The Effect of Algorithmic Trading on Liquidity in the Options Market

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Abstract

Algorithmic trading consistently reduces the bid-ask spread in options markets, regardless of firm size, option strike price, call or put option, or volatility in the markets. However, the effect on depth depends on the categorization of the data. The examination of the introduction of penny quotes provides a successful robustness test for the importance of algorithmic trading on liquidity. Overall, this study provides a controlled analysis of options with different levels of activity and different types of market participants across strikes/calls/puts/underlying stocks. Our findings also contribute to the extant literature on the characteristics of the liquidity of options markets during the growth period of algorithmic trading.

During the past several years the widespread development of automated order execution systems (algorithmic or algo trading) has transformed the financial markets. In particular, the promulgation of Order Protection Rule 611 under Regulation NMS in 2005 promoted the use of electronic trading and subsequently computerized algorithms. According to Rule 611, limit orders that are "immediately and automatically accessible" via an "Immediate or Cancel" (IOC) order have their prices protected from another trade execution at an inferior price. Consequently, Regulation NMS leveled the playing field across all U.S. exchanges regarding order executions.[1] These rule changes caused exchanges to compete based on trading fees, the speed of order handling, and the quality of execution in order to obtain a greater share of trading volume (Palmer, 2009). Because of the proliferation of electronic trading across all exchanges, the use of algorithms became indispensable for the trading process of institutions, market makers, and

[1] On April 6, 2005, the Securities and Exchange Commission adopted Regulation NMS, a series of initiatives designed to modernize and strengthen the national market system for equities. Regulation NMS was published in Securities Exchange Act Release No. 51808 (Jun. 9, 2005), 70 FR 37496 (Jun. 29, 2005) ("NMS Release"). These initiatives include: (1) Rule 610, which addresses the access to markets; (2) Rule 611, which provides inter-market price priority for displayed and accessible quotations; (3) Rule 612, which establishes minimum pricing increments; and (4) amendments to the joint-industry plans and rules governing the dissemination of market data. Rule 611, among other things, requires a trading center to establish, maintain, and enforce written policies and procedures reasonably designed to prevent "trade-throughs" – the execution of trades at prices inferior to protected quotations displayed by other trading centers. In order to be protected a quotation must be immediately and automatically accessible. (See Palmer (2009)).

professional traders. This resulted in algorithmic trading taking over the market making function for smaller size trades in the stock market due to its speed and cost advantages (see Hendershott and Moulton (2007)). More generally, Hendershott, Jones and Menkveld (2011) explain the use of algorithmic trading as follows:

> Algorithms are used to supply as well as to demand liquidity. For example, liquidity demanders use smart order routers (SORs) to decide the placement of a liquidity order, whereas liquidity suppliers such as hedge funds and broker-dealers use algorithms to supply liquidity. Overall, as trading became more electronic, it became easier and cheaper to replicate a floor trader's activity with a computer program doing algorithmic trading.

The growth of algorithmic trading has spurred interest in its potential effects on market dynamics (Hendershott and Riordan, 2009). In particular, such mechanized trading systems potentially could both reduce liquidity and increase volatility, particularly in times of market stress.[2] Two sides to the argument exist concerning the use of algorithmic trading. On the one hand, algos can increase competition and result in an increase in liquidity, thereby lowering the cost of immediacy. On the other hand, liquidity could decrease if algorithmic trades are used mainly to demand liquidity. For example, whereas limit order submitters supply liquidity by granting a trading option to others, liquidity demanders attempt to identify and pick-off beneficial trading opportunities by increasing the cost of submitting limit orders by causing spreads to widen. An example of liquidity demanders are algo traders executing large institutional blocks in short periods of time. Empirically, Hendershott et al. (2011) and Hendershott and Riordan (2009) find that the net effect of algo trading is to reduce bid-ask spreads and aid in the pricing efficiency in the stock market.

[2] The Flash Crash of May 6th, 2010 is an example of how algorithmic trading *may* have led to extreme volatility and the disappearance of liquidity. This potential liability of algorithmic trading has caused critics to support curbs to be placed on such trading. More recently, algorithmic trading also was criticized because of its "unfair" advantage over non-computerized traders, since algos possess a sub-second timing advantage in placing quotes and the related potential of front running of larger block orders. Here we concentrate on the effect of algorithmic trading on *options market* pricing for market scenarios other than the Flash Crash.

We extend the pioneering work of Hendershott et al. (2011) on the effects of algorithmic trading in the stock market to options. The importance of algorithmic trading for options on the demand side is found in the "Smart Routing" of options and the algorithmic execution of price improving multi-leg orders, as well as spread enhancing market-making activities across strikes, expirations, calls/puts, and on as many as seven options exchanges at once. Alternatively, the multitude of options challenges the ability of this market mechanism to generate liquidity for supply side activities. Supply side traders require execution of positions at current bid/ask prices such that the bid-ask spread widens and depth declines. Large supply side option orders challenge the ability of a potentially think market (such as options with many strikes, expirations, and exchanges) to consistently provide liquidity.

Preliminary evidence on the extent of algorithmic trading in the options markets is found in Figure 1, which shows the growth of OPRA message traffic from 2006 to 2008. Such activity is clearly visible in 2007 and increases in 2008. We examine the relation between algorithmic trading and liquidity by analyzing the bid-ask spread and the best bid-ask depth values for the Options Price Reporting Authority (OPRA) data feed for the flow of option messages as a proxy of algo trading. We differentiate between "call" and "put" options, and among "in-", "near-" and "out-of-the-money" options, as well as providing separate results by market capitalization, volume, and volatility quintiles. Given the liquidity differences among the various options groupings, we have the advantage of analyzing the effect of algo trading on liquidity for a wide range of instrumental characteristics. These results provide more definitive conclusions than stocks concerning the ability of algo trading to supply liquidity effectively across a wide range of different characteristics (option strikes/expirations/calls-puts), thereby determining to what extent bid-ask spreads and depth responds to non-human intervention. Such results and conclusions are critical to regulators who make decisions concerning the benefit of algorithmic trading relative to the risk of liquidity disappearing during flash crashes.

