and underling market capitalization are negative predictors of option quote stuffing episodes. Also, the probability of quote stuffing is higher as trading volume increases. The coefficient on *Option Expiratio*n is negative, indicating that the probability of quote stuffing is lower on option expiration, relative to non-option expiration days. However, Panel B of Table 9 shows the results of estimating eq. (7) with *Tspike* as the dependent variable, and we find that a trading spike is 1.76 times more likely to occur on an option expiration day, relative to non-option expiration days. Therefore, we fail to completely reject our sixth hypothesis that trading spikes and quote stuffing episodes are more frequently observed on option expiration days.

CONCLUDING REMARKS

In this study, we examine the market quality implications of quote stuffing and trading spikes in equity options markets. Quote stuffing refers to an order placement strategy whereby traders quickly enter and cancel a large number of orders. When orders are added to the book and canceled within nanoseconds, market participants have a more difficult time differentiating between genuine liquidity and “fake depth” (Angel, 2014). Although quote stuffing episodes are associated with large increases in order volume, the actual posted depth might actually be less as most of the quotes are flickering (Baruch and Glosten, 2013).

Our empirical analysis provides evidence that quote stuffing reduces order execution rates and lengthens time-to-execution. Therefore, quote stuffing has a negative effect on at least two important aspects of limit order execution quality. In fact, the probability of completing a trade is of first-order importance in the SEC’s definition of execution quality (Battalio, Corwin, and Jennings, 2015). Option quote stuffing and trading spikes create temporary frictions in trade prices, which has important practical implications. Analysts and other investment professionals use volatility forecast models (Hamid and Iqbal, 2004) and practitioners must account for these short-lived frictions in options markets in order to more accurately forecast volatility.

Our analysis also contributes to the literature that investigates the flow of information between the options and underlying equities markets (see Easley, O’Hara, and Srinivas, 1998; Chakravarty, Gulen, and Mayhew, 2004). We find that bid-ask spreads in the underlying securities increase following extreme quote stuffing episodes. There appears to be a one-minute lag between the option quote stuffing event and the liquidity reaction in the underlying equities, which suggests, but does not prove, that options trading contributes to price discovery in the underlying equities market. Overall, quote stuffing and trading spikes seem to cause temporary disturbances in market efficiency as volatility increases and order execution quality deteriorates.

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APPENDIX

APPENDIX 1: DESCRIPTIVE STATISTICS OF OPTION QUOTE STUFFING EPISODES

Table 1
Descriptive Statistics of Option Quote Stuffing Episodes

The sample consists of orders in 319 equity and ETF option classes around 2,585 identified quote stuffing episodes during the 21 trading days of October, 2016. Panel A reports statistics on the 319 option classes with at least one quote stuffing episode during the sample period. Panel B reports order statistics during the one-minute quote stuffing events. Panels C through E report the distribution of trading spikes across magnitudes, exchanges, option type (call or put), and tick size.

Panel A. Option Class and Underlying Stock Statistics

	Common Stocks				*ETFs*			
	# of option classes	Mean	Median	Std. Dev.	# of option classes	Mean	Median	Std. Dev.
Strike price	280	78.97	53.16	122.49	39	65.00	43.79	58.40
Days-to-expiration	280	57.55	47.17	35.48	39	55.27	49.44	21.65
Penny Pilot	280	0.58	1.00	0.49	39	0.74	1.00	0.44
Underlying trade price	280	79.57	52.53	124.52	39	64.58	39.54	58.45
Underlying size ($ billions)	280	47.06	19.51	76.90	39	13.88	4.25	32.74
S/X	280	1.01	1.00	0.09	39	1.03	1.01	0.11

Panel B. Order statistics during option quote stuffing episodes

	Mean	Median	Std. Dev.	Min	Max
Order Volume (# contracts)	482,888	17,988	2,637,709	16	50,646,795
# of Orders	16,422	1,793	41,523	8	427,284
# of Canceled Orders	16,354	1,771	41,411	6	427,284
Order Size (# contracts)	16.26	10.39	34.33	1.00	1,119.67
Order Price	9.60	4.84	14.85	0.18	187.15

Panel C. Quote stuffing episodes

# of standard deviations above mean	# of events	% of sample
[4,5)	206	7.97%
[5,6)	1184	45.80%
[6,7)	762	29.48%
[7,8)	252	9.75%
[8,□)	181	7.00%

Panel D. Option Quote stuffing episodes by option type

Exchange	# of events	% of sample
Call	1,462	56.56%
Put	1,123	43.44%
Penny Pilot	2,139	82.75%
Not Penny Pilot	446	17.25%

Panel E. Option Quote stuffing episodes by exchange

Exchange	# of events	% of sample
BZX	1,050	40.62%
EDGX	109	4.22%
NOM	1,426	55.16%

APPENDIX 2: MARKET QUALITY AROUND OPTION QUOTE STUFFING EPISODES

Table 2
Market Quality around Option Quote Stuffing Episodes

The sample consists of orders in 319 equity and ETF option classes around 2,585 identified quote stuffing episodes during the 21 trading days of October, 2016. We examine three market quality measures in options and three market quality measures in the underlying stocks. *Execution Rate* equals the average number of orders executed to total orders submitted. *Time-to-Execution* equals the number of seconds between order submission and execution. *S-T Volatility* equals the log of the high ask price minus the log of the low bid price. *% Quoted Spread* equals the difference between the ask price and the bid price, scaled by the midpoint. *% Effective Spread* equals $2D_k(P_k - M_k)/M_k$, where D_k is equal to +1 if the trade is a buy and -1 if the trade is a sell, P_k is the execution price, and M_k is the quote midpoint. Panel A reports average market quality statistics for the quote stuffing interval (minute 0) and the ten one-minute intervals before and after the event. Panel B reports a summary of the market quality measures around the quote stuffing episodes. We test for differences in means using simple t-tests. ***, **, and * denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

Panel A. Market quality around option quote stuffing episodes						
	Option market quality			Equity market quality		
Minute	Execution Rate	Time-to-Execution	S-T Volatility	S-T Volatility	% Quoted Spread	% Effective Spread
-10	12.02%	114.669	0.4116	0.0406	0.00071	0.00604
-9	10.82%	121.386	0.4918	0.0474	0.00071	0.00597
-8	12.21%	130.108	0.4275	0.0437	0.00073	0.00600
-7	12.23%	125.327	0.4169	0.0470	0.00073	0.00612
-6	8.06%	154.167	0.3917	0.0459	0.00072	0.00609
-5	9.57%	121.039	0.3733	0.0394	0.00071	0.00571
-4	9.88%	115.131	0.4237	0.0445	0.00072	0.00596
-3	6.92%	197.198	0.4902	0.0495	0.00071	0.00585
-2	9.49%	90.071	0.3390	0.0343	0.00068	0.00559
-1	8.37%	172.236	0.5815	0.0420	0.00071	0.00507
0	1.43%	331.477	0.7984	0.0538	0.00085	0.00567
1	7.06%	43.790	0.6395	0.0559	0.00106	0.00700
2	6.34%	50.562	0.5702	0.0510	0.00081	0.00564
3	7.27%	58.466	0.5141	0.0528	0.00079	0.00566
4	7.96%	86.689	0.5164	0.0501	0.00078	0.00622
5	9.87%	71.160	0.4886	0.0463	0.00077	0.00622
6	9.76%	72.958	0.5255	0.0392	0.00075	0.00625
7	8.22%	105.397	0.4456	0.0404	0.00072	0.00643
8	8.65%	87.416	0.4609	0.0513	0.00074	0.00604
9	8.76%	68.757	0.4528	0.0374	0.00073	0.00639
10	8.26%	78.107	0.4398	0.0519	0.00072	0.00583
Panel B. Summary						
Pre event window	9.96%	134.133	0.4347	0.0434	0.00071	0.00583
Event window [0,1)	1.43%	331.477	0.7984			
Event window [0,1]				0.0548	0.00095	0.00633
Post event window	8.22%	72.330	0.5053	0.0467	0.00075	0.00608
Differences						
Event - Pre	-8.53%***	197.344***	0.3637***	0.0114***	0.00024***	0.00051***
Event - Post	-6.79%***	259.147***	0.2931***	0.0081***	0.00020***	0.00026***

