Order Book Characteristics and Stock Price Pinning on Options Expiration

Old title: Stock Order Placement Strategies around Options Expirations

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This Version

September 2017

Keywords: Option expiration; manipulation; order dynamics; microstructure.

JEL Classification Codes: G12, G13, G14, G24.

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Abstract

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We employ the novel NASDAQ Totalview-ITCH order level data to analyze intraday stock trading patterns on options expiration days. We find evidence of intraday and end of the day limit order submissions by non-HFT clustered at round number strike prices that help drive closing trade price clustering. HFTs appear to step inside or outside the round number prices with fleeting orders that are either executed or deleted quickly within 2 seconds; such orders are more prevalent among optionable stocks, and also more prevalent on options expiration days. We discard the possibility that the observed fleeting orders are an effort to search for latent liquidity since, contrary to previous findings, we observe most fleeting orders are not placed within the NBBO. We also observe that high frequency odd-lot as well as hidden orders are less prevalent on options expiration days, suggesting traders' preferences for order visibility versus order execution.

Keywords: Option expiration, manipulation, order dynamics, microstructure, liquidity.
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1. Introduction

Stock price clustering has generated a significant debate in the literature about its causes. Much of the literature is based on final transactions prices, leaving unchartered the patterns in order submissions, modifications, and cancellations that culminate in the clustering of daily closing prices. Our paper extends and contributes to the literature on price clustering by using order level data to understand what traders are trying to do on option expiration dates and how. Order level data can unveil the mechanisms of clustering and overall traders' behavior much better than trade only data, and focusing on option expiration dates helps us segregate behaviors of sophisticated and regular traders to test price clustering theories using a novel research design. A noteworthy characteristic of option strike prices that is relevant for our study is that they are typically set at round number prices. Investors with large equity options positions would benefit from stock prices closing just above or just below option strike prices on options expiration days such as to render their options strategies profitable. A slight change in the settlement prices can determine option exercise and assignments and their related costs. In light of such incentive, sophisticated investors could employ trading strategies to nudge stock prices in a direction beneficial to their equity and option positions. Among others, our study analyzes the prevalence of fleeting orders (orders canceled within two or fifty milliseconds after submission), odd-lot orders, limit order clustering, and hidden orders on options expiration days. Some trading strategies could be tantamount to market manipulation and run afoul of SEC regulations. Spoofing is an example of order manipulation that employs aggressive order submission and cancellation.

This illegal practice involves submitting limit buy orders outside the spread to trick the market into thinking there is more demand for a security, potentially causing its price to rise. The same investor, sometimes using a different account to evade regulators, would then sell the same security at the higher price and immediately cancel the previous limit order used to trick the market. The SEC has recently announced charges against investors accused of engaging in this practice of order/market manipulation[1]. Quote stuffing, another illegal practice that involves submission and immediate cancellation of a large volume of orders to slow down competing high-frequency traders (HFT), is detailed in Egginton, Van Ness, and Van Ness (2016).

Stock prices can cluster for several reasons. Bourghelle and Cellier (2006) propose that stock price clustering in Euronext market is a result of limit order clustering. They argue that limit orders create price barriers and these price barriers cause stocks to spend an inordinate amount of time at some price levels. Their finding is consistent with the observations of Niederhoffer (1965) as well as Niederhoffer and Osborne (1966), who argue that clustering of limit orders on certain prices could "open up lucrative trading techniques" for sophisticated investors. Niederhoffer (1965) argues that clustering of individual stock trade prices is caused by congestion of limit orders. He argues that clustering of limit orders lead to price barriers and high volume is needed to push a stock through these price barriers. Niederhoffer and Osborne (1966) support this argument by showing that price barriers exist and stocks prices tend to reverse at these points. De Grauwe & Decupere (1992) document that price barriers exist and are significant in the dollar-yen market. Ahn et al. (2005) analyze trade and quote prices on the electronic limit order book of the Stock Exchange of Hong Kong (SEHK). They document that, while both transaction prices and

[1] See http://www.sec.gov/news/pressrelease/2015-273.html, http://www.sec.gov/news/pressrelease/2015-236.html, and http://www.reuters.com/article/us-finra-culture-idUSKBN0UJ1EH20160105

quote prices display significant clustering, the latter exhibit a much stronger pattern. Chiao and Wang (2009) find that limit order clustering exists in Taiwan Stock Exchange and this creates price barriers.

Traditionally, limit orders have been viewed as patient suppliers of liquidity. Hasbrouck and Saar (2009) challenge this notion by showing that with the advent of ever faster trading technology ‘fleeting orders’ (limit order deleted within two seconds) have become more prevalent, and that such orders have the purpose of absorbing or demanding hidden liquidity or consuming high frequency liquidity supply, not supplying it (Hasbrouck and Saar, 2009). Thus, it is important to distinguish the impact of these two types of limit orders to price clustering. Given the increased trend in high frequency trading, adjusting the definition of fleeting orders to mean those deleted within 50 milliseconds is appropriate.

The results and arguments of these studies suggest that stock price clustering on option expiration days is a consequence of clustering around strike prices. Ni, Pearson and Poteshman (2005) identify four possible causes for stock price clustering around option expiration. The first potential explanation is based on the model proposed by Avellaneda and Lipkin (2003), in which stock trading undertaken to maintain delta hedges on existing net purchased option positions moves stock prices toward strike prices as expiration date nears. The second explanation states that the clustering is caused by delta hedging (with the underlying stock) particular types of changes in option positions on the day of expiration. The third possible cause of stock price clustering is the unwinding of certain combined positions of stocks and options by investors on expiration days. The fourth explanation is based on the possible manipulation of stock prices by investors with written options in order to keep the options contracts out-of-the-money, thus eliminating the options writers' liability at expiration. The first and fourth explanations are found to be significant factors that cause the clustering of prices.

Ni, Pearson and Poteshman (2005) provide evidence that on expiration dates the closing prices of stocks with listed options cluster at option strike prices and on each expiration date, the returns of optionable stocks are altered by an average of at least 16.5 basis points. Krishnan and Nelken (2001) also report that shares of Microsoft close near integer multiples of $5 more frequently on expiration Fridays than on other trade dates. The findings of Ni, Pearson and Poteshman (2005) suggest that on option expiration days limit order submission characteristics for the underlying securities might be different than on regular days. We examine empirically if that is the case and evaluate the impact of various order submission and trading strategies that might be employed by market participants around option expiration that would lead to the observed stock price clustering. We contribute to the extant literature by employing the NASDAQ TotalView-ITCH[2] data feed to observe the pattern of limit order submission, order cancellation, order replacement and hidden order execution, and odd-lot activity around option expiration. Much of this information is not present in other intraday data such as the TAQ database that are widely used for microstructure academic research. Thus, we are able to contrast the use orders around options expiration day versus non-expiration days to detect trading patterns often employed by HFTs that involve slicing and dicing of larger orders to mask their true trading intentions.

[2] NASDAQ TotalView-ITCH is a direct data feed product offered by The NASDAQ Stock Market containing messages describing every order book events for stocks traded on the NASDAQ. These events include limit order submission, order cancellation/deletion, order replacement, hidden order execution, and order matching events. Using the information in this data feed it is possible to historically construct the order book for a given stock at every time of the day

Our analysis focuses on answering the following research questions: What are the prevalent order submission and modification tactics employed around option expiration? Is message activity noticeably higher on option expiration days? Are prices for liquidity providing orders closer to option strike prices than those for liquidity demanding orders? Are ‘fleeting’ orders more prevalent on options expiration days? Are odd lot orders more frequently employed by traders on options expiration days? The answers to these questions contribute to the market microstructure literature by elucidating the mechanics of stock pinning and bringing to light order submission and modification tactics that contribute to the well documented stock pinning phenomenon. Such insights are also valuable information for market participants and regulators. Lower odd-lot activity on options expiration day would suggest that traders in general are less preoccupied with equity order execution and its impact on stock price. Such behavior, together with elevated order cancellation activity, would be consistent with traders attempting to influence stock prices ahead of options expiration. If successful, such strategy, while not necessarily legal, would be profitable for holders of equity option contracts while avoiding the risks associated with actually trading or holding stock positions. Lower hidden order activity on options expiration days strengthens the argument that on these days traders have a preference for order visibility over order execution.

Aggressive order cancellations can harm market stability and it has been documented both in the equity and equity options market. Griffith and Van Ness examine the effects of an order cancellation fee introduced on the NASDAQ OMX PHLX exchange in August 2010. They find that the probability of option order cancelation on the NASDAQ OMX PHLX declined by 26% once the fee became effective, and that when compared with the NASDAQ Options Market, where no cancellation fees are imposed, the probability of order execution on the PHLX is 16.3% higher. Griffith and Van Ness also show that lower cancelation rates on the PHLX are associated with a decrease in effective spreads of approximately 20bps. Their study lays out compelling arguments in favor of introducing fees and regulations to reduce limit order cancelation rates.

Our study expands on Ni, Pearson and Poteshman's (2005) findings by analyzing order book events around option expiration that could lead to price clustering. One of the explanations offered by Ni, Pearson and Poteshman (2005) for the observed stock price clustering around option expiration is the potential stock price manipulation by investors with a large volume of outstanding open option contracts. They argue that market makers are unlikely to engage in such behavior because, as Cox and Rubinstein (1985) point out, regulators carefully monitor market makers' daily trading activity. Ni, Pearson and Poteshman (2005) provide evidence that proprietary traders are the most likely group of investors to attempt to influence stock prices and they have both the means and incentive for doing it. The mechanism employed for effecting this alleged manipulation remains an empirical question.

In this article, we investigate some potential tactics that would-be manipulators could employ. At first we focus on limit orders and examine the likelihood of limit order prices being close to option strike prices. This analysis is different to Ni, Pearson and Poteshman (2005) in several aspects: 1) They employ daily stock closing prices around option strike prices on option expiration days to document the presence of stock pinning around options expirations, while our study focuses on the analysis of intraday order book activity that leads to stock pinning; 2) through the use of detailed intraday data, we specifically investigate the pattern of hidden orders, order duration, and odd-lot orders around options expirations, and lastly 3) we merge our detailed order book data with TAQ-derived NBBO to detect order cancellation/deletion activity both within and outside NBBO around option expiration days. HFT submit mostly limit orders, supplying liquidity in a way similar to market makers. However, unlike market makers, HFTs generally supply liquidity on only one side of the book at a given moment during the trading day and are not committed to keep supplying it throughout the entire day. Therefore, in order to gain valuable insights into the mechanics of stock pinning, the analysis of intraday limit order placement, update, and cancellation is crucial and represents a material contribution to extant research in the field.