We find broad evidence to support the benefits of algorithmic trading to reduce the bid-ask spread measure of liquidity, as well as providing an analysis of conflicting results for the depth of the market. We support our analysis with a robustness check by using the introduction of penny quotes as an exogenous event to support the liquidity impact of message traffic. Our findings also support the Cao and Wei (2009) results of the existence of a material liquidity factor in the options market. Moreover, our spread and depth analysis of the different strike categories ("in-", "near-" and "out-of-the-money"), as well as both calls and puts, supports the breadth of liquidity in options. We also find a differential impact of the underlying stock market capitalization and volatility, and the option characteristic of volume, on option bid-ask spreads and depth. Thus, we provide evidence on liquidity commonalities in the options market.

In conclusion, our results add to the developing literature on the liquidity of options, as well as more specifically substantiate the beneficial liquidity impacts of algo trading.[3] Consequently, potential regulatory restrictions on algorithmic trading should consider the benefits of such strategies on complex markets such as options, as well as the disadvantages of much slower human traders who enter the market for fundamental reasons separate from algo liquidity supply effects from market making and related strategies.

I. Algorithmic Trading and Options

Our study contributes to two related strands of academic literature: The impact of algorithmic

[3] Microstructure research in options is complicated by the multitude of strike prices and expirations dates, the number of revisions in the bid-ask quotes, and the difficulty in obtaining data. Our findings add to the relatively thin literature on this direction as well as the even smaller subset of literature on option market liquidity (Vijh, 1990; Cao and Wei, 2009).

trading on the market environment and its impact on option market liquidity. The literature on the impact of algo trading in general is still at its infancy (Hasbrouck and Saar, 2010). In addition, the area of option market liquidity is a relatively nascent area compared to liquidity research on the equity and debt markets (Cao and Wei, 2009). The benefit of examining exchange-traded options is that it provides a natural laboratory for studying how trading mechanisms and the competitive structure of the industry affect market quality, given the large number of strike prices per underlying stocks and the relatively large number of exchanges trading options (Mayhew, 2002). Our paper ties a knot between these two fields by studying the impact of algo trading on option market liquidity.

The first area of algo research is the examination of the characteristics of algorithmic trading and algo trading strategies (especially the effect of the speed of transmission on trading strategies). Riordan and Storkenmaier (2008), Easley, Hendershott, and Ramadorai (2009), and Hasbrouck and Saar (2010) examine the effect of the speed of order transmission and algo strategies. For example, Riordan and Storkenmaier state that algo traders increase liquidity by reducing latency in order transmission from 50 ms to 10 ms, thereby reducing trading costs by 1 to 4 basis points.

The second area of research is the impact of algo trading on the market environment, such as information dissemination and the liquidity variables of bid-ask spread and depth. Hendershott and Riordan (2009), Brogaard (2010), Karagozoglu (2011), and Hendershott, Jones, and Menkveld (2011) are the primarily sources dealing with the impact of algo trading on market quality factors such as price discovery and liquidity. More specifically, Hendershott and Riordan examine the 30 DAX stocks, finding that algorithmic trades create a larger price impact than non-algorithmic trades and therefore tend to contribute more to price discovery. Brogaard investigates the impact of algo trading on equity market quality by using a dataset of 26 high-frequency traders in 120 stocks. He reports that high-frequency traders contribute to the liquidity provision in the market, that their trades improve price discovery more than trades of other market participants, and that their activity appears to lower volatility. Karagozoglu examines algorithmic trading in relation to futures markets, finding that spreads are decreased and market depth is increased in five different futures contracts. The only related liquidity study using options to examine market quality is Cao and Wei (2009), who show the existence of a material common liquidity factor in the options market, although they do not relate this common factor to algo trading; thus, option liquidity does have a factor that flows across the strike prices and calls and puts of an option series.[4]

Hendershott, Jones, and Menkveld (2011) is the most related research to this paper and forms the basis of the experimental design for our study. Hendershott, et al. uses a measure of NYSE message traffic as a proxy for algo trading to study its impact on the liquidity of stocks, without differentiating among the various strategies used by algo traders. They also include an event study approach around the introduction of autoquoting as an exogenous instrument to examine the effect of algorithmic trading. The authors document that an increase in the number of algorithmic trading messages affect the liquidity of only the largest stocks. For these stocks, liquidity improved in terms of a decline in the quoted and effective spreads, although quoted depth decreased. The use of the autoquoting period confirms the key results of their paper.

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[4] Regarding the general research on options not directly related to algo trading, Biais and Hillion (1991) and John, Koticha and Subrahmanyam (1991) develop models that examine the *equilibrium* bid and ask prices for individual equity options markets. Ho and Macris (1984) analyze the transaction price and bid-ask spread relation for AMEX individual equity options; George and Longstaff (1993) determine the cross-sectional differences among individual equity options for different strikes; Mayhew (2002) examines the effects of competition and market structure using individual equity option bid-ask spreads; and Cai, Hudson, and Keasey (2004) examine equities on the London Stock Exchange (LSE) and find a L-shape in the bid-ask spread, a two-humped shape for volume, and a U-shape for volatility.