APPENDIX 3: OPTION MARKET QUALITY AROUND OPTION QUOTE STUFFING EPISODES

Table 3
Option Market Quality around Option Quote Stuffing Episodes

The sample consists of orders in 319 equity and ETF option classes around 2,585 identified quote stuffing episodes during the 21 trading days of October, 2016. We use Ordinary Least Squares to examine the impact of quote stuffing on order execution quality and liquidity. *Execution Rate* equals the average number of canceled orders divided by the total number of order submitted. *S-T Volatility* equals the average difference in logs of the one-minute high ask price and one-minute low bid price. *Time-to-Execution* equals the average number of seconds between order submission and execution. *Qstuffing* equals one during the one-minute quote stuffing event and zero otherwise. *Post Qstuffing* equals one during the 20 one-minute trading intervals following the quote stuffing episode and zero otherwise. *BZX* and *EDGX* equal one if the order/modification message is sent to that particular exchange and zero otherwise. *S/X* equals the underlying stock price divided by the strike price. *Days Expire* is the number of days between order submission and option expiration. *Call* equals one if the order is for a call option and zero for a put option. *Cancel Speed* is the number of seconds between order submission and cancellation conditional on a complete order deletion. *Option Trade Size* is the average number of contracts attached to a particular execution order. *Option Volume* equals the option's average one-minute contract volume. *Option Trade Price* equals the option's mean one-minute execution price. *Underlying Volume* equal the underlying stock's average one-minute share volume. *Underlying MCAP* is the underlying stock's average daily market capitalization, measured in $billions. *Penny* equals one if the option is traded and quoted in pennies and zero otherwise. *ETF* equals one if the option class is an ETF and zero if it is a common stock. We include either day or event fixed effects. T-statistics are reported in parentheses obtained from standard errors clustered by option class. ***, **, and * denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

	Execution Rate		*Time-to-Execution (seconds)*		*S-T Volatility*	
	[1]	[2]	[3]	[4]	[5]	[6]
Qstuffing	-0.0895***	-0.0911***	197.2748***	83.5441**	0.1512***	0.4609***
	(-11.96)	(-11.84)	(4.90)	(2.37)	(3.51)	(9.99)
Post Qstuffing	0.0007	0.0021	-47.5607**	-79.6201***	-0.0219	-0.0068
	(0.21)	(0.68)	(-2.31)	(-3.54)	(-0.97)	(-0.28)
BZX	-0.1493***		-147.0375***		-0.0734	
	(-11.92)		(-4.37)		(-0.99)	
EDGX	-0.1388***		-256.1034***		-0.3957**	
	(-10.02)		(-4.12)		(-2.33)	
S/X	-0.0232	-0.0439	-1.2647	168.7779	-0.2008	-0.1412
	(-0.70)	(-0.91)	(-0.01)	(1.29)	(-0.99)	(-1.44)
Days-to-Expiration	-0.0001	-0.0001*	0.6002***	0.3871	0.0001	0.0003
	(-1.64)	(-1.68)	(2.65)	(1.27)	(0.10)	(0.83)
Call	0.0098**		43.3001**		0.0931*	
	(2.12)		(2.05)		(1.87)	
Cancel Speed	0.0000***	0.0000**	0.0542***	-0.0029	-0.0000	0.0000
	(3.19)	(2.50)	(2.99)	(-0.26)	(-1.40)	(0.78)
Option Trade Size	-0.0001***	-0.0001*	0.1297	-0.0925	-0.0032***	-0.0019***
	(-2.82)	(-1.91)	(0.92)	(-0.79)	(-3.31)	(-3.29)
Option Volume	0.0000***	0.0000*	-0.1347**	-0.0153	0.0019***	0.0012***
	(3.14)	(1.66)	(-2.20)	(-0.59)	(3.49)	(3.18)
Option Trade Price	0.0000	-0.0001	-0.8142***	-0.6107***	0.0062***	0.0054***
	(0.14)	(-1.18)	(-3.18)	(-2.97)	(3.45)	(3.45)
Underlying Volume	-0.0000	0.0000**	0.0006***	0.0008***	0.0000***	0.0000***
	(-0.71)	(2.13)	(3.12)	(3.75)	(6.32)	(9.21)
Underlying MCAP	-0.0001		-0.1490**		0.0019***	
	(-1.26)		(-2.02)		(4.18)	
Penny	-0.0698***		-160.9540***		0.2386	
	(-5.20)		(-3.87)		(1.61)	
ETF	-0.0327***		-136.8089**		0.1209	
	(-2.84)		(-2.12)		(0.50)	
Constant	0.3020***	0.1281***	623.7562***	171.1943	0.5103*	0.9575***
	(6.57)	(2.66)	(4.54)	(1.22)	(1.81)	(9.10)
Day FE	Yes	No	Yes	No	Yes	No
Event FE	No	Yes	No	Yes	No	Yes
R^2	0.1640	0.0204	0.0195	0.0073	0.1926	0.0775
N	41,542	41,542	41,542	41,542	41,542	41,542

APPENDIX 4: EQUITY MARKET QUALITY AROUND OPTION QUOTE STUFFING EPISODES

Table 4
Equity Market Quality around Option Quote Stuffing Episodes

The sample consists of orders in 319 equity and ETF option classes around 2,585 identified quote stuffing episodes during the 21 trading days of October, 2016. We use Ordinary Least Squares to examine the impact of quote stuffing on market quality in the underlying equities. *Qstuffing Event* equals one during the two one-minute segments during and after the option quote stuffing episodes and zero otherwise. *Post Qstuffing* equals one during the 14 one-minute trading intervals following the quote stuffing event and zero otherwise. *Underlying Price* is the average one-minute stock price. *Underlying Volatility* is the average one-minute stock volatility, measured as the difference in the log of the high ask price and log of the low bid price. *Underlying Trades* is the average one-minute number of trades in a given stock. We include event fixed effects, τ_j, and report t-statistics in parentheses obtained from standard errors clustered at the stock level. ***, **, and * denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

Equity market quality around option quote stuffing episodes			
	S-T Volatility	% Quoted Spread	% Effective Spread
	[1]	[2]	[3]
Qstuffing	0.0054	0.0001***	0.0004**
	(1.320)	(6.983)	(1.996)
Post Qstuffing	0.0009	-0.0000	0.0001
	(0.435)	(-0.494)	(1.128)
Underlying Price	0.0150***	-0.0000***	-0.0005***
	(34.961)	(-5.689)	(-20.112)
log(Underlying Trades)	0.0038***	0.0000***	-0.0004***
	(2.759)	(2.999)	(-5.649)
Underlying Volatility		0.0001***	0.0196***
		(7.227)	(96.548)
Constant	-1.8596***	0.0016***	0.0666***
	(-34.101)	(7.876)	(22.350)
Event FE			
R^2	0.0170	0.0021	0.1162
N	73,901	73,846	73,901

APPENDIX 5: DESCRIPTIVE STATISTICS OF OPTION TRADING SPIKES

Table 5

Descriptive Statistics of Option Trading Spikes

The sample consists of order executions in 217 equity and ETF option classes around 1,619 identified trading spikes during the 21 trading days of October, 2016. Panel A reports statistics on the 217 option classes with at least one trading spike during the sample period. Panel B reports trade statistics during the one-minute trading spikes. Panels C through E report the distribution of trading spikes across spike magnitudes, exchanges, option type (call or put), and tick size.