We also extend the literature by examining modern order splitting strategies that sophisticated investors can employ to mask their true intentions by slicing and dicing their orders into small odd lots. As O'Hara et al. (2014) point out, odd-lot trades have become a significant portion of the market (average of 24% per stock and as high as 60% for some stocks) and these trades are mostly driven by high frequency traders rather than retail investors. They show that "odd-lot trades have higher informational content than round-lot or mixed-lot trades." Prior to December 2013 odd-lot trades were not reported to the consolidated tape and could be used by traders to hide their intraday trading activity. Despite the fact that odd-lot trades are now reported to the consolidated tape and thus are no longer 'hidden' from the market, they can still be used for slicing and dicing large orders into small lots to minimize price impact. On option expiration days, if one of the goals of HFT traders is to actually push stock prices towards or away from option strike prices by attracting the attention of market participants to their orders, the use of hidden or small odd-lot trades for optionable stocks should decline on these days. In this paper we shed light on the prevalence of odd-lot trades on option expiration days versus other days.

An investor who has written a large number of options contracts earns a measurable economic benefit by ensuring that these contracts expire out-of-the-money. For instance, if there is no manipulation, a stock would close at a given price S_T and a given option on this stock with strike K would expire in-the-money. Manipulating the stock to cause the option to instead expire out-of-the-money prevents the investor from experiencing a loss equal to the absolute value of the difference between the unmanipulated stock price S_T and K, for each share in the option contract. Therefore, from a purely economic point of view, it is advantageous for such investor to influence the stock price in his/her favor as long as the cost of doing so does not exceed the avoided loss in the written options contracts. Since market makers adjust their quotes in reaction to order submissions and cancellations, a sophisticated investors could influence the price of a stock by quickly submitting and subsequently cancelling orders without incurring major costs other than those related to NASDAQ's excessive messaging penalty exceeding certain thresholds[3] and execution costs for orders that could not be cancelled on time. The direction of stock price movement that would benefit an options trader depends on whether said trader has written or purchased a given option contract and whether such contract is a put or call option. The competing interests of these options traders create the dynamic that leads to stock price clustering. Similar to Hendershott, Jones, and Menkveld (2011), we calculate the number of electronic messages per $100 of trading volume as a proxy for electronic message traffic. Electronic messages include order submissions, cancellations, and trade execution but are mainly driven by limit order submissions and cancellations. We interpret a statistically significant increase in this measure around stock option expiration as evidence of potential price manipulation.

Hidden orders are another possible tactic sophisticated investors could use to influence stock prices. Higher ratio of hidden to total order volume around option expiration, when compared to other times, would suggest the employment of such tactic as long as the hidden order volume is positively related to the open interest in written option contracts by proprietary traders. Otherwise,

[3] See http://www.nasdaqtrader.com/Trader.aspx?id=PriceListTrading2

the opposite conclusions can be drawn as traders also often hide orders to defend against manipulation.

Although our study brings attention to the equity limit order activity on options expiration days and its potential implications to market stability and stock price clustering, our findings could also serve as evidence of elevated order cancellation activity in the equity market and a potential motivation for regulatory changes. In the options market, the limit order cancellation fee introduced by the NASDAQ OMX PHLX in August 2010 appears to have had a net positive impact on market quality based on the evidence reported by Griffith and Van Ness. Conversely, the analysis by Friederich and Payne (2015) of the order-to-trade ratio imposed by the Italian Stock Exchange in April 2012 suggests a reduction in liquidity and quoted depth.

In addition to regulatory changes, new trading platforms may also mitigate the impact of aggressive order cancellation and overall HFT activity on non-HFT traders and investors. For instance, IEX in the U.S. and Aequitas in Canada prioritize orders from agency brokers over those coming from HFT traders. Nonetheless, these are new exchanges with small market shares and thus minimal overall impact. According to IEX's website its market share on August 7, 2017 was 2.509%.

Regarding the increased HFT and order cancellation activity in the equity market documented in our study as well as the increased limit order cancelation in the equity options market documented by Griffith and Van Ness, a change in equity option settlement procedures might be enough to dissuade such behavior. Since the closing price of the underlying stock the day before option expiration is the deciding factor in the moneyness of an equity option at expiration, the incentive to manipulate this single price is clear. In that sense, the observed stock price clustering around option strike prices on options expiration days is not all that surprising. If instead, the equity option settlement were based on the volume-weighted average price (VWAP) for the day prior to expiration the importance of the closing price that day would be greatly diminished along with the incentive to manipulate it. While we observed clustering of closing stock prices over our sample period, the same was not true for daily VWAPs (See Appendix A). Of course any possible changes to options settlement procedures may lead to unintended consequences. A potential drawback of tying options settlement to VWAPs is that VWAPs might be considered 'state' by the close of the day. For instance, a major news announcement regarding a given stock late in the day could have a dramatic impact on its closing price without greatly impacting the VWAP for the day. Nevertheless, the average absolute percentage difference between VWAP and closing prices on options expiration day over our sample period was 0.69% for the CBOE optionable universe and 0.59% for the sixty optionable stocks in our sample. Taking into consideration every trading day during our sample period this difference is 0.71% for the CBOE optionable universe and 0.60% for the sixty optionable stocks in our sample.

Our detailed analysis of intra-day equity limit order activity not only contributes to the microstructure academic literature but also yields valuable insights into the underlying microstructure activity of equity markets around equity options expirations and possible remedies for promoting greater market stability and fairness.

2. Data

We use the NASDAQ TotalView ITCH data feed to examine in detail the composition of the limit order book and the determinants of price impact for our sample stocks around option expiration. The data feed includes time-stamped limit order submissions, replacement, execution, deletions, as well as hidden order executions for all NASDAQ stocks from 7:00a.m. EST, when the system starts accepting orders, through 8:00p.m. EST when the system stops accepting orders for the day. Using the information in the data feed it is possible to reconstruct the limit order book historically. We utilize the trade direction indicator in the data feed for limit order and hidden order execution to classify trades into buyer and seller initiated in our stock price impact analysis. Each order is uniquely identified by an order reference number allowing for the calculation of order lifetime, even for those orders that go through several iterations of cancel-replacements before being finally executed or deleted.

We match the time of each limit order arrival from the NASDAQ TotalView feed with the time of the National Best Bid and Offer (NBBO) from the TAQ database to determine whether each arriving limit order is placed inside or outside the spread[4]. The NBBO from the TAQ database, coupled with Lee and Ready's (1993) algorithm, is often the benchmark for estimating trade direction. In our study, we are able to know with certainty the trade direction of each order added to the NASDAQ order book thanks to the buy/sell indicator included in each add order message from the NASDAQ TotalView dataset. We use this indicator to classify the direction of fleeting orders.

Our sample is constructed from the CBOE universe of stocks with underlying options. We identify 3,292 unique equity symbols with associated option volume reported by the CBOE during 2014. We keep only symbols for common stocks and ADRs while discarding those for entities such as ETFs (exchange traded funds) and REITs (real estate investment trusts). We then match the symbols against the CRSP (Center for Research in Securities Prices) database to form

[4] Although the NASDAQ-ITCH dataset has timestamps at the nanosecond level, we matched to the NBBO from TAQ on the nearest second in order to keep the final dataset size more manageable.

terciles based on market capitalization as of year-end 2014. We select the top 20 stocks from each tercile to form our base initial sample of optionable stocks with high options activity. As a control group, we select a matched sample of stocks with low options activity. The matched sample is constructed by selecting firms from the same CBOE dataset with options activity averaging fewer than 100 contracts per month during 2014 and no more than 200 contracts traded in any given month. Such a control sample can be formed only for the second and third terciles which will be the focus of our analysis for the difference in difference tests. Henceforth we refer to these firms as 'non-optionable.' We match these non-optionable stocks to the base sample of optionable stocks on the first two digits of the SIC code, and then pick the ones closest in market capitalization. Because the prevalence of options is more widespread among larger capitalization stocks, we did not construct a low option activity matched sample for the largest capitalization tercile in our base universe. Thus, our sample universe consists of a total of 100 stocks: 60-stock base sample divided into market capitalization terciles plus a matched sample of 40 stocks for the two lower terciles.

For each of these 100 stocks in our sample we obtain complete NASDAQ Totalview-ITCH data for all quarterly option expiration Fridays (third Friday of the contract month) for the twelve months from April 2014 through March 2015. For our difference-in-difference (diff-in-diff, hereafter) analysis, we also collect data from the prior and subsequent Fridays. Non-option expiration Friday's serve as the control period. For robustness and to ensure that weekly options (especially for larger firms) do not cloud our analysis, we also collect data from the mid-month Wednesdays for each of the aforementioned twelve months. To ensure that Wednesday benchmark is not systemically different we create an alternative benchmark with four days around March 31, 2015. For brevity, in the remainder of this paper we refer to quarterly option expiration Fridays as simply option expiration Fridays or option expiration day. In total, our analysis includes data from 52 trading days. Table 1 contains summary characteristics of the stocks in our sample.

3. Intraday trading patterns on option expiration Fridays

In this section of the paper we investigate several trading patterns observed on options expiration days and discuss the role of these patterns in contributing to the clustering of stock closing prices.

3.1. Limit order price clustering around option strikes

Several studies document trade and quote price clustering, but few examine limit order price clustering. Among the few, Cooney et al. (2003) show that NYSE investors submit more limit orders with even eighths prices than odd eighth prices, while Chiao, Wang (2009) use Taiwan Stock Exchange data to provide strong evidence of clustering in limit order prices and conclude that price clustering is underestimated when only trade data (excluding limit orders) are considered. The focus of our paper in on the dynamics of stock price clustering around option strike prices. Ni, Pearson and Poteshman (2005) is an extensive study of trade day closing stock prices clustering on options expiration days, but it does not address the intra-day dynamics that culminate in the clustering of stock prices at the close. The granularity of our data makes analysis at the intraday limit order level possible. While the expiration day closing price of a stock is the determining factor in the moneyness of stock options at expiration, examining the microstructure mechanics of intraday trading that culminated in the closing price is essential for understanding trading behavior.