II. Data

Options microstructure research provides several challenges related to data structure. First, the number of strike prices and expiration dates multiplies the number of data series, with the different strikes/expirations possessing differing price response characteristics. Second, the number of quote revisions (algo messages) has geometrically increased over the past few years, creating data analysis and storage issues. Finally, data availability for all quotations for all stock options for all exchanges is limited. Thus, unlike organized microstructure data for the equity markets, there is dearth of comprehensive microstructure research for exchange-traded options.

The data for this study employs the Options Price Reporting Authority (OPRA) data feed. The OPRA feed consists of trade execution and the best bid and offer quotes and size from *each* of the seven U.S. equity options exchanges. OPRA flags each quote with an indicator stating the quote's bid-ask relative to the national best bid and offer (NBBO). We employ the Baruch Options Data Warehouse database of options, which processes the full OPRA feed and generates data extracts and statistics on trade and quote messages.

This paper uses data for calendar years 2007 and 2008, representing 2,328,185 unique options series on 5,100 underlying equities, ETFs and indexes. The two years of data contain 311,567,675 trades and approximately 1.3 trillion quotes, requiring 65 terabytes of disk storage. We focus on 2007 and 2008 because algorithmic trading in options markets increased starting in 2007 (as shown in Figure 1) and because 2008 provides a unique opportunity to examine how volatility affects both the spread and depth of options markets, especially in terms of the relation between algorithmic trading and the financial crisis. In addition, our research design and time interval includes the introduction of penny quotes for options markets, which was initiated in 2007.

We compute the quoted spread for each option series for each stock employed in this study by determining the average National Best Bid and Offer (NBBO) bid-ask spread over the entire trading day for each day in both years, as well as the total dollar value for each options series traded. In this process we employ the traditional filters for spreads and depth. For example, we ignore negative spreads and stub quotes (a quote with a zero bid and a very large ask, such as 199,999).[5] The data on market capitalization, and equity returns for the calculation of the daily volatility, are obtained from COMPUSTAT and CRSP.

III. Liquidity Measures and Methodology

A. Liquidity, Algo Trading, and Control Measures

Our goal is to examine the relation between algorithmic trading and the liquidity of the associated options market by using the number of messages as the measure of algorithmic trading in the market.[6] Algorithmic trading is variously reported to account for 50% to 70% of the total volume in today's equity market, implying that both the amount and changes in algo trading messages dominate the number of messages in a market.

We examine the relation between message traffic and both the bid-ask spread and depth measures of liquidity in cross sectional panel regressions, where controls are established for the underlying firm size, volatility of the underlying stock, and the dollar volume of option trading. We examine panel regressions employing every intraday bid-ask quote and depth observation

[5] Only "eligible" quotes are employed. An eligible quote is a NBBO quote representing a firm (i.e. "executable") quote that is neither a stub quote nor not a zero price bid quote; quotes with zero size bids or offers are also ignored. All stub quotes are removed from the database, which includes initial opening and closing stub quotes, as well as "non-firm" quotes at the start of the day. The messages include both quotes and trades; however, more than 99.95% of the option messages are quotes. Therefore, for options, messages and bid-ask quotes are effectively equivalent.

[6] Hendershott et al. suggest either a measure of message traffic normalized by volume, or the use of raw message traffic to represent algorithmic trading. We employ raw message traffic; however, we do control for the volume of trading in the regression analysis. The results are unchanged when message traffic normalized by volume of trading is employed.

and accumulate this data into daily algo messages and daily average bid-ask spread and depth data. The volume and volatility control variables are total values for the day. Separate values for the spread and depth are calculated for each option strike, expiration, and call/put for each underlying stock. The percentage spread is calculated as follows:

$$Percentage\ Spread = \left(\frac{(Ask - Bid)}{0.5(Ask + Bid)} \right)(100) \tag{1}$$

where bid and ask prices are the NBBO values.

Depth is calculated as:

$$Depth = \left(\frac{(BestAskSize + BestBidSize)}{2} \right) \tag{2}$$

We sort the options based on three different criteria: (1) by market capitalization of the underlying instruments (stocks and ETFs, generally referred to generically as "stocks"); (2) by dollar volume traded for the options over the entire year; and (3) by volatility of the underlying stocks. We sort the options based on the market capitalization of the underlying stocks into quintiles in descending order, choosing the largest forty stocks from each group. Therefore, we examine the option series data for 200 underlying equities of stratified capitalizations. As noted, we also sort the option series by the respective option trading volume generated by all of the exchanges for the entire year, as well as sorting independently by the volatility of the underlying stock, again in descending order.

We employ the Garman-Klass (1980) measure to calculate the daily stock volatility, as defined by:

$$Var(GK) = \frac{1}{2}\left[\ln(High) - \ln(Low)\right]^2 - \left[2\ln(2) - 1\right]\left[\ln(Open) - \ln(Close)\right]^2 \tag{3}$$

The Garman-Klass measure allows for an examination of volatility within an interval as opposed to the traditional volatility measures that examine volatility between or across intervals. As noted by Garman and Klass, their measure is eight times more efficient than using a close-to-close measure of volatility.[7]

For each sort the first quintile represents stocks with the highest values for that variable, whereas quintile five represents stocks with the lowest quintile values for that variable. For each sort we classify the option series into "call" and "put" options, and further into "in-", "near-" and "out-of-the-money" options. The "in-", "near-" and "out-of the money" option groups are created by employing the following procedure: First, we calculate the difference between the stock price of the last trade and the strike price, labeled the "stock-strike difference." The option is grouped as a near-the-money option if the stock-strike difference is within 2.5 (5) points for stocks below (above) $20. It is grouped as an out-of-the-money call option if the stock-strike difference is -2.5 to -10 (-5 to -20) for stocks below (above) $20, and an in-the-money call option if the difference is 2.5 to 10 (5 to 20) for stocks below (above) $20. Signs are reversed for put options. Options outside these ranges possess little trading interest and therefore are removed from the analysis.