Panel A. Option class and underlying stock characteristics

	Common Stocks				*ETFs*			
	# of option classes	Mean	Median	Std. Dev.	# of option classes	Mean	Median	Std. Dev.
Strike price	184	86.96	54.33	143.00	33	71.99	48.12	62.06
Days-to-expiration	184	51.98	44.83	30.19	33	48.93	45.03	19.35
Penny Pilot	184	0.78	1.00	0.42	33	0.76	1.00	0.44
Underlying trade price	184	88.18	55.66	147.00	33	71.41	47.78	60.90
Underlying size ($ billions)	184	64.91	29.51	89.70	33	15.80	4.74	35.28
S/X	184	1.00	0.99	0.05	33	1.02	1.00	0.07

Panel B. Trade Statistics during option trade spikes

	Mean	Median	Std. Dev.	Min	Max
Trade Volume (# contracts)	361.00	157.00	644.82	7.00	8,188.00
# of Trades	27.87	20.00	24.88	5.00	293.00
Trade Size (# contracts)	12.77	7.50	17.47	1.00	191.11
Trade Price	5.58	1.26	77.92	0.02	3,046.47

Panel C. Distribution of option trade spikes

# of standard deviations above mean	# of events	% of sample
[6,7)	97	5.99%
[7,8)	825	50.96%
[8,9)	406	25.08%
[9,10)	151	9.33%
[10,11)	74	4.57%
[11,∞)	66	4.08%

Panel D. Trade spikes by exchange

Exchange	# of events	% of sample
BZX	1,122	69.30%
EDGX	34	2.10%
NOM	463	28.60%

Panel E. Trade spikes by option type		
Exchange	# of events	% of sample
Call	908	56.08%
Put	711	43.92%
Penny Pilot	1,438	88.82%
Not Penny Pilot	181	11.18%

APPENDIX 6: MARKET QUALITY AROUND OPTION TRADING SPIKES

Table 6
Market Quality around Option Trading Spikes

The sample consists of orders in 217 equity and ETF option classes around 1,619 identified trading spikes during the 21 trading days of October, 2016. We examine three market quality measures in options and three market quality measures in the underlying stocks. *S-T Volatility* equals the log of the high ask price minus the log of the low bid price. *Cancel Rate* equals the average number of orders canceled to total orders submitted. *Time-to-Cancel* equals the number of seconds between order submission and cancellation. *% Quoted Spread* equals the difference between the ask price and the bid price, scaled by the midpoint. *% Effective Spread* equals $2D_k(P_k - M_k)/M_k$, where D_k is equal to +1 if the trade is a buy and -1 if the trade is a sell, P_k is the execution price, and M_k is the quote midpoint. Panel A reports average market quality statistics for the quote stuffing interval (minute 0) and the ten one-minute intervals before and after the event. Panel B reports a summary of the market quality measures around the quote stuffing episodes. We test for differences in means using simple t-tests. ***, **, and * denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

Panel A. Market quality around option trade spikes						
	Option market quality			*Equity market quality*		
Minute	S-T Volatility	Cancel Rate	Time-to-Cancel	S-T Volatility	% Quoted Spread	% Effective Spread
-10	0.4255	94.34%	72.83	0.03111	0.00051	0.00524
-9	0.5442	94.23%	68.00	0.05837	0.00052	0.00590
-8	0.6064	94.81%	72.18	0.03844	0.00051	0.00480
-7	0.5128	95.13%	70.50	0.04015	0.00052	0.00505
-6	0.5801	94.63%	73.25	0.04515	0.00060	0.00479
-5	0.5323	95.22%	77.87	0.04010	0.00051	0.00494
-4	0.5369	96.28%	80.99	0.04681	0.00051	0.00505
-3	0.6144	95.60%	80.24	0.05106	0.00051	0.00513
-2	0.5674	94.75%	90.50	0.03808	0.00051	0.00516
-1	0.7485	93.67%	98.62	0.04134	0.00051	0.00464
0	1.4572	93.27%	181.33	0.04442	0.00055	0.00501
1	0.8231	92.82%	67.14	0.04365	0.00057	0.00530
2	0.7015	95.10%	60.19	0.05084	0.00055	0.00485
3	0.6726	94.63%	61.00	0.04871	0.00053	0.00557
4	0.6773	93.77%	56.82	0.03822	0.00052	0.00507
5	0.5993	95.00%	62.91	0.06154	0.00053	0.00565
6	0.4999	95.10%	65.16	0.03665	0.00053	0.00510
7	0.5727	95.18%	62.60	0.04739	0.00052	0.00541
8	0.5664	94.61%	66.18	0.04873	0.00054	0.00547
9	0.6314	94.84%	63.21	0.04768	0.00052	0.00476
10	0.6281	94.63%	57.98	0.03448	0.00051	0.00475
Panel B. Summary						
Pre event window	0.5668	94.86%	78.50	0.04306	0.00052	0.00507
Event window [0,1)	1.4572	93.27%	181.33			
Event window [0,1]				0.04403	0.00056	0.00516
Post event window	0.6372	94.57%	62.32	0.04602	0.00053	0.00518
Differences						
Event - Pre	0.8904***	-1.60%	102.83***	0.00097	0.00004***	0.00009
Event - Post	0.8200***	-1.30%	119.01***	-0.00199	0.00003***	-0.00002

APPENDIX 7: OPTION MARKET QUALITY AROUND OPTION TRADING SPIKES

Table 7
Option Market Quality around Option Trading Spikes

The sample consists of orders in 217 equity and ETF option classes around 1,619 identified trading spikes during the 21 trading days of October, 2016. We use Ordinary Least Squares to examine the impact of trading spikes on market quality. *S-T Volatility* equals the average difference in logs of the one-minute high ask price and one-minute low bid price. *Cancel Rate* equals the average one-minute number of canceled orders divided by the total number of order submitted. *Time-to-Cancel* equals the average number of seconds between order submission and cancellation. *Tspike* equals one during the one-minute trading spike and zero otherwise. *Post Tspike* equals one during the 20 one-minute trading intervals following the trading spike and zero otherwise. *BZX* and *EDGX* equal one if the order/modification message is sent to that particular exchange and zero otherwise. *S/X* equals the underlying stock price divided by the strike price. *Days Expire* is the number of days between order submission and option expiration. *Call* equals one if the order is for a call option and zero for a put option. *Cancel Speed* is the number of seconds between order submission and cancellation conditional on a complete order deletion. *Option Trade Size* is the average number of contracts attached to a particular execution order. *Option Volume* equals the option's average one-minute contract volume. *Option Trade Price* equals the option's mean one-minute execution price. *Underlying Volume* equal the underlying stock's average one-minute share volume. *Underlying MCAP* is the underlying stock's average daily market capitalization, measured in $billions. *Penny* equals one if the option is traded and quoted in pennies and zero otherwise. *ETF* equals one if the option class is an ETF and zero if it is a common stock. We include either day or event fixed effects. T-statistics are reported in parentheses obtained from standard errors clustered by option class. ***, **, and * denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