Before we embark on our intra-day limit order price clustering analysis, we confirm the presence of end-of-day price clustering in our data consistent with previous research (See Appendix A). After confirming closing stock price clustering, we proceed to analyze the various order book characteristics that could potentially show the mechanics of clustering. We employ diff-in-diff regressions to examine how close the order prices are to an integer multiple of $5 for various subgroupings. We also employ diff-in-diff logistic regressions to estimate the odds ratio of intra-day order pricing within $0.125 of an integer multiple of $5 for the following subgroups: 1) all limit orders, limit orders that are eventually executed, and fleeting limit orders deleted within two seconds (we also segment those deleted within 50 milliseconds). Limit orders that are eventually executed most likely represent orders submitted by liquidity demanders. Traders submitting fleeting orders are tougher to classify. While it is easy to argue such traders are likely sophisticated and/or HFTs, whether they are suppliers or demanders of liquidity is not as clear. Such orders could either be pinging for hidden orders when submitted within the spread, or used in 'spoofing' when submitted well outside the NBBO. Specifically, we estimate the following two relations

$$Dist\_mult5 = \beta_0 + \beta_1 EDAY + \delta_0 OPTIONS + \delta_1 EDAY \cdot OPTIONS + \varepsilon \tag{1}$$

$$\text{Ln}\left[\frac{P(Mult5)}{1 - P(Mult5)}\right] = \beta_0 + \beta_1 EDAY + \delta_0 OPTIONS + \delta_1 EDAY \cdot OPTIONS + \varepsilon \tag{2}$$

where $Dist\_mult5$ is the distance in dollars of the order price to the nearest integer multiple of \$5, $EDAY$ is a binary variable set to 1 if the order is submitted on an options expiration day and set to zero otherwise, $OPTIONS$ is a binary variable set to 1 if the order is for a stock from our optionable universe and set to zero otherwise, and $P(Mult5)$ is the probability that the order price is within $0.125 of an integer multiple of $5, which we define as "price clustering", more specifically, stock price clustering around options strike prices. The somewhat arbitrary distance of $0.125 to an integer multiple of $5 was employed in order to be consistent with the definition used in prior literature.

Our goal is to determine if option expiration days and stock optionality are significant factors in the likelihood of stock price clustering for each subgroup. Furthermore, we calculate least square means for the dependent variables in each diff-in-diff regression to compare their values for optionable stocks on option expiration versus non-option expiration days and contrasting this difference with the corresponding difference for non-optionable stocks. For optionable stocks, we expect a smaller price differential to an integer multiple of $5 and/or a higher likelihood of price clustering on option expiration days versus non-expiration days as evidence of intra-day limit order prices clustering around option strikes. The evidence is even more compelling for the association between clustering and option expirations when the same is true for optionable but not for non-optionable stocks. The results of the estimations for relation (1) are reported in Table 2. All regression coefficients are significant confirming that availability of options and high option contract volume are related to the clustering of order prices around an integer multiple of $5 on option expiration days. The smaller the difference between order prices and an integer multiple of $5, the stronger the evidence of stock order prices clustering around option strike prices. Table 3 contains the least square means of the order price distance (or difference) to an integer multiple of $5. Considering orders submitted over the entire trading day, orders for optionable stocks are closer (smaller difference) to an integer multiple of $5 when compared with orders for non-optionable stocks (See Panel A in Table 3). Order prices on option expiration days are also closer to an integer multiple of $5 versus orders from non-option expiration Fridays. Both of these results are consistent with stock price clustering on options expiration days being concentrated in optionable stocks. Nonetheless, it would be safe to assume that most of the volume associated with stock price clustering occurs towards the closing. Appendix A shows daily closing stock price clustering but not clustering for daily VWAPs.

3.2. Order duration and 'Fleeting Orders'

Over 95% of the limit orders in our sample are deleted or updated prior to execution. This figure is consistent with Hasbrouck and Saar's (2009) findings that only 7.99% of limit orders submitted achieve even partial execution. In fact, they report that "36.69% of limit orders are cancelled within two seconds of submission. " Such orders are labeled 'fleeting orders' in their study. We adopt the same definition in our paper but also use the criterion of deletion within fifty milliseconds as an alternative way of defining fleeting orders. This is consistent with other more recent studies and is a reflection of the continued acceleration in trading velocity. As Hasbrouck and Saar (2009) argue, limit orders deleted immediately after submission defy the traditional notion of limit orders being providers of liquidity. Such fleeting orders can be viewed as demanders, rather than suppliers of liquidity. We investigate whether fleeting orders are more prevalent on option expiration days and whether they are more likely to be for optionable stocks. At first, we measure order duration and use diff-in-diff regression to check if the limit orders for optionable stocks on option expiration days have shorter duration. We estimate the following relation.

$$Dur = \beta_0 + \beta_1 EDAY + \delta_0 OPTIONS + \delta_1 EDAY \cdot OPTIONS + \varepsilon \tag{3}$$

where Dur is order duration in seconds and the independent variables are as previously described in relation (1). We measure order duration as the time elapsed between order submission and eventual order update, deletion or execution, whether it be partial or in full. In our dataset (NASDAQ Totalview-ITCH) limit order submissions are identified via messages 'A', ‘F’, and ‘U’. ‘A’ represents limit orders entered without a MPID (Market Participant ID), ‘F’ represents limit orders entered with a MPID, and ‘U’ represents orders that came into being via an update of another existing order. The end of life of a limit order in our study is signaled by messages ‘D’ (deleted), ‘U’ (updated), ‘E’ (executed), ‘X’ (partial cancelled), or ‘C’ (executed in whole or in part with a different price)[5]. In our definition of fleeting orders we only consider those that are deleted in whole or updated.

In our analysis including all limit orders, we find that order duration is significantly shorter on option expiration days (93.28 vs. 94.04 seconds) and for optionable stocks (63.97 vs. 123.35 seconds). In order to determine whether the observed shorter duration is being driven by higher proportional incidences of fleeting orders, we run diff-in-diff logistics regressions to examine the odds ratio of fleeting orders on option expiration days and for optionable stocks. We estimate the following regression using the two aforementioned definitions for fleeting orders.

$$\mathrm{Ln}\left[\frac{P(F)}{1-P(F)}\right] = \beta_0 + \beta_1 EDAY + \delta_0 OPTIONS + \delta_1 EDAY \cdot OPTIONS + \varepsilon \qquad (4)$$

where $P(F)$ represents the probability of a fleeting order, and the other independent variables are as described earlier in equation (1).

We report in Table 6 the least square means of order duration for our sample period measured three different ways: the first column is the average duration for the entire sample, and the next two are the average durations further controlled by fleeting orders (duration shorter than 2 sec, or 50 milliseconds respectively in two separate estimations). Panel A contains the results for all orders placed during market hours, while Panel B reports the results for the subset of

[5] A complete list of all order book event message is available in the NASDAQ TotalView-ITCH 5.0 interface specification manual.

orders submitted during the last 15 minutes of trading. Under every scenario considered in Table 6, order duration is shorter for optionable stocks versus non-optionable stocks and for order expiration Fridays versus non-option expiration Fridays. We also find that compared with non-optionable stocks, the odds for fleeting orders for optionable stocks in our sample universe are significantly higher, and that fleeting orders are more prevalent on options expiration Fridays versus other Fridays. Our findings are consistent with those of Griffith and Van Ness in the options market where they observed options order cancellation activity to be significantly higher on options expiration (versus non-expiration) days. These results strongly suggest that HFTs are more active on options expirations Fridays and that their trading activity is more likely to involve optionable stocks. When such orders are consistently placed several ticks away from the NBBO the argument that these orders are evidence of spoofing activity becomes stronger. Table 6 reports the stock optionality and option expiration day effects on the log odds ratio for fleeting orders. A positive (negative) log odds ratio (see dependent variable in equation (4)) means that the probability of a fleeting order is greater (lower) than the probability of not having a fleeting order. In Panel A of Table 6, under the fleeting order definition of order duration less than or equal to two seconds, the log odds ratio for the option expiration day effects are both positive. This means that orders are more likely to be fleeting than not . Under the more stringent definition of fleeting order as having duration of no more than 50 milliseconds, these same log odds ratios are negative, i.e. the probability of fleeting orders are lower than the probability of non-fleeting orders. In relative terms based on the effects analyzed, the odds of fleeting orders for optionable stocks are consistently higher than for non-optionable stocks, and this effect is stronger on option expiration days. These findings hold for either definition of fleeting order (2 seconds or 50 milliseconds duration) and whether the analysis includes orders for the entire trade day or just the last fifteen minutes before the market close as reported in Panel B of Table 6. It is safe to assume that fleeting orders are attributed to high frequency traders (HFT) so our results suggest HFTs are significantly more active on option expiration days and place more orders for optionable stocks.

Overall, so far we see evidence of significantly shorter order duration and higher likelihood of fleeting orders on option expiration days for optionable stocks with high options trading activity. In the next subsection, we try to put forth a unique perspective as to what is a potential motivation for employing fleeting orders as a strategy for stock pinning. In the process, we offer some new perspective on fleeting orders.

3.3. Trade direction of fleeting orders

Most of the empirical literature on price impact involves the impact of trades. The same is true on the theoretical side such as the Kyle (1985) model where an insider's information is progressively revealed by his/her trades' impact on price. There are some notable exceptions on the empirical side. Eiser et al. (2009) study the impact of market orders, limit orders and cancellations on price, Hautsch, and Huang (2009) employ impulse response functions to analyze the price impact of market orders and limit orders, and Cont et al. (2014) model the instantaneous impact of order book events (market orders, limit orders, and cancellations) on equity prices by using a single variable, denoted as order flow imbalance, representing the net order flow at the best bid and ask. Nonetheless, the notion that actual trades yield important insights about informed traders is widely accepted in microstructure research, thus the importance trade data analysis.