We call the above sample the general sample (or non-penny quote sample), since we remove the stocks with penny quote options from the sample in order to provide inferences on the impact of message traffic (algorithmic trading) independent of the effects of the penny pilot on option market activity.[8]

B. Panel Regressions

For the general sample we estimate the following OLS regressions for each category as follows:

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[7] Efficiency in this context refers to the reduction in the error of the estimate.
[8] The penny pilot option project and its importance are described in the next sub-section.

$$l_{it} = \alpha_i + \beta_i A_{it} + \delta_{it} X_{it} + \epsilon_{it} \tag{4}$$

where l_{it} is the liquidity variable (either the bid-ask spread or the depth), A_{it} is the message traffic representing algorithmic trading, and X_{it} is the set of control variables, i.e. market capitalization, the Garman-Klass volatility of the underlying stock, and the dollar trading volume of the stock's options.

We conduct our tests of option algorithmic trading in two phases. In the first phase we examine the relation between algorithmic trading and liquidity by examining the bid-ask spread and the depth of the market for the non-penny quote (general sample) options. For this step we filter the non-penny quote options so as to provide inferences of message traffic (algorithmic trading) and market quality on option market activity, independent of the consequences of moving from the five/ten cent quotes to penny quotes. In the second phase we design a model for a robustness check (and to establish causality) by picking the introduction of penny quotes in 2007 and 2008 to option series affected by the penny quotes as an exogenous factor that could potentially increase the incidence of algorithmic trading. In fact, the reason to change to penny quotes for stock options was not to benefit algorithmic trading. However, a smaller tick size theoretically should create more quote changes using the penny quote procedure, especially for the more active stock options (American Stock Exchange, 2007; Louton, Saraoglu, and Holowczak, 2009). Moreover, more frequent quotes provide critical new information concerning the fair price of an option to algorithms. Thus, the immediate feedback traders receive from penny quotes should increase algorithmic trading activity, which is especially crucial to options given their extensive number of strikes and expiration dates.

C. The Penny Pilot as a Robustness Check

Our approach to *verifying* the relevance of algorithmic trading is to explore the relation between message traffic and option market liquidity by using stocks with option penny quotes. The penny quote sample period starts one month before the penny quote initiation date and ends one month after the penny quote initiation. Note that the transition to option penny quotes occurred in three phases during this time period; we examine each phase independently.[7]

We estimate the following regressions for the sample with penny quotes:

$$l_{it} = \alpha_i + \gamma_t + \beta_i A_{it} + \delta_{it} X_{it} + \epsilon_{it} \tag{5}$$

where l_{it} is the liquidity variable (either bid-ask spread or depth), A_{it} is the message traffic representing algorithmic trading, and X_{it} is the set of control variables such as market capitalization, Garman-Klass volatility of the underlying stock, and the trading volume of the option. Equation (5) includes the additional variable γ_t to represent the time dummy for before and after the penny quotes were introduced. Since our principal goal in this analysis is to understand the effects of algorithmic liquidity supply on market quality, we employ the penny-quote dummy (γ_t) as an instrument for algorithmic trading in the panel regression framework. By including time dummies in the panel specification, we can employ non-penny quoted stocks as controls, comparing the penny-quoted stocks to the not-yet-penny-quoted stocks. The percentage spread and depth used in the penny quote analysis is measured in the same manner as with the total sample. The penny quote regression model is calculated using the GMM (Generalized Method of Moments) procedure.

III. Results

A. Basic Statistics

Tables 1 and 2 show the basic call and put statistics, respectively, by option category for each quintile for the spread, depth, and algorithmic messages, as well as for the control variables of market capitalization, Garman-Klass volatility, and dollar option volume. The average quoted

[7] We separate the general sample and the penny quote sample. This separation provides the opportunity to interpret the results and present inferences for each sample independently. We also examine an integrated sample (not shown here), finding that the results were not significantly different than the general and penny quote samples.

spread as a percentage of the option price is smallest for the in-the-money options, next largest for the near-the-money options, and largest for the out-of-the-money options. This is logical given the size of the prices for the in-, near-, and out-of-the-money option categories. An important characteristic of the option series is that the spreads are almost always higher for the 2008 relative to 2007, with larger differences and spreads occurring for the smaller stocks (lager numbered quintiles). Moreover, the increase in the spread is larger for the “in-” and “out-of-the-money” groups than for the “near-the-moneys.”

The depth in Tables 1 and 2 is substantially higher for the first quintile of stocks, which is associated with institutional interest in these options. The depth is much smaller for the other quintiles. Moreover, the near-the-money options possess the largest depth for quintiles one to three. The most striking depth results are for 2008, where the depth for quintile one is typically less than half of the depth existing in 2007; however, the depth for the other quintile is often *larger* in 2008 than in 2007. This result indicates the extent of evaporating liquidity in the options market for the largest stocks due to the financial crisis and increase in algorithmic trading.

The number of algorithmic messages is substantially higher for the first quintile, which is consistent with the underlying stocks for this quintile being the largest and potentially most active stocks. Moreover, the number of algo messages increase significantly from 2007 to 2008, especially for puts and quintile 1,with quintile 5 being the lone exception. In terms of the control variables, the Garman-Klass volatility for 2008 increases by a factor of six for the first quintile and by a factor of 2.3 for quintile five. The market capitalization and dollar volume variables remained relatively stable over the two year period for most categories.