	S-T Volatility		Cancel Rate		Time-to-Cancel	
	[1]	[2]	[3]	[4]	[5]	[6]
Tspike	0.5456***	0.9005***	0.0052	-0.0036	109.7216***	66.8153***
	(8.91)	(16.11)	(1.02)	(-0.85)	(6.77)	(4.68)
Post Tspike	0.0025	0.0001	0.0035**	0.0028	-5.0778	-11.9460**
	(0.15)	(0.01)	(2.08)	(1.55)	(-0.84)	(-2.33)
BZX	-0.2722***		0.1801***		-119.3373***	
	(-3.20)		(21.28)		(-3.57)	
EDGX	-0.8065***		0.1854***		-139.2034***	
	(-6.66)		(14.90)		(-4.15)	
SX	-0.1285	-0.2071	0.0276	0.0465	112.6322	134.3720
	(-0.49)	(-1.41)	(0.88)	(0.88)	(1.64)	(1.31)
Days-to-Expiration	0.0004	0.0015***	0.0000	-0.0000	-0.1488	-0.3311
	(0.57)	(2.99)	(0.20)	(-0.11)	(-0.85)	(-1.30)
Call	-0.0056		-0.0057*		22.7015*	
	(-0.10)		(-1.67)		(1.87)	
Cancel Speed	-0.0001***	0.0000	-0.0000***	-0.0000		
	(-3.53)	(0.24)	(-5.32)	(-1.23)		
Option Trade Size	-0.0043***	-0.0019***	0.0001***	0.0000	0.3207*	0.2151*
	(-4.91)	(-5.24)	(2.63)	(1.02)	(1.77)	(1.81)
Option Volume	0.0011***	0.0006***	-0.0000	0.0000	-0.0216	0.0160
	(4.64)	(4.05)	(-0.30)	(0.41)	(-1.23)	(1.33)
Option Trade Price	0.0067***	0.0057***	-0.0000	0.0000	-0.0921	-0.0982
	(2.80)	(2.98)	(-0.25)	(1.20)	(-0.49)	(-0.52)
Underlying Volume	0.0000***	0.0000***	-0.0000	-0.0000	-0.0000	0.0000
	(4.94)	(7.68)	(-1.40)	(-0.73)	(-0.26)	(0.24)
Underlying MCAP	0.0024***		-0.0000		-0.1504**	
	(3.19)		(-0.25)		(-2.08)	
Penny	0.1225		0.0167**		-81.6288***	
	(0.92)		(2.00)		(-2.61)	
ETF	0.1998		-0.0034		24.0597	
	(0.98)		(-0.56)		(0.57)	
Constant	0.6167**	0.9297***	0.7393***	0.8935***	199.3051**	21.2721
	(2.34)	(6.14)	(18.63)	(21.32)	(2.58)	(0.21)
Day FE	Yes	No	Yes	No	Yes	No
Event FE	No	Yes	No	Yes	No	Yes
R^2	0.1989	0.1044	0.2924	0.0034	0.0227	0.0023
N (all specifications)	30,452	30,452	30,452	30,452	30,452	30,452

APPENDIX 8: EQUITY MARKET QUALITY AROUND OPTION TRADING SPIKES

Table 8
Equity Market Quality around Option Trading Spikes

The sample consists of orders in 217 equity and ETF option classes around 1,619 identified trading spikes during the 21 trading days of October, 2016. We use Ordinary Least Squares to examine the impact of trading spikes on market quality in the underlying equities. *Tspike* equals one during the two one-minute segments during and after the option trading spike and zero otherwise. *Post Tspike* equals one during the 14 one-minute trading intervals following the option trading spike and zero otherwise. *Underlying Price* is the average one-minute stock price. *Underlying Volatility* is the average one-minute stock volatility, measured as the difference in the log of the high ask price and log of the low bid price. *Underlying Trades* is the average one-minute number of trades in a given stock. We include event fixed effects, τ_j, and report t-statistics in parentheses obtained from standard errors clustered at the stock level. ***, **, and * denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

Equity market quality around Option Trading Spikes			
	S-T Volatility	% Quoted Spread	% Effective Spread
	[1]	[2]	[3]
Tspike	0.00307	0.00002***	0.00026
	(0.566)	(3.295)	(0.906)
Post Tspike	0.00235	-0.00001***	0.00010
	(0.890)	(-2.616)	(0.703)
Underlying Price	0.02612***	-0.00000***	-0.00027***
	(49.783)	(-4.894)	(-9.239)
log(Underlying Trades)	0.00305	0.00001***	-0.00091***
	(1.446)	(4.700)	(-8.009)
Underlying Volatility		0.00004***	0.01887***
		(10.189)	(80.818)
Constant	-2.79851***	0.00058***	0.03936***
	(-48.023)	(11.629)	(12.260)
Event FE	Yes	Yes	Yes
R^2	0.04443	0.00308	0.10940
N	55,163	55,163	55,163

APPENDIX 9: QUOTE STUFFING AND TRADING SPIKES ON OPTION EXPIRATION DAYS

Table 9
Quote Stuffing and Trading Spikes on Option Expiration Days

We use logistic regression to examine the likelihood of a quote stuffing event and/or trading spike occurring on the option expiration day (October 21, 2016). The dependent variable in Panel A is an indicator variable equal to one during an option quote stuffing episode and zero otherwise. The dependent variable in Panel B is an indicator variable equal to one during an option trading spike and zero otherwise. *Expire* is a dummy variable equal to one if the order is submitted/modified on October 21, 2016 (option expiration) and zero otherwise. The remaining control variables are defined in the test. ***, **, and * denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

Panel A. Probability of Quote Stuffing Episodes

Independent Variable	b	se	z ratio	prob.	Odds Ratio
Expire	-0.2419**	0.0974	-2.48	0.013	0.7851
Call	-0.0220	0.0424	-0.52	0.604	0.9782
SX	-0.4851**	0.2139	-2.27	0.023	0.6156
Cancel Speed	0.0003***	0.0000	12.23	0.000	1.0003
Option Trade Size	-0.0036**	0.0016	-2.31	0.021	0.9964
# of Option Trades	0.0235***	0.0032	7.41	0.000	1.0238
Option Trade Price	0.0012**	0.0005	2.38	0.018	1.0012
# of Underlying Trades	0.0007***	0.0000	18.22	0.000	1.0007
Underlying MCAP	-0.0024***	0.0002	-14.77	0.000	0.9976
Constant	-2.3442***	0.2199	-10.66	0.000	0.0959
Pseudo R^2	0.0569				
N	41,542				

Panel B. Probability of Trading Spikes

Independent Variable	b	se	z ratio	prob.	Odds Ratio
Expire	0.5673***	0.1229	4.62	0.000	1.7635
Call	0.1653**	0.0699	2.37	0.018	1.1798
SX	0.4459	0.3017	1.48	0.139	1.5619
Cancel Speed	0.0002***	0.0000	8.14	0.000	1.0002
Option Trade Size	-0.0052**	0.0023	-2.27	0.023	0.9948
# of Option Trades	0.1662***	0.0069	24.26	0.000	1.1808
Option Trade Price	0.0014***	0.0004	3.53	0.000	1.0014
# of Underlying Trades	-0.0007***	0.0002	-3.93	0.000	0.9993
Underlying MCAP	-0.0033***	0.0003	-9.60	0.000	0.9967
Constant	-4.4839***	0.3206	-13.99	0.000	0.0113
Pseudo R^2	0.3821				
N	30,452				

FIGURES

FIGURE 1: EXAMPLES OF OPTION QUOTE STUFFING EPISODES

Figure 1
Examples of Option Quote Stuffing Episodes

This figure provides several examples of the extreme quote stuffing episodes observed in this study. Panel A shows a quote stuffing event for IBM call options at 11:39 a.m. on October 25th, 2016. Panel B displays a quote stuffing event for American Airlines Group Inc. (AAL) on the EDGX from 12:08 p.m. on October 27th, 2016. Panel C shows an extreme quote stuffing episode for Delta Air Lines, Inc. (DAL) call options on the NOM at 10:33 on October 13th, 2016.