In the general microstructure research setting, trade direction (buy or sell) is based on the active side of the trade, such as a market order executed against a specialist's book or a limit order, since it is assumed this would be side where informed traders would participate. But every trade has a buyer and a seller. In an environment with algorithm and HFT traders the passive side may be the one conveying the true intentions of informed traders. For example, an algorithm or HFT trying to buy a large number of shares of a given stock will likely break it up into several small limit orders across platforms in search of the best execution. When these passive limit orders execute against active sell orders, market data will normally flag these as a "sell" orders, the opposite intention of the HFT. O'Hara (2015) provides an excellent explanation of this phenomenon accompanied by convincing empirical evidence. Our study is not clouded by this phenomenon since we analyze trade direction at the limit order data level, and thus the most likely true intention of HFT traders.

We hypothesize that the majority of traders placing fleeting orders have the intention of cancelling the order prior to it being submitted, and most likely have the goal of masking their true trading intentions and/or influencing prices. On options expirations days, fleeting orders could be a virtually costless way for traders to influence equity prices in a direction favorable to their options positions. If the goal is to pin the stock price at around an options strike price, different traders will have different objectives depending on their options positions. We examine if trade direction of fleeting orders is related to the proximity of the stock price to an options strike price, i.e. an integer multiple of \$5. We posit that when the stock price is just under an integer multiple of \$5, fleeting orders are more likely to be 'BUY' orders. Conversely, when the stock price is just over an integer multiple of \$5, fleeting orders are more likely to be 'SELL' orders. A stock currently trading within a range bound by a given integer n multiple of \$5 and $\$5(n+1)$ will be closer to the lower bound of the range when the price is less than $\$5n + \$2.5$, and closer to the upper bound when the price is greater than or equal to $\$5n + \$2.5$. A numerical example helps to clarify the intuition. Let us consider a stock trading at $44.95 with large options positions at $40 and $45 strike prices. Investors whose options positions become profitable if the stock closes above $40 would have little incentive to influence the stock price as it is already well above that target. Investors whose options positions would become profitable if the stock closes below $40 face the daunting task of 'pushing down' the stock a full $4.95 from its current price and would likely be discouraged from expending too much effort in influencing the stock price. The real tug of war would be between the investors whose options positions would become profitable if the stock closes just below or just above the $45 strike price. Among these latter groups of investors, those profiting from the stock closing just below $45 already have a profitable position but would likely be willing to protect their profits should the stock price start to climb towards the $45 strike price. The more incentivized group would be those who would profit if the stock closes above $45. These investors are more likely to employ trading tactics to attempt to nudge the stock price above the $45 strike. If fleeting orders are used as part of a tactic to spur buy orders from other investors it is more likely that such fleeting orders would be BUY orders in this instance since the stock price is just below an options strike price.

We merge our ITCH data order book trade messages with the NBBO data constructed from TAQ data using SAS code available at the homepage for Craig Holden at the Kelley School of Business at Indiana University in line with the methodology in Holden and Jacobsen (2014). In order to keep the resulting dataset size manageable, our NBBO calculation employ the TAQ data at one second frequency, while the ITCH data are in nanoseconds. Consequently, our merged records will be based on the most recent NBBO observed in the past one second. We use the midpoint of the NBBO as the current price for a given stock when comparing with each of the arriving order book messages from the NASDAQ-ITCH data. Using 2004 data, Hasbrouck and Saar (2009) find that most of the fleeting orders are placed within the NBBO, which they interpret as having the primary goal of searching for latent hidden liquidity. In contrast, we find that 60% of the fleeting orders during our 2014-2015 sample period are placed outside the NBBO observed in the most recent one second. This suggests that in 2014-2015 a large number of fleeting orders may have been submitted for purposes other than searching for hidden latent liquidity.

We find that fleeting orders are more likely to be BUY orders when the stock price is above the midpoint of the $5*n*—$5*(n+1)* range, and more likely to be SELL orders otherwise. This suggests traders placing such orders could be attempting to push the stock price up towards the next options strike price via fleeting BUY orders and vice-versa for SELL orders. This finding is statistically significant for our sample period using orders placed throughout the entire trading day. Because a move of $2.50 represents a significant daily move for most stocks, it would be difficult for even sophisticated traders to influence such a move on a liquid stock without actually executing a single trade. Thus, we examine the odds of fleeting buy orders when the current NBBO is no more than $1 below the next strike price (integer multiple of $5) and contrast it with the odds when the current NBO is no more than $1 above the next strike price. The results of this analysis are reported in Table 9. Note that the odds of a fleeting order being a BUY are significantly higher when the NBBO is just below the next strike price versus when the NBBO is just above it. These results hold whether data for the entire trading day or just the last fifteen minutes of trading are employed.

3.4. Hidden Orders

Hasbrouck and Saar (2009) suggest that aggressive limit orders that are quickly cancelled may be the result of traders searching for latent liquidity provided by hidden orders and quickly cancelling the order when the liquidity is not there. We have already demonstrated that fleeting orders are more prevalent on options expiration days and are also more likely to be for optionable stocks. Therefore, this larger number of fleeting orders are more likely to “find” the latent liquidity provided by hidden orders, resulting in more hidden order execution for optionable stocks on options expirations days. Nonetheless, whether the execution of hidden orders contribute to stock pinning hinges on the proximity of the execution prices to an integer multiple of \$5. That would suggest execution at prices around equity options strike prices.

In our sample, among all order life ending order book events, about 0.5% of orders are executed against hidden liquidity. However, since most added limit orders are deleted and only about 4.6% are executed against visible liquidity, hidden orders represent about 12% of all orders being executed. The arrival time and size of a hidden order is not available in the TotalView-ITCH dataset; a trade message is generated with the order execution time stamp when one side of the trade is a hidden order. We examine the contribution of hidden orders to ‘stock pinning’ on options expiration days by measuring the likelihood of hidden order execution prices being within \$0.125 of an integer multiple of \$5. Similar to our analysis of fleeting orders in section 3.2, we run diff-in-diff logistics regressions to examine the odds ratio of the execution price for a hidden order being within \$0.125 of an integer multiple of \$5 on option expiration days and for optionable stocks. We estimate the following regression:

$$\mathrm{Ln}\left[\frac{P(H125)}{1-P(H125)}\right] = \beta_0 + \beta_1 EDAY + \delta_0 OPTIONS + \delta_1 EDAY \cdot OPTIONS + \varepsilon \qquad (5)$$

where $P(H125)$ represents the probability of the execution price of a hidden order being within an integer multiple of $5, and the other independent variables are as described earlier in relation (1).

Considering our entire sample universe, we find that hidden order execution prices are more likely to be within $0.125 of an integer multiple of $5 for optionable stocks on options expirations day. The results are reported in Table 7. At first blush these results suggest hidden orders contribute significantly to stock pinning on options expiration day. However, excluding the large capitalization stocks in our universe, for which there are no matching non-optionable stocks, these results do not hold. The results for this subsection of our sample universe is also included in Table 7. Intuitively, it appears more logical that any investor, interested in nudging the price of a stock closer to or away from an options strike price by spoofing the order book with the objective of profiting from an options position, would be better served by placing an aggressive non-hidden order. The same thought process can be extended to odd-lot orders which we examine in the following section.

3.5. Odd-lot orders

O'Hara et al. (2014) show that odd-lot trading, contrary to the odd-lot theory[6], is increasingly employed by algorithmic and high-frequency trading, and that odd-lot trades carry higher informational content than round-lot trades. They also raise the issue of market transparency since prior to December 2013 odd-lot trades were not reported to the consolidated tape and were not reflected in the TAQ database which is widely used by academic researchers.

[6] Odd-lot theory is a technical analysis theory (or indicator) based on the premise that retail investors are the primary users of odd-lot trades and that retail investors are uninformed and always wrong. Therefore, one could profit from a strategy that would trade against odd-lot trading activity direction.

The use of odd-lot trades is consistent with HFT and algorithmic traders slicing and dicing larger orders into smaller batches to minimize price impact. Given the historic lack of transparency in such trades, splitting orders into odd-lot trades also achieves the purpose of 'hiding' the trade from the market, further decreasing the potential impact of these trades on market prices. This is especially beneficial to traders attempting to effect a large buy or sell order while minimizing price moves against them before the entire order is completed. Conversely, a trader with large equity options positions on expiration day is less likely to be concerned with equity price impact minimization and may in fact have opposing goals. For instance, a trader with a written call (put) equity option would profit from 'pushing' the price of the underlying stock just below (above) the option strike price at expiration as long as the cost of doing so does not exceed the potential profits from the options position. The execution of a large buy (sell) order on a given stock should lead to temporarily higher (lower) prices for such stock and if the goal is to maximize price impact the use of odd-lots would be avoided. But employing such strategy for the sole purpose of profiting from an option position on the underlying stock is extremely risky as the potential loss from the equity trade could more than offset the potential profit from the equity option position. Therefore, while we have presented evidence of heightened HFT activity on options expiration day, we would a priori expect overall lower of odd-lot trading activity on these days.

Similar to our analysis of the odds ratio for fleeting orders, we employ a diff-in-diff logistics regression to examine the option expiration day and the stock optionality effect on the probability of odd-lot trades. We estimate the following relation

$$\mathrm{Ln}\left[\frac{P(ODD)}{1-P(ODD)}\right] = \beta_0 + \beta_1 EDAY + \delta_0 OPTIONS + \delta_1 EDAY \cdot OPTIONS + \varepsilon \qquad (6)$$

where $P(ODD)$ represents the probability of an odd-lot order, and the other independent variables are as described earlier in relation (1). We also compute least square means for the effects of stock optionality and option expiration day on odds ratio for odd-lot trades. We report the results in Table 8. We observe that the likelihood of odd-lot trades are lower for optionable stocks versus non-optionable stocks and also lower on option expiration Fridays versus non-option expiration Fridays. This is true for the entire trading day as a whole and for the last fifteen minutes of trading in our data sample. The effect of stock optionality on odd-lot trades may be impacted by the stock prices. A round-lot of high priced stocks such as Apple Inc (AAPL closed at $115.01 on August 19, 2015) and Johnson & Johnson (JNJ closed at $99.31 on August 19, 2015) would imply a very large minimum trade of $11,501 for AAPL and $9,931.00 for JNJ for a 100 share round lot. Therefore, higher average prices for optionable stocks in our sample universe would suggest higher likelihood of smaller odd-lot orders for these stocks, but the opposite is observed. The option expiration day effect is not impacted by differences between two different group of stocks since the same universe of stock is used in the calculation of the odds ratio for odd-lots on both option expiration and non-option expiration Fridays.