B. *Spread Results*

This section examines the bid-ask spread results for the general sample for 2007 and 2008. Our goal is to understand the effects of algorithmic trading on the liquidity of options. Tables 3 and 4 provide the quintile spread results sorted in terms of each of the control variables in quintile descending order for 2007 and 2008, respectively. Table 3 shows that the standardized spread decreases with increasing message traffic for all categories and both years for the market capitalization sort.[9] The number of messages is larger for the larger capitalization firms (e.g. quintile 1), therefore the coefficients are smaller in these cases. More importantly, the statistical significance of the message traffic variable almost always is larger for the larger firms such as quintile one, showing that the consistency and reliability of the results is stronger for quintile one. Moreover, the decrease in the spread is significant for all quintiles and option categories. The volume ranking by quintiles shows the same decrease in spreads and decline in significance on the market capitalization results, although quintiles 4 and 5 often are not significant. The volume quintile results are consistent since the largest capitalized companies often possess the largest options dollar volume.

Tables 3 and 4 also show that the spread declines with message traffic for the volatility sorted groups. However, the significance level of the spread decrease for these results is consistently the greatest for the *lowest* volatility group (i.e. quintile five). This result is intuitive since the *highest* volatility group (quintile 1) should include active options for the more volatile smaller cap stocks in this group which would be more diverse in their response to algo trading as well as be less liquid, whereas the lowest volatility group (quintile 5) would include larger capitalized firms; thus, the largest significance for the spread decrease for the volatility grouping

[9] We also examine the spread and depth results after removing the data for the financial crisis time period in 2008. We follow Anand, Puckett, Irvine, and Venkataraman (2011) to determine the crisis time period. The results for the crisis period in 2008 are essentially equivalent to the entire 2008 year, and are available upon request.

is in quintile five whereas the most significant results for the market capitalization and volume sorted results discussed above are in quintile one.

C. Depth Results

Depth as a measure of liquidity has received minimal attention in the literature. In particular, in relation to algo trading only Hendershott et al. (2011) examines the roll of depth, finding that depth actually *declines* as algo trading increases. Thus, this measure of liquidity may actually be reduced due to the frequent quote revisions associated with algo trading. The reasoning by Hendershott et al. is based on the smaller trade size created by certain strategies for algo trading, although the evidence is anecdotal.

Tables 5 and 6 show that our analysis of depth for options typically *increases* as algo trading increases, especially for the market capitalization and volatility groupings, contrary to the market capitalization results of Hendershott et al.. Unlike the spread results, there is no pattern in the size of the significance values across quintiles or option categories. For the volume grouping the results are mixed, both in terms of the sign and whether the quintiles are significant, although the quintile one results often are most significant. Overall, there is no conclusive pattern for the depth variable using the volume sorted quintiles. These results can be due to algorithmic trading orders being sliced into smaller orders and executed in batches rather than being executed as large volume orders.

D. The Penny Pilot as an Exogenous Event

We next examine the penny pilot quotation for options as an exogenous factor that could potentially increase the incidence of algorithmic trading. The penny pilot program for options was a Securities and Exchange Commission (SEC) initiative to quote stock options with the most activity in terms of pennies rather than nickels/dimes in order to decrease price spreads, provide better prices to retail customers, and reduce the payment for order flow. For our purposes, the introduction of penny quotes for the options market during 2007 and 2008 provides an opportunity to examine the effects of an exogenous factor. In fact, although algorithmic trading is not the intentioned beneficiary of the penny pilot program, by design it promotes the practice of algorithmic trading. Thus, a smaller tick size caused by penny quotes should create more quote changes, especially for the more active stock options (American Stock Exchange, 2007). Moreover, more frequent quotes provide critical new information concerning the fair price of an option. Thus, the immediate feedback that traders receive from penny quotes is consistent with an increase in algorithmic trading activity, which is especially crucial for option trading because of the complexity of their strike/expiration/multiple exchange structure.

Table 7 presents the basic statistics for the penny quote sample. The penny quote sample we employ possesses basic characteristics that are almost equivalent to the first volume sorted quintile in the general sample; the explanation for this similarity is that the stocks used for the penny pilot in 2007/2008 are large capitalization stocks that possess very actively traded options. As with the general sample, the average spread as a percentage of the price for the penny stocks is smallest for the in-the-money options, next largest for the near-the-money options, and largest for the out-of-the-money options. The depth is typically largest for the near-the-money options for calls and the out-of-the-money options for puts. The depth is consistent with the results for the first quintile of the market capitalization ranking for the general option sample. This is consistent with both the penny quote sample and the first quintile from the general sample being dominated by underlying stocks that are of interest to institutions. Also, the number of algo messages is substantially higher for the near-the-money group, since near-the-moneys are the most active category.

Phase I of the penny pilot program (PPP) was adopted by six options exchanges on January 26th of 2007 and included 13 securities; Phase II of the PPP began on September 28, 2007 and included 22 securities; and Phase III began on March 28, 2008 and covered 28 securities. Our underlying general sample in 2007 and 2008 excludes these penny pilot securities. With the introduction of the penny pilot there were two major changes that could confound our results. First, penny quotes should increase the slicing and dicing of orders, since smaller-sized orders can be placed at better prices. Second, there could be more effective market making due to the existence of algo traders and their speed and number advantages. However, there could be less depth in the market due to less clustering of orders around the NBBO because of such slicing and dicing of algorithmic orders.

For each phase we examine one month before and one month after the penny quote is introduced. Thus, we generate daily panel regressions according to the specification in equation (2). Tables 8 presents the spread results for all three phases. In the penny quote sample the results for the “in-”, “near-” and “out-of-the-money” categories show interesting differences. the bid-ask spread declines with message traffic, consistent with the general sample, for all 12 regressions (three penny pilot phases) for the near- and out-of-the-money option groups, but is not significant for the in-the-money regressions.