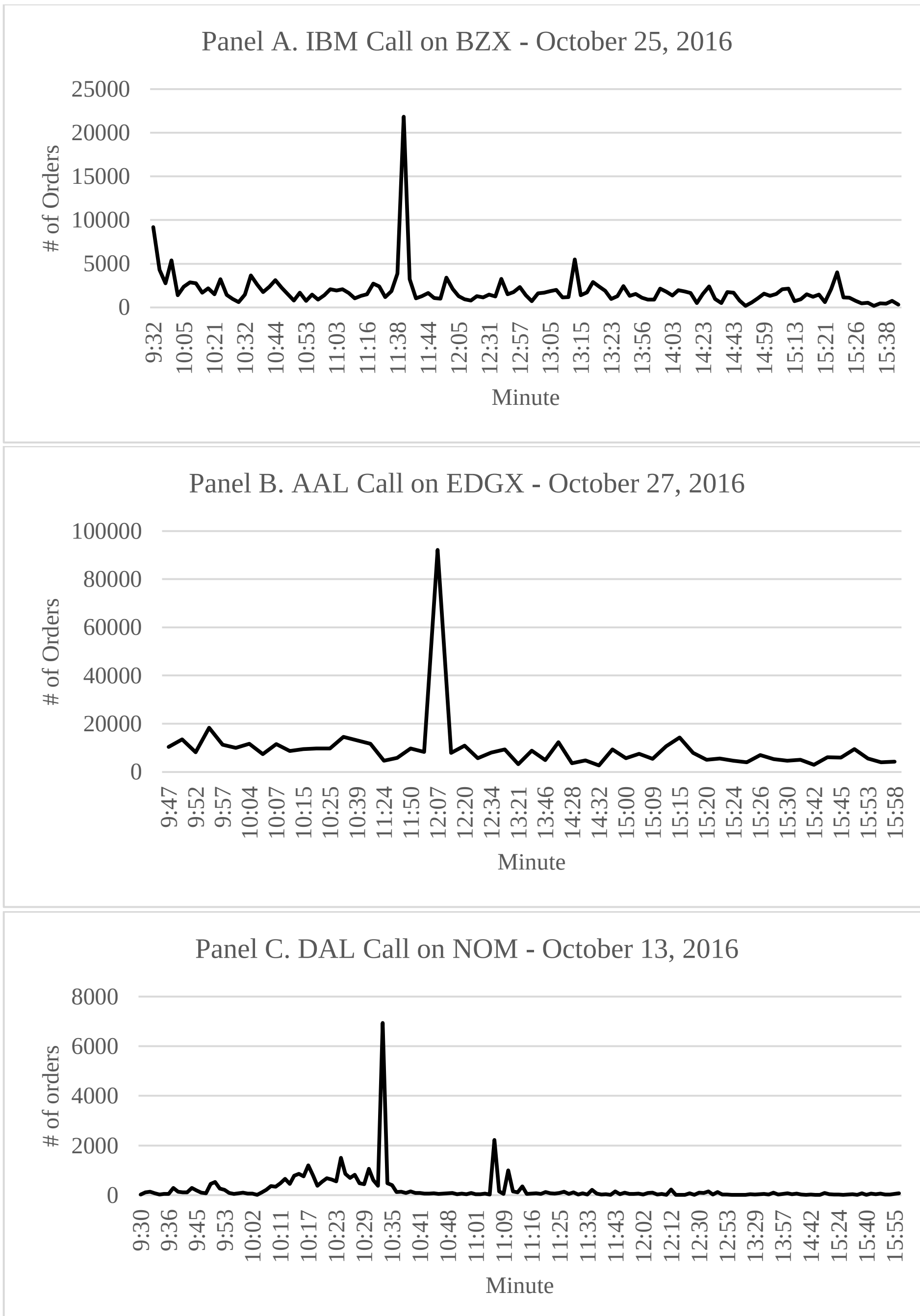
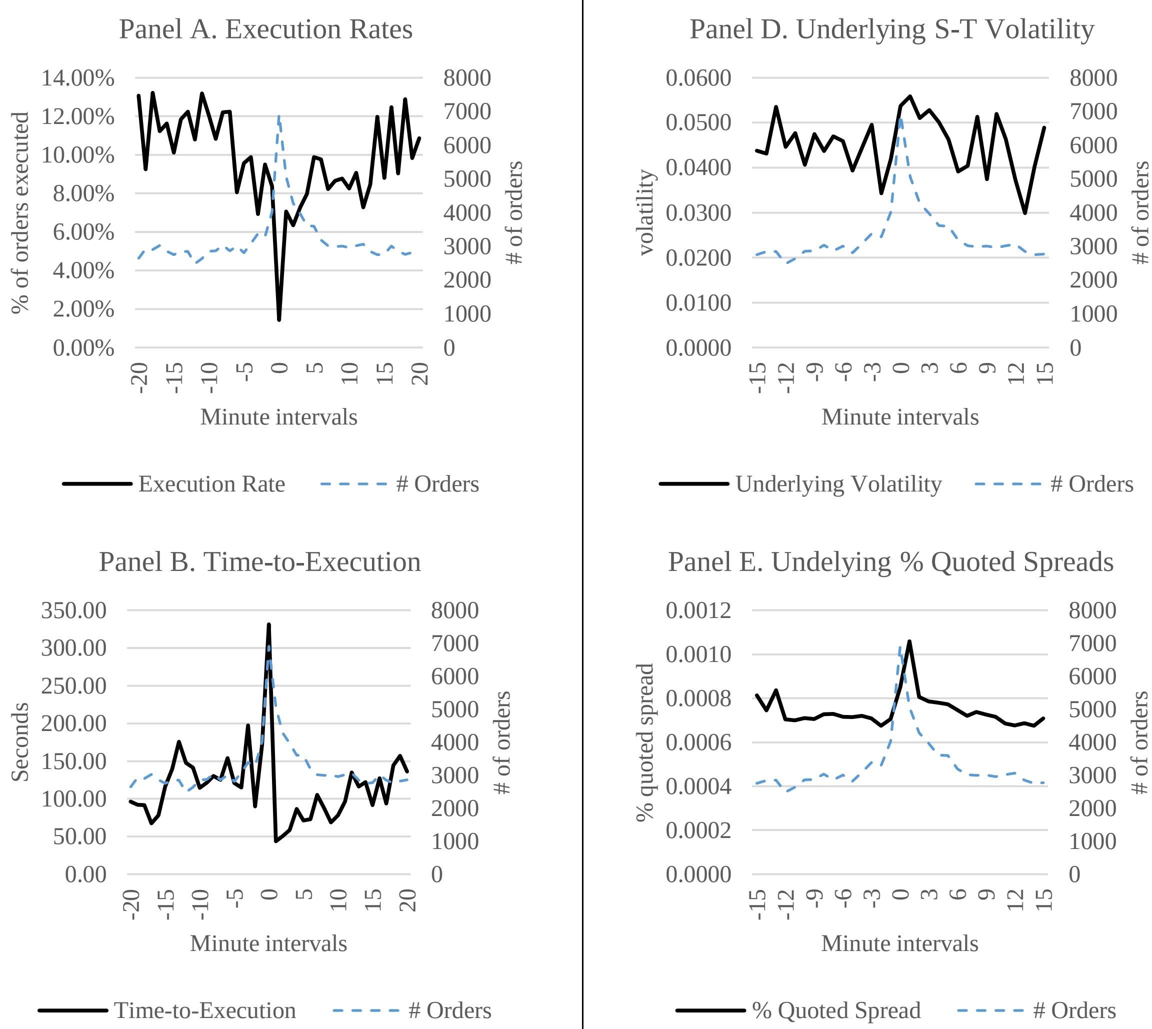