In section 3.2, based on evidence provided by higher frequency of fleeting orders, we conclude that HFT traders are more active on option expiration days and are more like to place orders for optionable stocks. Despite increased activity by HFT traders on option expiration Fridays and O'Hara et al.'s (2014) conjecture about them using odd-lots, we find that odd-lot trades are less prevalent on option expiration days and less prevalent for optionable stocks. On option expiration days, a trader with a large position in stock option contracts would benefit from the price of the underlying stock closing either just above or just below his/her option position strike price depending on the type of contracts (Call or Put) and whether the trader is long or short these contracts. For such traders, minimizing the impact of trades or orders on the price of the stock underlying their options contracts might be secondary. More beneficial would be to focus on trading tactics that could actually ‘influence’ stock closing prices in a way to maximize their option position profits. Under this assumption, the decreased activity in odd-lot trading on option expiration day is not necessarily an indication of decreased HFT activity, but a reflection of different goals HFTs may have on such days.

4. Robustness Checks

For robustness, we perform a matched pair fixed effect analysis using average daily data from our sample. This is similar to the methodology employed by Boehmer, Jones and Zhang (2013). Since the main focus of our study is to investigate the options expiration day effect on a given stock, we perform a fixed effect matched sample where each stock is matched against itself on quarterly option expiration Friday versus the benchmark value of the measured variable on the following non-expiration Friday of the same month. The idea is to isolate the effect of quarterly options expirations for a given stock. We also employ an indicator variable to pick up differences for optionable versus non-optionable stocks, plus another indicator to flag the twenty stocks in our sample in the highest market capitalization tercile for which there are no matching stocks. As a control variable, we use the difference in daily VIX closing values for the two matched Fridays in a given month. The specific model evaluated is:

$$Y_{it} = \alpha_0 + \beta_0 Y_{t+1} + \beta_1 OPTIONABLE_i + \beta_2 LCAP_i + \beta_3 VIX\_DIFF_t + \varepsilon_{it} \qquad (5)$$

where Y_{it} is the daily average of the measured quantity Y measured on options expiration day, Y_{t+1} is the daily average of the same measured quantity for the same stock on the benchmark Friday the week after options expiration day, $OPTIONABLE_i$ is an indicator set to 1 for stocks in our optionable universe and set to 0 otherwise, $LCAP_i$ is an indicator variable set to 1 for stocks in the highest market capitalization tercile in our sample universe and set to 0 otherwise, and VIX_DIFF_t is the VIX closing level on options expiration day less the VIX closing level on the benchmark Friday.

If the daily averages of the dependent variable does not change significantly from option expiration Friday to the benchmark Friday, the β_0 coefficient should not be statistically different than 1, while the coefficients for the other independent variables should be insignificant. However, a paired t-test shows that with the exception of the percentage of execution prices within $0.125 of an integer multiple of $5, the daily averages for the other studied variables are statistically different from benchmark on options expiration Fridays. Table 10 contains the results of such t-tests. Order duration is shorter and fleeting orders are more likely on options expiration day. These results are consistent with those reported in the main empirical results reported in Tables 2 through 8. However, using daily averages we find odd lot orders more likely on options expiration day.

Table 11 contains the results of the estimation of relation (5). In most of the cases, the value of the observed variable on options expiration day has a significant relation to the value of this variable on the benchmark Friday and also show a significant relation to the other control variables.

5. Summary and Conclusions

We examine the intraday trading patterns and limit order price clustering on NASDAQ around equity options expiration days. Our analysis focuses on identifying patterns that lead to the observed stock pinning on options expirations days. We systematically construct a sample of 100 optionable stocks consisting of twenty stocks in three categories (large, mid, and small capitalization) plus a matching non-optionable control sample for the mid and small capitalization categories. Since most large capitalization stocks are optionable, finding a matching sample for the large capitalization category is not feasible.

We observe that on options expiration days, orders are more likely to be submitted with a price closer to an option strike price. We assume options strike prices are integer multiples of $5 and measure proximity to an options strike price as being within $0.125 of an integer multiple of $5. Our findings are consistent with stock pinning and hold for the limit order book data for the entire trading day as well as when the analysis is limited to the last fifteen minutes of trading. We also observe a heightened incidence of fleeting orders on options expiration days for optionable stocks. We interpret this finding as evidence of elevated HFT activity on those days. We define fleeting orders two different ways: 1) orders with a duration of up to two seconds consistent with Haasbrouck and Saar (2009) and, 2) orders with a duration of only up to fifty milliseconds to account for the increased speed in trading over the past few years.

Contrary to Haasbrouck and Saar (2009), we find that most of the fleeting orders are not placed within the NBBO. Our finding suggests that the goal of these trading orders are other than the search of latent hidden liquidity. By matching with the quote midpoint of the NBBO, we observe that fleeting orders are more likely to be BUY orders when the NBBO quote midpoint is closer to the next highest integer multiple of $5. This order submission pattern suggests that traders with option positions could be attempting to nudge the NBBO quote midpoint closer to or past the next options strike price.

We also examine the role of hidden orders in stock pinning. While we find increased hidden order execution on options expirations days, we attribute most of that increase to the heightened fleeting order activity. We do not find evidence of hidden order execution prices being closer to options strike prices on options expiration days for optionable stocks, other than for the largest capitalization tercile in our sample universe.

Finally, we also observe that odd lot orders are less likely to be employed on options expirations days. O'Hara et al. (2014) discuss how odd lot orders are more likely to be submitted by HFT traders with the intention of slicing and dicing a large order and masking the true ultimate size of their orders. Although we find heightened activity of HFT traders on options expirations days, using odd lot orders to minimize trade price impact would not be consistent with the goal of pushing the stock price closer to or just above an options strike price. Thus, HFTs appear to be using novel trading strategies to meet specific target prices on option expiration days.

Table 1. Sample universe

The population of CBOE list of optionable stocks with highest options activity in 2014 is divided into three market capitalization terciles (MCap) and top 20 stocks from each category is selected to form the base sample. The matched control sample was selected from stocks with the least amount of option trading activity and matched against the base sample on SIC code and market capitalization.

Base Sample with Highest Options Activity						Matched Control Sample with Lowest or No Options Activity			
Ticker	Company Name	MCap Cat.	Rank	SIC	MCap ($bn)	Ticker	Company Name	SIC	MCap ($bn)
AAPL	Apple Inc	0	1	3571	647.4				
XOM	Exxon Mobil Corp	0	2	2911	391.5				
MSFT	Microsoft Corp	0	3	7372	382.9				
JNJ	Johnson & Johnson	0	4	2834	292.7				
WFC	Wells Fargo & Co	0	5	6020	284.4				
WMT	Wal-Mart Stores Inc	0	6	5331	276.8				
GE	General Electric Co	0	7	9997	253.8				
PG	Procter & Gamble Co/The	0	8	2840	246.1				
JPM	JPMorgan Chase & Co	0	9	6020	233.9		Control Sample of non-optionable stocks is unavailable for top Market Capitalization Category		
CVX	Chevron Corp	0	10	2911	212.1				
ORCL	Oracle Corp	0	11	7372	197.5				
PFE	Pfizer Inc	0	12	2834	196.3				
VZ	Verizon Communications Inc	0	13	4812	194.1				
BAC	Bank of America Corp	0	14	6020	188.1				
KO	Coca-Cola Co/The	0	15	2086	184.9				
BUD	Anheuser-Busch InBev NV	0	16	2082	180.1				
INTC	Intel Corp	0	17	3674	175.5				
T	AT&T Inc	0	18	4812	174.2				
FB	Facebook Inc	0	19	7370	173.5				
C	Citigroup Inc	0	20	6199	163.9				
SEE	Sealed Air Corp	1	1	2670	9.0	SWM	Schweitzer-Mauduit Intl Inc	2621	1.3
XL	XL Group PLC	1	2	6351	8.9	RNR	Renaissancere Holdings Ltd	6331	3.7
NAVI	Navient Corp	1	3	6111	8.9	FMD	First Marblehead Corp	6141	0.1
WFT	Weatherford International PLC	1	4	1381	8.9	VET	Vermilion Energy Inc	1311	5.2
CSC	Computer Sciences Corp	1	5	7370	8.9	SNPS	Synopsys Inc	7372	6.8
ASML	ASML Holding NV	1	6	3559	8.8	KMT	Kennametal Inc	3540	2.8
UNM	Unum Group	1	7	6321	8.8	AXS	Axis Capital Holdings Ltd	6331	5.2
CIT	CIT Group Inc	1	8	6172	8.8	AGM	Federal Agriculture Mtg Cp	6111	0.3
IPG	Interpublic Group of Cos Inc/The	1	9	7311	8.7	JKHY	Henry (Jack) & Associates	7373	5.1
VAR	Varian Medical Systems Inc	1	10	3845	8.7	BIO	Bio-Rad Laboratories Inc	3826	2.9

Table 1. Sample universe – Cont'd

. The population of CBOE list of optionable stocks with highest options activity in 2014 is divided into three market capitalization terciles (MCap) and top 20 stocks from each category is selected to form the base sample. The matched control sample was selected from stocks with the least amount of option trading activity and matched against the base sample on SIC code and market capitalization.