Table 9 presents the depth results for the penny quote sample. Except for one case the depth significantly decreases. These results contradict the depth results for the market capitalization and volatility groupings for the general sample.[10] However, unlike the general sample, the decline in depth for the penny pilot sample is a natural consequence of the introduction of smaller penny quotes with more frequent quote revisions, as well as due to an

[10] Of course, the in-the-money results can be related to thin trading.

increase in the slicing of orders into smaller sizes.[11]

These penny quote results are consistent with the results for the volume ranking of the first quintile of the general sample. In addition, the penny quote sample results for both the spread and depth for the options are similar to those of Hendershott et al. (2011) for equities. In general, the penny quote stocks are the most active and/or liquid stocks in the market, and therefore the increase in message traffic means a smaller spread due to a greater liquidity supply because of a larger number of (algorithmic) market makers, and a decreased depth due to the slicing and dicing of orders. Therefore, with increased message traffic, both the trading cost and the depth is reduced.

E. Discussion of Results

Overall, our results differ from Hendershott et al. (2011) in obvious ways, especially in terms of the signs on the depth variable. These differences stem from the fact that our study examines stock options, whereas Hendershott et al. analyzes stocks. For example, Hendershott et al.'s discussion focuses o the most liquid stocks (quintile 1) of the market capitalization group, whereas our larger market capitalization group does not necessarily employ the most active options. In fact, the volatility of the underlying stocks is a predominant motivation for trading options, with the volatility grouping showing a positive increase in depth for both 2007 and 2008. The volume of option trading is the most transparent method of determining the most active options. In fact, the volume sorting sample results closely mirror the Hendershott et al. results for both spreads and depth, i.e. the spread and depth these variables typically decline with higher message traffic, with this relation existing with less significance as the comparison changes from quintile one to quintile five. Finally, note that the decline in depth is consistent with the slicing and dicing of orders from buy side algorithms, as well as by the competition on

[11] See the "Penny Quoting Pilot Program Report" by the American Stock Exchange (2007).

the algorithmic liquidity supply side, which potentially can lead to a smaller size offered by each market maker at the best bid and offer. Moreover, for the penny quote sample the results mirror quintile one of Hendershott, et al.

IV. Conclusions

Empirical research on the market impact of algorithmic trading is important for both policy makers and market participants because of the potential impact of algo trading on the bid-ask spread and the depth of the market. Previous research examines the impact of algo trading on the stock and futures market. We extend this research on a market with various levels of trading activity due to different stocks, a range of strike prices, different expiration dates, and a multitude of exchanges. These factors make the application of algorithmic trading more difficult, as well as more useful. We employ the Options Price Reporting Authority (OPRA) data feed, using the flow of messages as a proxy of algo trading. Thus, our results offer evidence on the liquidity impacts of algorithmic trading in the options market. In addition, we employ the introduction of penny quotes in option markets as an exogenous event to test the liquidity impact of message traffic.

Given the liquidity differences among the various groups of options, we have the advantage of examining the effect of algorithmic trading on liquidity in a more in-depth context. Our analysis of the general sample for 2007 and 2008, and sorting them by the characteristics of the underlying stock (by market capitalization and volatility) as well as by dollar option volume, provides evidence that supports Hendershott et al. (2011). Moreover, we provide an explanation as to why a reduction in depth with algorithmic trading can exist, as with our penny quote sample and the results found in Hendershott et al.

The issue of liquidity in financial markets is a timely and crucial factor. Additional analysis of more complicated and integrated markets such as options would provide crucial information to aid appropriate regulatory interests in making the markets "fair and efficient." Moreover, further investigation of the impacts of algorithmic traders on the markets is essential in determining the tradeoffs between the additional liquidity algo traders provide in normal markets versus the potential for market crashes when algo traders remove their liquidity, as happened for the Flash Crash.

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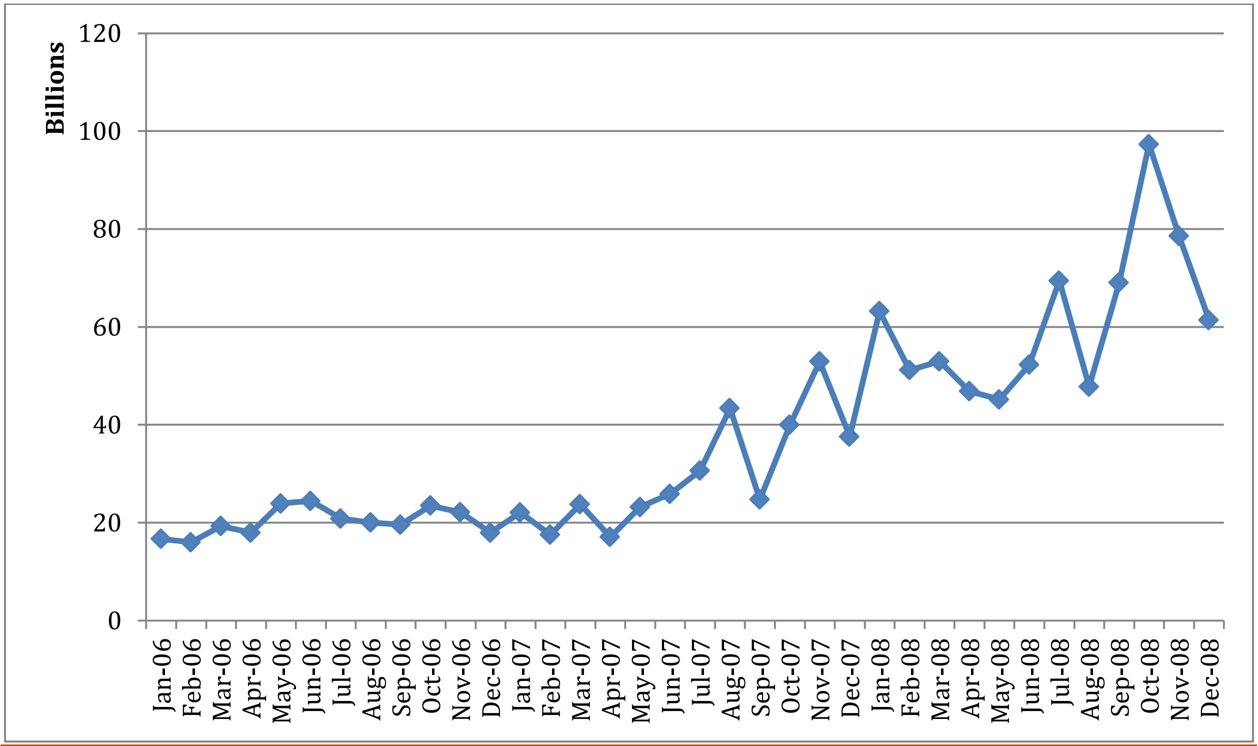
Figure 1