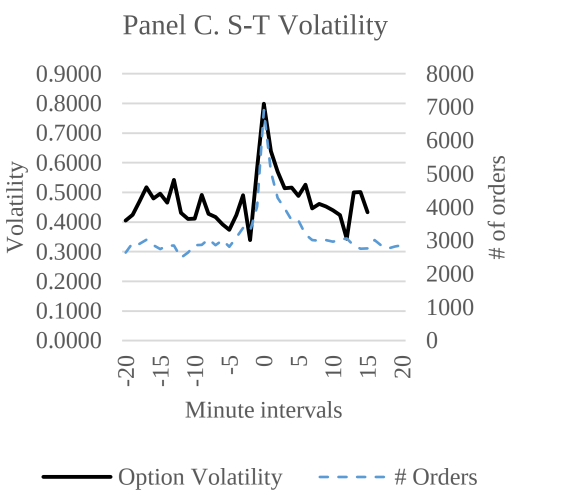
FIGURE 2: MARKET QUALITY AROUND OPTION QUOTE STUFFING EPISODES

Figure 2
Market Quality around Option Quote Stuffing Episodes

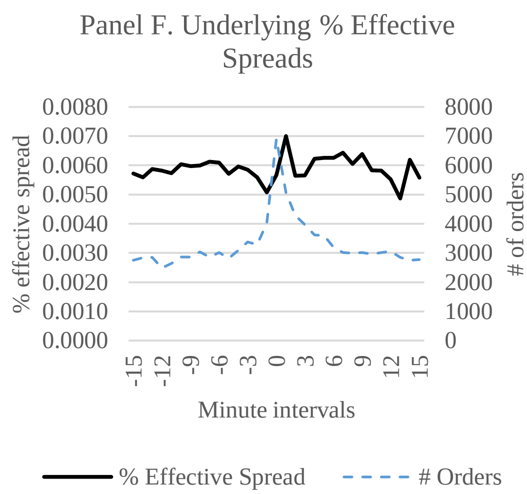
This figure plots average one-minute market quality for the 20-minutes before and after the quote stuffing episodes. The light dotted line is the average number of orders submitted for an option class during a specified minute, while the solid dark line is the average market quality measure.

Option Market Quality	*Equity Market Quality*





Panel C. S-T Volatility
Volatility
# of orders
0.9000
0.8000
0.7000
0.6000
0.5000
0.4000
0.3000
0.2000
0.1000
0.0000
8000
7000
6000
5000
4000
3000
2000
1000
0
-20
-15
-10
-5
0
5
10
15
20
Minute intervals
Option Volatility
Orders



Panel F. Underlying % Effective Spreads
% effective spread
# of orders
0.0080
0.0070
0.0060
0.0050
0.0040
0.0030
0.0020
0.0010
0.0000
8000
7000
6000
5000
4000
3000
2000
1000
0
-15
-12
-9
-6
-3
0
3
6
9
12
15
Minute intervals
% Effective Spread
# Orders

FIGURE 3: EXAMPLES OF OPTION TRADING SPIKES

Figure 3
Examples of Option Trading Spikes

This figure provides several examples of the option trading spikes examined in this study. Panel A shows a trading spike for Caterpillar Inc. (CAT) call options at 11:22 a.m. on October 25, 2016 on the BZX. Panel B shows an intense trading spike for Bank of America (BAC) call options at 12:00 p.m. on October 27, 2016 on the NOM. Panel C shows a trading spike for Deutsche Bank (DB) put options at 3:38 p.m. on October 31, 2016 on the EDGX.