Base Sample with Highest Options Activity						Matched Control Sample with Lowest or No Options Activity			
Ticker	Company Name	MCap Cat.	Rank	SIC	Mkt Cap ($bn)	Ticker	Company Name	SIC	Mkt Cap ($bn)
VMC	Vulcan Materials Co	1	11	1400	8.7	TPC	Tutor Perini Corp	1540	1.2
CPN	Calpine Corp	1	12	4991	8.6	WCN	Waste Connections Inc	4953	5.5
EXPD	Expeditors Int'l of Washington Inc	1	13	4731	8.6	ATO	Atmos Energy Corp	4924	5.6
MBLY	Mobileye NV	1	14	7372	8.6	GIB	CGI Group Inc CL A	7373	10.7
SCG	SCANA Corp	1	15	4931	8.6	GXP	Great Plains Energy Inc	4911	4.4
HBAN	Huntington Bancshares Inc/OH	1	16	6020	8.6	SIVB	SVB Financial Group	6020	5.9
ALKS	Alkermes PLC	1	17	2834	8.6	MTX	Minerals Technologies Inc	2810	2.4
RKT	Rock-Tenn Co	1	18	2650	8.5	SON	Sonoco Products Co	2650	4.4
LKQ	LKQ Corp	1	19	5010	8.5	WSO	Watsco Inc	5070	3.2
PPC	Pilgrim's Pride Corp	1	20	2015	8.5	SXT	Sensient Technologies Corp	2860	2.9
CSOD	Cornerstone OnDemand Inc	2	1	7370	1.9	NICE	Nice Systems Ltd	7372	1.9
ISIL	Intersil Corp	2	2	3674	1.9	HELE	Helen Of Troy Ltd	3634	1.8
POST	Post Holdings Inc	2	3	2040	1.9	ACCO	Acco Brands Corp	2780	1.0
ING	ING Groep NV	2	4	6311	1.9	RLI	RLI Corp	6331	2.1
CUDA	Barracuda Networks Inc	2	5	7370	1.9	BLKB	Blackbaud Inc	7370	2.0
VA	Virgin America Inc	2	6	4512	1.9	BRS	Bristow Group Inc	4522	2.3
SMTC	Semtech Corp	2	7	3674	1.9	PLT	Plantronics Inc	3661	2.3
HMSY	HMS Holdings Corp	2	8	6411	1.9	BRO	Brown & Brown Inc	6411	4.7
MTZ	MasTec Inc	2	9	1623	1.9	GVA	Granite Construction Inc	1600	1.5
INFN	Infinera Corp	2	10	3576	1.8	CUB	Cubic Corp	3578	1.4
MBI	MBIA Inc	2	11	6351	1.8	PUK	Prudential Plc	6311	1.4
ENTG	Entegris Inc	2	12	3559	1.8	ROLL	RBC Bearings Inc	3562	1.5
PFPT	Proofpoint Inc	2	13	7372	1.8	FICO	Fair Isaac Corp	7373	2.3
ATW	Atwood Oceanics Inc	2	14	1381	1.8	DWSN	Dawson Geophysical Co	1382	0.1
DF	Dean Foods Co	2	15	2020	1.8	PICO	Pico Holdings Inc	2070	0.4
MDCO	Medicines Co/The	2	16	2834	1.8	REV	Revlon Inc -Cl A	2844	1.8
GES	Guess? Inc	2	17	2330	1.8	PCH	Potlatch Corp	2421	1.7
MR	Mindray Medical International Ltd	2	18	3845	1.8	CMN	Cantel Medical Corp	3845	1.8
LL	Lumber Liquidators Holdings Inc	2	19	5211	1.8	FCFS	First Cash Financial Svcs	5900	1.6
THOR	Thoratec Corp	2	20	3845	1.8	GB	Greatbatch Inc	3845	1.2

Table 2. Analysis of option volume and option expiration day effects on order price proximity to an integer multiple of $5.

This table contains the results of general linear model fitting using maximum likelihood. Dist_mult5 represents the distance in dollars of the order price to an integer multiple of $5. The number in parentheses below the parameter estimates are t-values. Options flag is set to 1 for stocks in our optionable universe, and set to 0 otherwise. EDay is set to 1 for orders submitted on CBOE's quarterly equity options expiration Fridays, and set to 0 otherwise. Model is estimated for the following subgroups: all limit orders, executed limit orders, and fleeting (deleted within 2 sec or 50 milliseconds) orders. Panel A contains the results for orders placed during market open hours. Panel B contains the results for orders placed in the last 15 minutes of trading. Sample period includes every quarterly option expiration Friday from April 2014 through March 2015 plus the Fridays the week prior and the week following options expiration. ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

	Intercept	Options	EDay	EDay x Options
Panel A: During normal market hours				
All Limit Orders	1.2208*** (15660.0)	0.0426*** (153.75)	-0.0060*** (-62.99)	-0.0098*** (-28.75)
Executed Limit Orders	1.2343*** (3895.0)	0.0107*** (7.25)	-0.0305*** (-77.17)	0.0684*** (37.66)
Fleeting Orders (2 sec)	1.2219*** (13005.1)	0.0353*** (91.59)	-0.0006*** (-5.48)	-0.02597*** (-55.02)
Fleeting Orders (50 ms)	1.2146*** (11200.1)	0.03522*** (76.64)	0.0065*** (48.36)	-0.0334*** (-59.00)
Panel B: During last 15 minutes of trading				
All Limit Orders	1.2425*** (3812.64)	0.0141*** (13.45)	0.0066*** (16.08)	0.0060*** (4.50)
Executed Limit Orders	1.2563*** (1275.02)	-0.0089** (-2.57)	0.0106*** (8.40)	0.0248*** (5.56)
Fleeting Orders (2 sec)	1.2570*** (3186.9)	-0.01478*** (-10.62)	0.0136*** (27.69)	0.0038** (2.13)
Fleeting Orders (50 ms)	1.2603*** (2784.9)	-0.0205*** (-12.25)	0.0199*** (35.12)	-0.0017 (-0.81)

Model: $Dist\_mult5 = \beta_0 + \beta_1 EDAY + \delta_0 OPTIONS + \delta_1 EDAY \cdot OPTIONS + \varepsilon$

Table 3. Least square means of order price distance to an integer multiple of $5 for optionable and option expiration day effects.

This table contains the least square means of order price distance in dollars to an integer multiple of $5. The lower the number, the close the order price is to an integer multiple of $5. The number in parentheses below the parameter estimates are p-values for the test of the hypothesis that the least square means for the two effects above are equal to each other. Options flag is set to 1 for stocks in our optionable universe, and set to 0 otherwise. EDay is set to 1 for orders submitted on CBOE's quarterly equity options expiration Fridays, and set to 0 otherwise. Panel A contains the results for orders placed during market open hours. Panel B contains the results for orders placed in the last 15 minutes of trading. Sample period includes every quarterly option expiration Friday from April 2014 through March 2015 plus the Fridays the week prior and the week following options expiration.

Panel A: During regular market hours

Effects		Least Square Means			
Options	**EDay**	**All orders**	**Exec. Order**	**Fleet(2sec)**	**Fleet(50ms)**
0		1.2555	1.2639	1.2438	1.2364
1		1.2178	1.2191	1.2216	1.2178
		(<.0001)	(<.0001)	(<.0001)	(<.0001)
	0	1.2312	1.2434	1.2259	1.2220
	1	1.2421	1.2396	1.2395	1.2322
		(<.0001)	(<.0001)	(<.0001)	(<.0001)
Options * EDay					
0	**0**	1.2476	1.2829	1.2305	1.2230
0	**1**	1.2634	1.2450	1.2571	1.2498
1	**0**	1.2148	1.2038	1.2212	1.2210
1	**1**	1.2208	1.2343	1.2219	1.2146

Panel B: During last 15 minutes of trading

Effects		Least Square Means			
Options	**EDay**	**All orders**	**Exec. Order**	**Fleet(2sec)**	**Fleet(50ms)**
0		1.2629	1.2651	1.2509	1.2489
1		1.2458	1.2616	1.2638	1.2702
		(<.0001)	(0.1167)	(<.0001)	(<.0001)
	0	1.2591	1.2749	1.2651	1.2691
	1	1.2495	1.2519	1.2496	1.2500
		(<.0001)	(<.0001)	(<.0001)	(<.0001)
Options * EDay					
0	**0**	1.2691	1.2828	1.2596	1.2580
0	**1**	1.2566	1.2474	1.2422	1.2398
1	**0**	1.2490	1.2669	1.2706	1.2802
1	**1**	1.2425	1.2563	1.2570	1.2603

Table 4. Analysis of optionality and option expiration day effects on likelihood of order prices being within \$0.125 of an integer multiple of \$5.

This table contains the results of logistics regressions of the option volume and option expiration day effects on the likelihood of order prices being within \$0.125 of an integer multiple of \$5. Mult5 is a binary variable set to 1 if the order price is within \$0.125 of an integer multiple of \$5 and set to 0 otherwise. The dependent variable is the natural log odds for Mult5=1, i.e. $\ln\left(\frac{P(Mult5=1)}{1-P(Mult5=1)}\right)$. Options flag is set to 1 for stocks in our optionable universe, and set to 0 otherwise. EDay is set to 1 for orders submitted on CBOE's quarterly equity options expiration Fridays, and set to 0 otherwise. The number in parentheses below the parameter estimates are Wald Chi-square statistics. Model is estimated for the following subgroups: executed limit orders, and fleeting (deleted within 2 sec or 50 milliseconds) orders. Panel A contains the results for orders placed during market open hours. Panel B contains the results for orders placed in the last 15 minutes of trading. Sample period includes every quarterly option expiration Friday from April 2014 through March 2015 plus the Fridays the week prior and the week following options expiration.

	Intercept	**Options**	**EDay**	**EDay x Options**
Panel A: During normal market hours				
Executed Limit Orders	-2.8244***	0.1141***	-0.0808***	-0.2778***
	(2166328)	(178.71)	(1108.93)	(619.84)
Fleeting Orders (2 sec)	1.6746***	0.2453***	0.0682***	0.0252***
	(2.183E7)	(23758.6)	(23414.4)	(162.87)
Fleeting Orders (50 ms)	1.7328***	0.3021***	0.0528***	0.0087***
	(1.683E7)	(23178.7)	(10152.9)	(12.72)
Panel B: During last 15 minutes of trading				
Executed Limit Orders	-2.8054***	-0.1117***	-0.1027***	0.1473***
	(228178)	(26.78)	(178.67)	(28.41)
Fleeting Orders (2 sec)	1.6536***	0.1737***	0.0393***	-0.0463***
	(1244084)	(978.77)	(444.23)	(43.17)
Fleeting Orders (50 ms)	1.7104***	0.3126***	0.0258***	-0.0432***
	(965572)	(1911.91)	(138.68)	(22.58)

Model:

$$\text{Ln}\left[\frac{P(Mult5)}{1-P(Mult5)}\right] = \beta_0 + \beta_1 EDAY + \delta_0 OPTIONS + \delta_1 EDAY \cdot OPTIONS + \varepsilon$$

Table 5. Least square means of log odds ratio that the order price is within $0.125 of an integer multiple of $5 for optionable and option expiration day effects.