OPRA Message Traffic per Month in Billions of Messages



This figure examines the growth in option messages for before and during the study period.

Table 1: Summary Statistics for Calls

		CALLS 2007					CALLS 2008				
		Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Quoted Spread											
	in	0.0240	0.0520	0.0730	0.1040	0.1720	0.0390	0.0930	0.1240	0.2180	0.2200
	near	0.0860	0.2060	0.2840	0.5090	0.5740	0.0760	0.2240	0.3480	0.4990	0.6990
	out	0.2760	0.4060	0.6150	0.8140	0.7920	0.3180	0.4880	0.7480	1.0010	1.2810
Quoted Depth											
	in	665	77	60	46	19	387	74	55	41	50
	near	1,768	145	74	44	21	764	182	75	46	43
	out	1,160	125	57	34	22	701	103	58	39	30
Messages											
	in	32,713	8,025	4,064	1,653	1,494	42,865	14,107	4,866	1,906	909
	near	41,861	7,331	3,434	1,573	1,206	74,134	11,998	4,542	1,992	1,098
	out	26,916	4,140	1,776	1,018	1,550	46,271	7,811	2,973	1,386	873
GK Volatility											
	in	7.01947	11.0200	11.9430	19.8429	33.9894	42.1542	37.9620	43.7990	51.9070	73.5807
	near	7.01947	11.0200	11.9430	19.8429	33.9894	42.1542	37.9620	43.7990	51.9070	73.5807
	out	7.01947	11.0200	11.9430	19.8429	33.9894	42.1542	37.9620	43.7990	51.9070	73.5807
Market Cap											
	in	17.0658	14.9900	14.3680	13.5043	13.2806	16.8769	14.9660	13.9270	13.1640	12.6521
	near	17.0658	14.9900	14.3680	13.5043	13.2806	16.8769	14.9660	13.9270	13.1640	12.6521
	out	17.0658	14.9900	14.3680	13.5043	13.2806	16.8769	14.9660	13.9270	13.1640	12.6521
Volume											
	in	1238.0480	299.2944	234.4949	282.4840	61.1345	632.8810	399.7656	235.3451	81.7114	181.8925
	near	2831.8604	240.7275	109.7671	63.6481	45.7641	2257.5096	230.8528	72.1126	42.8126	26.0978
	out	963.9726	78.8107	47.1090	31.2650	217.3550	708.951	95.1252	29.6912	16.3591	13.7386

Based on the option code we divide the data into call and put options and then into in-, near-, and out-of-the-money strikes. The table provides daily averages for each variable for the call options for the general sample for 2007 and 2008. We group/rank the options by the underlying's (equity's) market capitalization. For each quintile we then provide averages for the quoted spread, quoted depth, number of messages, Garman-Klass volatility, market capitalization and dollar option volume by each equity subgroup and for calls and puts and "in-", "near-" and "out-of-the-money" options. The values for the market capitalization and volatility variables are equivalent for the in-, near-, and out-of-the-money categories since they are based on the underlying stocks. Dollar option volume is the average per strike price for each stock in the category and then divided by 100 (the strikes include those without a trade but with a quote).

Table 2: Summary Statistics for Puts

		PUTS 2007					PUTS 2008				
		Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Quoted Spread											
	in	0.0313	0.0677	0.1295	0.2514	0.2773	0.0371	0.0916	0.1226	0.1816	0.2768
	near	0.0814	0.2022	0.2712	0.4329	0.5295	0.0632	0.1928	0.2921	0.4543	0.5843
	out	0.2445	0.5072	0.6026	1.0273	0.7164	0.2089	0.3871	0.5737	0.8737	1.3039
Quoted Depth											
	in	619	91	59	39	27	426	92	56	45	41
	near	1,975	151	72	42	26	843	188	77	47	40
	out	1,706	121	51	35	17	711	102	56	38	32
Messages											
	in	36,700	8,187	3,973	1,411	905	47,843	13,609	4,771	2,444	1,335
	near	40,163	7,027	3,549	1,499	1,285	69,149	11,585	4,620	2,094	1,256
	out	25,143	3,537	1,718	1,872	954	41,296	7,107	3,009	1,551	1,169
GK Volatility											
	in	7.01947	11.024	11.943	19.843	33.989	42.1542	37.96192	43.799	51.9068	73.5807
	near	7.01947	11.024	11.943	19.843	33.989	42.1542	37.96192	43.799	51.9068	73.5807
	out	7.01947	11.024	11.943	19.843	33.989	42.1542	37.96192	43.799	51.9068	73.5807
Market Cap											
	in	17.0658	14.99	14.368	13.504	13.281	16.8769	14.96557	13.927	13.1639	12.6521
	near	17.0658	14.99	14.368	13.504	13.281	16.8769	14.96557	13.927	13.1639	12.6521
	out	17.0658	14.99	14.368	13.504	13.281	16.8769	14.96557	13.927	13.1639	12.6521
Volume											
	in	2101.8805	368.0625	373.0354	91.5764	108.5181	897.4038	462.8728	254.1447	122.1596	72.5502
	near	3529.1479	194.3081	99.5504	42.5228	87.6818	2831.0195	227.7973	85.5088	53.0268	30.8512
	out	1011.6183	88.3165	39.2363	19.9890	16.2646	944.0373	97.2319	38.8053	26.3321	23.4810