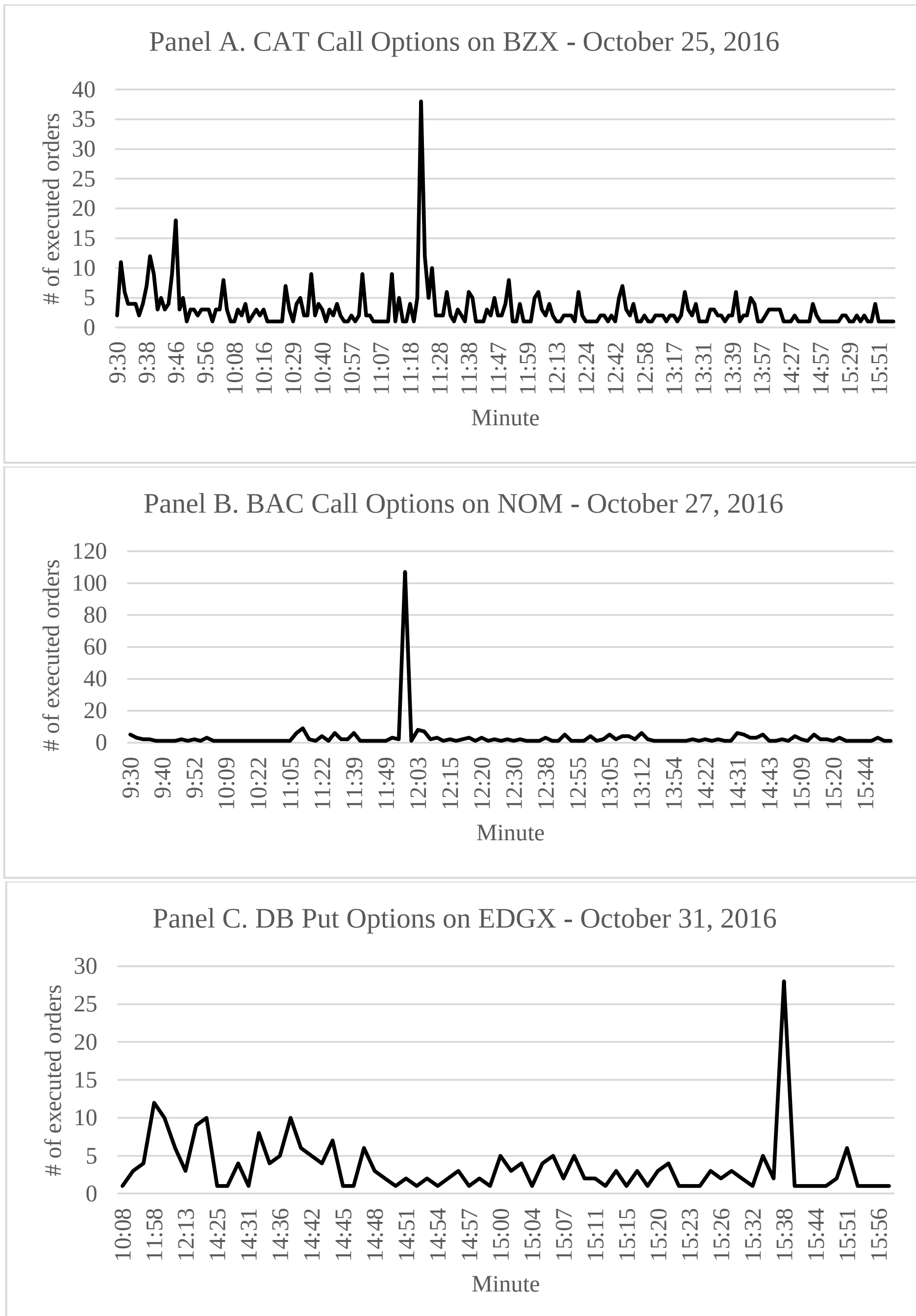
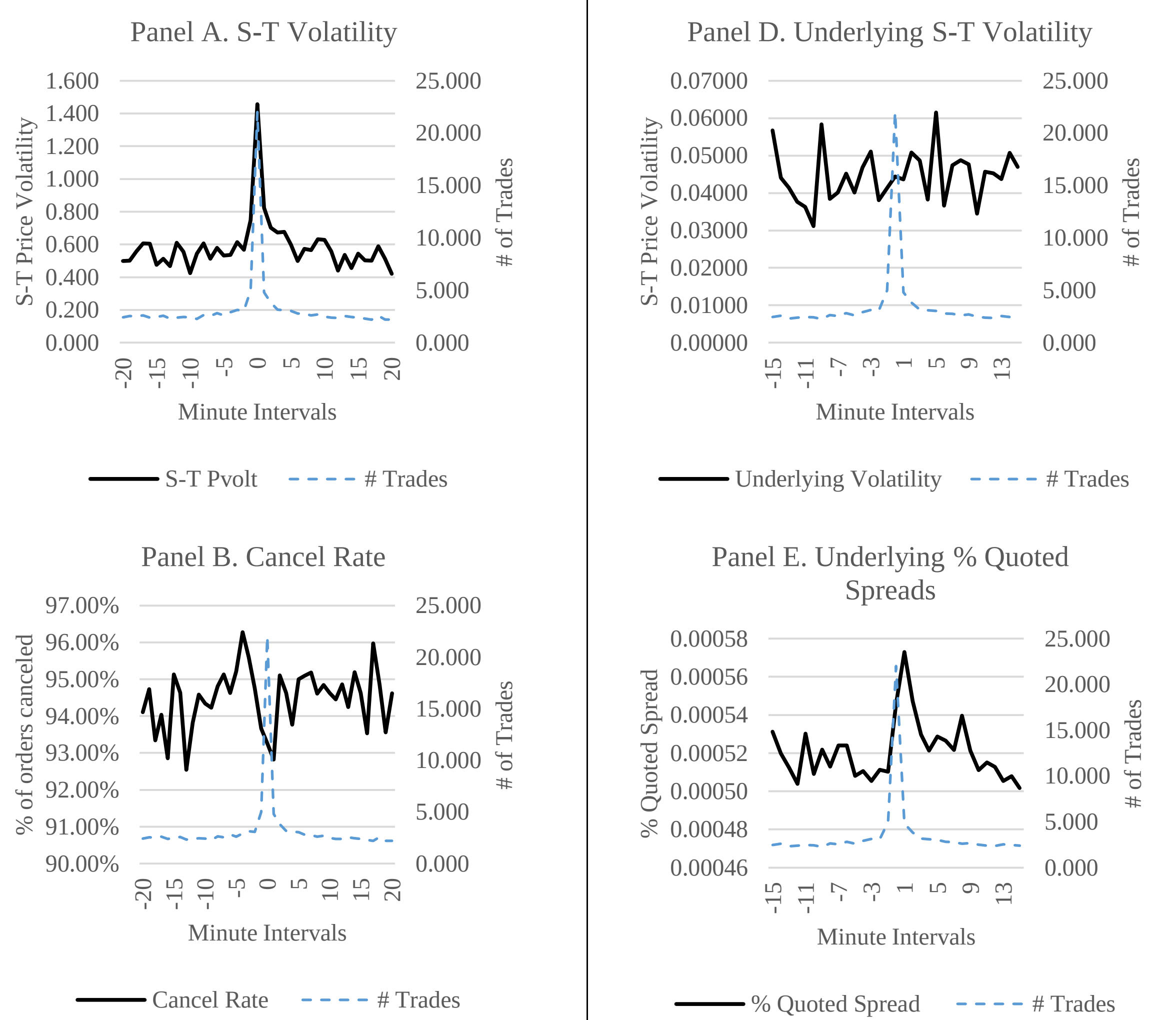


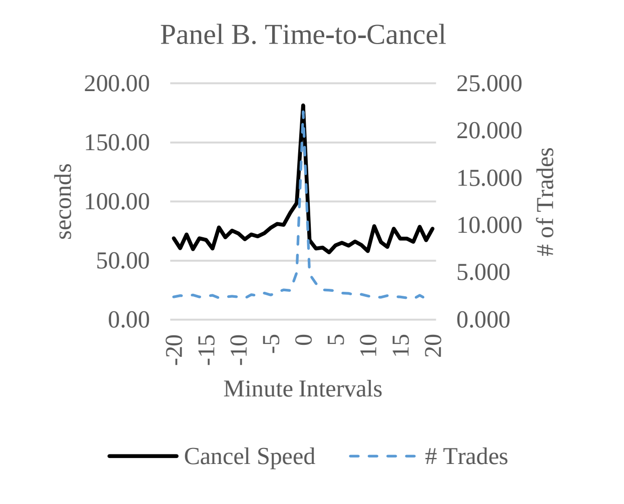
FIGURE 4: MARKET QUALITY AROUND OPTION TRADING SPIKES

Figure 4
Market Quality around Option Trading Spikes

This figure plots market quality measures in options and equities markets for the 20-minutes before and after extreme trading spikes in options. The light dotted line is the average number of executed orders for an option class during a specified minute, while the solid dark line is the average market quality measure during that same one-minute interval.