This table contains the least square means of log odds ratio that the order price is within $0.125 of an integer multiple of $5. Mult5 is a binary variable set to 1 if the order price is within $0.125 of an integer multiple of $5 and set to 0 otherwise. This table contains the least square means of the natural log odds for Mult5=1, i.e. $\ln\left(\frac{P(Mult5=1)}{1-P(Mult5=1)}\right)$. The higher the number, the higher the odds that the order price is within $0.125 of an integer multiple of $5. Options flag is set to 1 for stocks in our optionable universe, and set to 0 otherwise. EDay is set to 1 for orders submitted on CBOE's quarterly equity options expiration Fridays, and set to 0 otherwise. Panel A contains the results for orders placed during market open hours. Panel B contains the results for orders placed in the last 15 minutes of trading. Sample period includes every quarterly option expiration Friday from April 2014 through March 2015 plus the Fridays the week prior and the week following options expiration.

Panel A: During regular market hours

Effects		Least Square Means		
Options	EDay	Exec. Order	Fleet(2sec)	Fleet(50ms)
0		-2.8896	1.9666	2.0656
1		-2.8648	1.7087	1.7592
	0	-2.9870	1.8781	1.9410
	1	-2.7673	1.7972	1.8838
Options * EDay				
0	**0**	-3.0688	2.0133	2.0964
0	**1**	-2.7103	1.9199	2.0348
1	**0**	-2.9052	1.7428	1.7856
1	**1**	-2.8244	1.6746	1.7328

Panel B: During last 15 minutes of trading

Effects		Least Square Means		
Options	EDay	Exec. Order	Fleet(2sec)	Fleet(50ms)
0		-2.8948	1.8238	2.0143
1		-2.8567	1.6733	1.7233
	0	-2.8903	1.7566	1.8709
	1	-2.8612	1.7405	1.8667
Options * EDay				
0	**0**	-2.8725	1.8203	2.0056
0	**1**	-2.9171	1.8273	2.0231
1	**0**	-2.9081	1.6929	1.7362
1	**1**	-2.8054	1.6536	1.7104

Table 6. Least square means of order duration and odds of fleeting orders after controlling for optionality and option expiration day effects.

This table contains the least square means of order duration in seconds controlled for various effects. It also contains the log odds ratio that the order is fleeting (deleted within 2 seconds or 50 milliseconds). F is a binary variable set to 1 if the order is fleeting and set to 0 otherwise. This table contains the least square means of the natural log odds for F=1, i.e. $\ln\left(\frac{P(F=1)}{1-P(F=1)}\right)$. The higher the number, the higher the odds of a fleeting order. Options flag is set to 1 for stocks in our optionable universe, and set to 0 otherwise. EDay is set to 1 for orders submitted on CBOE's quarterly equity options expiration Fridays, and set to 0 otherwise. Panel A contains the results for orders placed during market open hours. Panel B contains the results for orders placed in the last 15 minutes of trading. Sample period includes every quarterly option expiration Friday from April 2014 through March 2015 plus the Fridays the week prior and the week following options expiration.

Panel A: During regular market hours

Effects		Least Square Means				
			Duration controlling for:		Odds	Odds
Options	EDay	Duration	Fleet(2 sec)	Fleet(50ms)	Fleet(2 sec)	Fleet(50 ms)
0		123.35	111.80	89.90	-0.2244	-0.7951
1		63.97 (<.0001)	76.56 (<.0001)	56.92 (<.0001)	0.3009	-0.2748
	0	94.04	94.73	73.93	0.0378	-0.5307
	1	93.27 (<.0001)	93.62 (<.0001)	72.90 (<.0001)	0.0387	-0.5392
Options * EDay						
0	**0**	122.57	221.81	178.94	-0.2239	-0.7895
0	**1**	124.13	224.57	180.67	-0.2249	-0.8007
1	**0**	65.52	156.40	116.77	0.2995	-0.2718
1	**1**	62.41	149.19	110.92	0.3023	-0.2777

Panel B: During last 15 minutes of trading

Effects		Least Square Means				
			Duration controlled for:		Odds	Odds
Options	EDay	Duration	Fleet(2 sec)	Fleet(50ms)	Fleet(2 sec)	Fleet(50 ms)
0		25.25	24.28	18.87	-0.0935	-0.7261
1		17.79	21.51	15.93	0.3178	-0.2622
	0	21.81	23.15	17.52	0.0998	-0.5123
	1	21.22	22.84	17.28	0.1245	-0.4760
Options * EDay						
0	**0**	25.50	48.45	37.76	-0.1177	-0.7549
0	**1**	24.99	48.63	37.73	-0.0693	-0.6972
1	**0**	18.12	43.38	32.30	0.3173	-0.2697
1	**1**	17.46	41.99	31.41	0.3183	-0.2547

Table 7. Least square means of log odds ratio of a hidden order execution within \$0.125 of an integer multiple of \$5 for optionable and option expiration day effects

This table contains the least square means of log odds ratio of a hidden order. H125 is a binary variable set to 1 if the execution price of a hidden order is within \$0.125 of an integer multiple of \$5. This table contains the least square means of the natural log odds for H125=1, i.e. $\ln\left(\frac{P(H125=1)}{1-P(H125=1)}\right)$. The higher the number, the higher the odds that the execution price of a hidden order is within \$0.125 of an integer multiple of \$5. Options flag is set to 1 for stocks in our optionable universe, and set to 0 otherwise. EDay is set to 1 for orders submitted on CBOE's quarterly equity options expiration Fridays, and set to 0 otherwise. The odds ratio is calculated for the entire trading day and for the last fifteen minutes of trading. Sample period includes every quarterly option expiration Friday from April 2014 through March 2015 plus the Fridays the week prior and the week following options expiration.

		Least Square Means of Odds Ratio			
Effects		**All Orders**		**Excl. Large Caps**	
Options	**EDay**	**All Day**	**Last 15 min. of Trading**	**All Day**	**Last 15 min. of Trading**
0		-2.8875	-2.8684	-2.8875	-2.8684
1		-2.8450	-2.8404	-2.9289	-2.7588
		(0.0021)	(0.3609)	(0.0075)	(0.0013)
	0	-2.9461	-2.8667	-2.9031	-2.7456
	1	-2.7863	-2.8422	-2.9132	-2.8816
		(<.0001)	(0.4234)	(0.5138)	(<.0001)
Options * EDay					
0	**0**	-3.0404	-2.8820	-3.0404	-2.8820
0	**1**	-2.7345	-2.8548	-2.7345	-2.8548
1	**0**	-2.8517	-2.8514	-2.7658	-2.6092
1	**1**	-2.8382	-2.8295	-3.0919	-2.9083

Table 8. Least square means of log odds ratio of an odd-lot order for optionable and option expiration day effects

This table contains the least square means of log odds ratio of an odd-lot order. ODD is a binary variable set to 1 if an order quantity is for 1 to 99 shares and set to 0 otherwise. This table contains the least square means of the natural log odds for ODD=1, i.e. $\ln\left(\frac{P(ODD=1)}{1-P(ODD=1)}\right)$. The higher the number, the higher the odds that the order is for an odd-lot. Options flag is set to 1 for stocks in our optionable universe, and set to 0 otherwise. EDay is set to 1 for orders submitted on CBOE's quarterly equity options expiration Fridays, and set to 0 otherwise. The odds ratio is calculated for the entire trading day and for the last fifteen minutes of trading. Sample period includes every quarterly option expiration Friday from April 2014 through March 2015 plus the Fridays the week prior and the week following options expiration.

Effects		Least Square Means Odds Ratio of Odd Lots	
Options	**EDay**	**All Day**	**Last 15 min. of Trading**
0		-1.2249	-1.3101
1		-2.5347	-2.9640
	0	-1.8752	-2.1080
	1	-1.8844	-2.1661
Options * EDay			
0	**0**	-1.2399	-1.2943
0	**1**	-1.2100	-1.3259
1	**0**	-2.5105	-2.9217
1	**1**	-2.5588	-3.0063

Table 9. Least square means of log odds ratio that trade direction of fleeting orders is Buy versus Sell based on NBBO proximity to the next higher option strike price.

This table contains the least square means of log odds ratio that the order direction of fleeting orders is BUY depending on NBBO proximity to the next higher option strike price. DBuy is a binary variable set to 1 if the buy/sell indicator for the order in the NASDAQ ITCH data set is Buy and set to 0 otherwise. This table contains the least square means of the natural log odds for DBuy=1, i.e. $\ln\left(\frac{P(DBuy=1)}{1-P(Dbuy=1)}\right)$. The higher the number, the higher the odds that the order trader direction is BUY. \$1Below is set to 1 when the NBBO is within \$1 below the nearest strike price (integer multiple of \$5), and set to -1 when the NBBO is within \$1 above the nearest strike price. It is set to 0 otherwise, but these results are not tabulated. EDay is set to 1 for orders submitted on CBOE's quarterly equity options expiration Fridays, and set to 0 otherwise. The analysis is performed separately for the entire trading day (All day) and the last fifteen minutes of trading (Last 15 minutes). Sample period includes every quarterly option expiration Friday from April 2014 through March 2015 plus the Fridays the week prior and the week following options expiration.