Option Market Quality	*Equity Market Quality*




Panel B. Time-to-Cancel
200.00
150.00
100.00
50.00
0.00
seconds
25.000
20.000
15.000
10.000
5.000
0.000
# of Trades
-20
-15
-10
-5
0
5
10
15
20
Minute Intervals
Cancel Speed
Trades

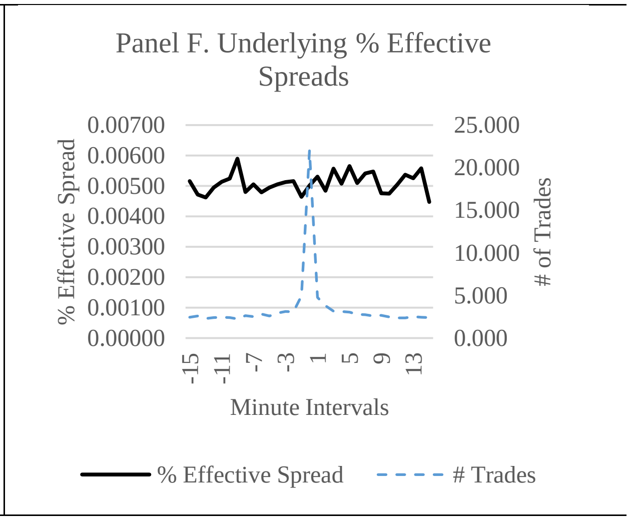
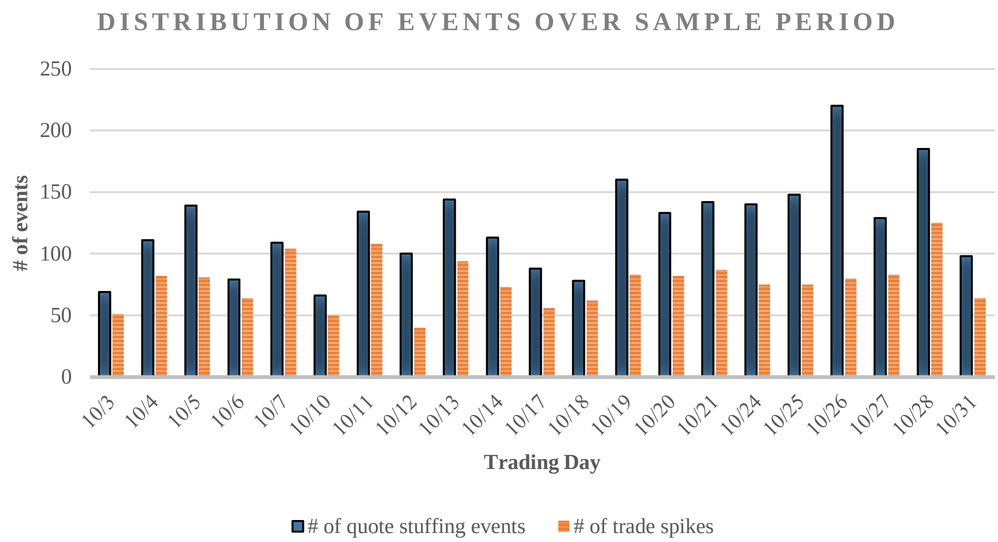

Panel F. Underlying % Effective Spreads
0.00700
0.00600
0.00500
0.00400
0.00300
0.00200
0.00100
0.00000
% Effective Spread
25.000
20.000
15.000
10.000
5.000
0.000
# of Trades
-15
-11
-7
-3
1
5
9
13
Minute Intervals
% Effective Spread
# Trades

FIGURE 5: DISTRIBUTION OF QUOTE STUFFING AND TRADING SPIKES OVER SAMPLE PERIOD

Figure 5

Distribution of Quote Stuffing and Trading Spikes over Sample Period

This figure plots the distribution of both quote stuffing episodes and trading spikes across the 21 sample days in October, 2016.



VITA

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EDUCATION

Ph.D. Student, Business (Finance), University of Mississippi, Expected May 2017

M.S. Financial Economics, Utah State University, May 2012

B.S. Managerial Economics, Utah State University, May 2011

WORK EXPERIENCE

Graduate assistant, University of Mississippi, August 2013 – present

Options drafter, Royal Bank of Scotland, Salt Lake City, UT, December 2012 – August 2013

Investment banker, Wells Fargo, Logan, UT, June 2012 – November 2012

Teaching assistant, Utah State University, August 2011 – June 2012

Insurance producer, Farmers Insurance, Salt Lake City, UT, October 2010 – August 2011

Sales manager, Security Networks, San Antonio, TX, May 2009 – August 2010

Volunteer Service, Non-profit Organization, Sofia, Bulgaria, August 2006 – August 2008

PUBLICATIONS

Box, T. and T. Griffith, (2016). "Price Clustering Asymmetries in Limit Order Flows." F*inancial Management,* 45(4), 1041-1066.

Blau, B. and T. Griffith, (2016). "Price Clustering and the Stability of Stock Prices." *Journal of Business Research,* 69(10), 3933-3942.

Blau, B., T. Brough, and T. Griffith, (2017). "Bank opacity and the efficiency of stock prices." *Journal of Banking and Finance*, *76*, 32-47.

Griffith, T., B. Van Ness, and R. Van Ness, "High-Frequency Traders and Short-term Volatility." Forthcoming, *Journal of Trading.*

WORKING PAPERS

Battalio, R., Griffith, T. and R. Van Ness, "Make-Take Fees versus Order Flow Inducements: Evidence from the Nasdaq PHLX."

Griffith, T. and A. Liebenberg, "Adverse Selection in External Reinsurance Assumption."

Griffith, T. and B. Roseman, "Making Cents of Tick Sizes." (under review, *Journal of Financial and Quantitative Analysis*)

Cox, J. and T. Griffith, "Political Uncertainty and Market Quality."

Fuller, K. and T. Griffith, "Market Frictions in Mergers and Acquisitions."

DISSERTATION

Essay 1: "Order Cancellations, Fees, and Execution Quality in U.S. Equity Options."

Essay 2: "Market Structure Rules in U.S. Equity Options."

Essay 3: "Quote Stuffing and Trading Spikes in U.S. Equity Options."

CONFERENCE PRESENTATIONS

Box, T. and T. Griffith, "Price Clustering Asymmetries in Limit Order Flows." Presented at the Financial Management Annual Meeting in October 2015.

Fuller, K. and T. Griffith, "Target Firm Price Efficiency." Presented at the Southern Finance Association Annual Meeting in November in 2015.

Box, T. and T. Griffith, "Price Clustering Asymmetries in Limit Order Flows." Presented at the Southern Finance Association Annual Meeting in November in 2015.

Griffith, T. and A. Liebenberg, "Leave Reinsurance (Assumption) to the Professionals." Presented at the American Risk and Insurance Association in 2015.

INDUSTRY SERVICE PUBLICATIONS

Griffith, T. and A. Liebenberg, "Underwriting Performance of Leading Insurers in Mississippi – 2014", *Independent Insurance Agents of Mississippi*, 35(4), 33-42.

Griffith, T. and A. Liebenberg, "Underwriting Performance of Leading Insurers in Mississippi – 2013", *Independent Insurance Agents of Mississippi*, 34 (4), 33-42.

AWARDS

2016 University of Mississippi Graduate Achievement Award for Ph.D. Degree
2013-2016 University of Mississippi Graduate Teaching and Research Assistant
Western Athletic Conference Academic Honors

Western Athletic Conference Honors in Cross Country and Track and Field
Utah State University Whiteside's Scholar Athlete

TEACHING EXPERIENCE

Course	Term	Average Evaluation
Business Finance II	Summer 2014	4.00 out of 5
Business Finance II	Summer 2015	4.06 out of 5
Business Finance I	Fall 2015	4.21 out of 5
Business Finance I	Spring 2016	4.25 out of 5
Business Finance II	Summer 2016	4.85 out of 5
Financial Markets and Institutions	Fall 2016	
Business Finance I	Fall 2016	

REFEREE EXPERIENCE AND SERVICE

Referee for *Journal of Banking and Finance*
Discussant, Financial Management Annual Meeting, October 2015
Discussant, Southern Finance Association Annual Meeting, November 2015