Panel A: During regular market hours

Effects		Least Square Means	
EDay	**$1Below**	**All Day**	**Last 15 min. of Trading**
0		-0.2920	-0.3132
1		-0.3075	-0.2905
		(<.0001)	(<.0001)
	-1	-0.3230	-0.3047
	1	-0.2782	-0.2893
		(<.0001)	(<.0001)
EDay * $1Below			
0	**-1**	-0.3326	-0.3318
0	**1**	-0.2743	-0.3062
1	**-1**	-0.3135	-0.2775
1	**1**	-0.2821	-0.2724

Table 10. Paired t-tests: Option Expiration Friday minus Benchmark Friday following Expiration (1,188 pairs)

Variable	Mean Diff	95% CL Mean		Pr > |t|
Order Duration	-32.035	-41.534	-22.536	<.0001
Price dist. to integer mult. of $5	0.0143	-0.028	0.0567	0.5072
Pct. Exec. within $0.125 of mult. $5	0.0001	-0.0117	0.0119	0.9862
Pct. of odd lot orders	0.0045	0.00036	0.0087	0.033
Pct. of Fleeting (< 2sec) orders	0.0224	0.0172	0.0276	<.0001
Pct. of Fleeting (< 50msec) orders	0.0177	0.0130	0.0225	<.0001

Table 11. Coefficients in matched regressions — Option Expiration Friday vs Benchmark Friday After Expiration (1,188 pairs)

Dep. Variable	Dep. Var. Friday After Exp.	Optionable Dummy	Large Cap Dummy	Daily VIX	R^2 (%)
Order Duration	0.475***	-44.94***	-23.57***	-7.81***	56.3
Price dist. to integer mult. of $5	0.379***	0.039	-0.066	0.0097	14.4
Pct. Exec. within $0.125 of mult. $5	0.0516	-0.0061	0.0132	-0.002	0.20
Pct. of odd lot orders	0.911***	-0.004	-0.017***	0.0023***	78.5
Pct. of Fleeting (< 2sec) orders	0.635***	0.025***	0.049***	0.008***	60.2
Pct. of Fleeting (< 50msec) orders	0.639***	0.024***	0.044***	0.004***	60.4

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Appendix A

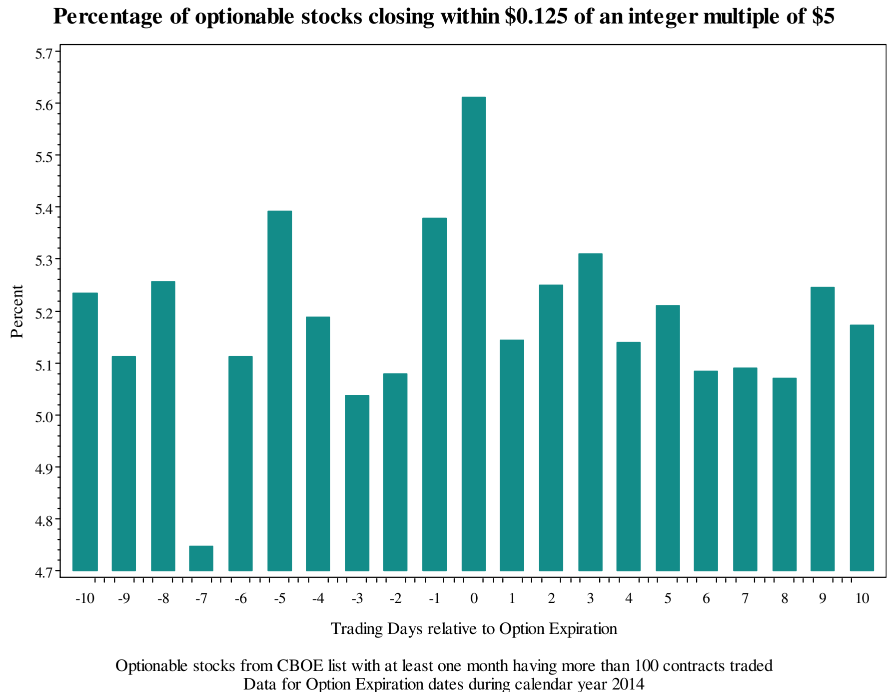
Prior to our detailed intraday analysis, we confirm the presence of daily closing prices around options strike prices in our data. In line with previous analyses, we interpret higher relative percentage of optionable stocks that close within \$0.125 of an integer multiple of \$5[7] on options expiration day versus other days as evidence of stock price clustering. Figure A1 shows the percentage of optionable (Panel A) and non-optionable (Panel B) stocks closing within \$0.125 of an integer multiple of \$5 across ten trading days preceding and following options expiration day. It is clear that in Panel A the percentage of stocks on options expiration day (trade date zero) is significantly higher than those observed on non-expiration days. Like Ni, Pearson and Potashman (2005), we compute z-statistic for the null hypothesis that the percentage on trade date zero is drawn from the same population as those from the other twenty non-expiration days. We obtain a highly significant z-statistic of 7.5 and thus reject the null hypothesis of no clustering for optionable stocks with a p-value of less than 0.01. The

[7] In most cases, the CBOE lists option strikes price for stocks in multiples of \$5. For stocks priced above \$200, option strikes are often in multiples of \$10. For lower priced stocks odd multiples of \$2.50 are also used for option strikes. In more rare instances, due to stock splits and/or stock dividends, strike prices that are neither integers nor multiples of \$2.50 are also possible. Since the publishing of Ni, Pearson and Poteshman (2005) the CBOE has also created stock options with strike prices in increment of \$1. For more information on the CBOE \$1 and \$2.50 strike price program see http://www.cboe.com/tradtool/strikepriceprograms.aspx.

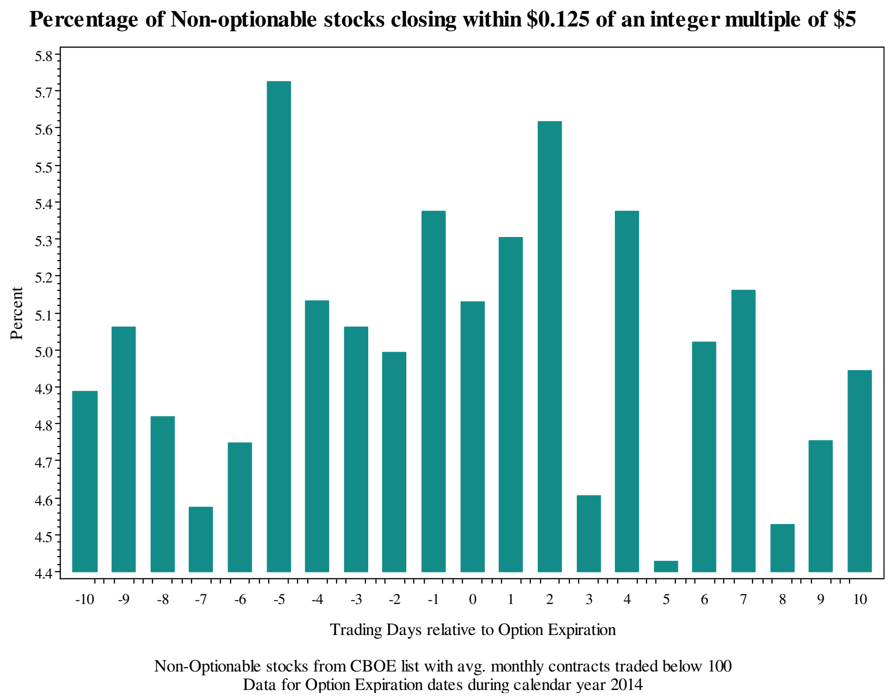
probability of closing stock prices clustering at option strike prices is high on option expiration dates for optionable stocks with high options market activity. Using the data from Panel B the null hypothesis of no clustering cannot be rejected for non-optional stocks or stocks with low options activity. It is important to note that since 2002, the end of the sample period in Ni, Pearson and Potashman (2005), weekly options have gained in popularity. Therefore, trade dates -5, -10, +5, and +10 represent Fridays when weekly (not quarterly) options expire. Nonetheless, quarterly options expiration days still exhibit a significantly higher percentage of stock price clustering for optionable stocks on quarterly option expiration dates versus other days.

Figure A1. Percentage of stocks closing within $0.125 of an integer multiple of $5.
This figure plots the percentage of optionable (Panel A) and non-optionable (Panel B) stocks closing within $0.125 of an integer multiple of $5 across trading days around quarterly options expiration Fridays (Trade date 0). Panel C shows the percentage of optionable stocks with daily VWAPs within $0.125 of an integer multiple of $5. Relative trade date +1 is the Monday after options expiration while trade date -5 is the Friday prior to options expiration. Optionable and non-optionable stocks are selected from the CBOE universe of optionable stocks as described in section 2. Daily closing prices are from CRSP for the 2014 calendar year.

Panel A:

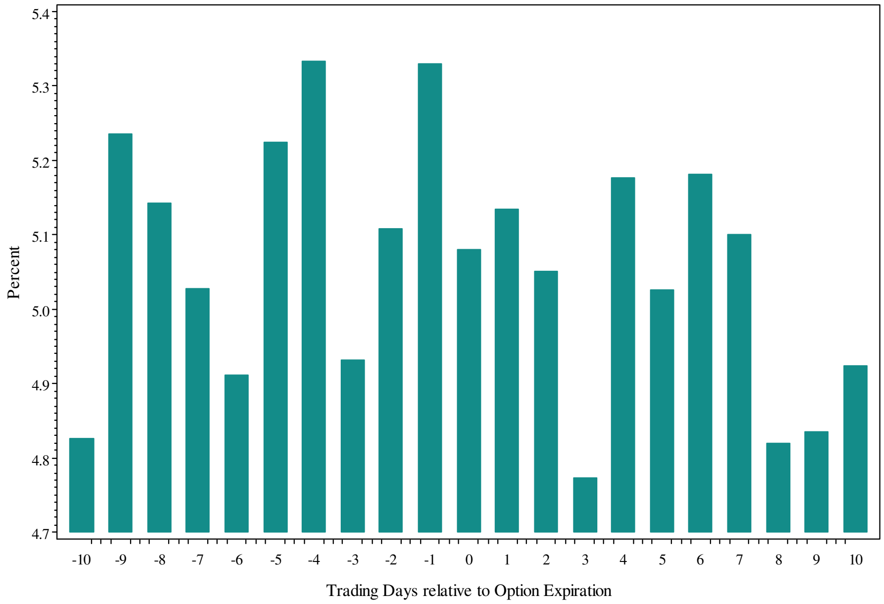


Panel B:



Panel C:

Percentage of optionable stocks VWAP within $0.125 of an integer multiple of $5



Sixty Optionable stocks from Sample Universe
Data for Option Expiration dates during calendar year 2014