Based on the option code we divide the data into call and put options and then into in-, near-, and out-of-the-money strikes. The table provides daily averages for each variable for the put options for the general sample for 2007 and 2008. We group/rank the options by the underlying's (equity's) market capitalization. For each quintile we then provide averages for the quoted spread, quoted depth, number of messages, Garman-Klass volatility, market capitalization and dollar option volume by each equity subgroup and for calls and puts and "in-", "near-" and "out-of-the-money" options. The values for the market capitalization and volatility variables are equivalent for the in-, near-, and out-of-the-money categories since they are based on the underlying stocks. Dollar option volume is the average per strike price for each stock in the category and then divided by 100 (the strikes include those without a trade but with a quote).

Table 3: The Effect of Algorithmic Trading on Bid-Ask Spreads (2007, Calls)

CALLS (IN) 2007								
Group/Sorting Criteria	Q1	Q2	Q3	Q4	Q5	Volume	Market Cap	GK Volatility
Qspread for Volume	-0.0001	-0.0011	-0.0057	-0.0032	-0.0051	-0.5043	-3.7400	0.1462
	(-55.21)	(-32.94)	(-17.71)	(-1.95)	(-0.62)	(-1.31)	(-77.93)	(65.97)
Qspread for Market Cap	-0.0001	-0.0004	-0.0022	-0.0017	-0.0025	-0.1478	-3.1800	0.0000
	(-66.69)	(-28.04)	(-22.80)	(-23.31)	(-2.28)	(-4.66)	(-56.65)	(77.42)
Qspread for GK Volatility	-0.0004	-0.0001	-0.0001	-0.0002	-0.0002	-14.400	-13.4300	6.9487
	(-22.76)	(-10.37)	(-15.74)	(-19.99)	(-43.34)	(-7.45)	(-45.20)	(22.92)
CALLS (NEAR) 2007								
Qspread for Volume	-0.0008	-0.0096	-0.0231	-0.0121	-0.0104	-29.4100	3.8200	0.3635
	(-48.14)	(-49.88)	(-31.60)	(-8.02)	(-2.06)	(-101.58)	(8.30)	(13.57)
Qspread for Market Cap	-0.0007	-0.0007	-0.0132	-0.0078	-0.0141	-34.1100	13.6300	0.0000
	(-40.75)	(-13.67)	(-39.04)	(-18.92)	(-7.38)	(-107.77)	(18.80)	(14.29)
Qspread for GK Volatility	0.0003	-0.0002	-0.0007	-0.0008	-0.0009	-62.7400	-39.5400	2.1600
	(2.46)	(-0.33)	(-0.96)	(-12.73)	(-40.47)	(-68.82)	(-27.54)	(14.94)
CALLS (OUT) 2007								
Qspread for Volume	-0.0020	-0.0271	-0.0478	0.0014	0.0060	-102.5100	8.6900	1.0900
	(-40.68)	(-38.15)	(-16.34)	(0.30)	(1.09)	(-197.35)	(9.92)	(27.63)
Qspread for Market Cap	-0.0016	-0.0022	-0.0476	-0.0120	-0.0075	-102.5100	22.4400	0.0002
	(-28.93)	(-18.90)	(-27.06)	(-10.88)	(-1.96)	(-179.58)	(15.48)	(30.40)
Qspread for GK Volatility	-0.0019	-0.0007	-0.0007	-0.0023	-0.0031	-122.2100	-16.8200	1.5600
	(-6.88)	(-8.02)	(-6.23)	(-16.28)	(-35.78)	(-85.85)	(-7.00)	(10.15)

Table 3: The Effect of Algorithmic Trading on Bid-Ask Spreads (2007, Puts) Continued…

PUTS (IN) 2007

Group/Sorting Criteria	Q1	Q2	Q3	Q4	Q5	Volume	Market Cap	GK Volatility
Qspread for Volume	-0.0002	-0.0022	-0.0136	-0.0052	-0.0219	-4.6400	-2.8500	0.1606
	(-19.86)	(-15.85)	(-8.66)	(-0.80)	(-1.43)	(-28.72)	(-13.14)	(20.39)
Qspread for Market Cap	-0.0002	-0.0004	-0.0038	-0.0019	-0.0111	-4.39	-5.0900	0.0000
	(-19.03)	(-18.61)	(-10.90)	(-9.27)	(-3.16)	(-23.98)	(-13.50)	(11.55)
Qspread for GK Volatility	-0.0004	-0.0006	-0.0001	-0.0004	-0.0002	-18.51	-22.5400	-0.1015
	(-5.23)	(-10.40)	(-8.22)	(-13.88)	(-26.05)	(-25.45)	(-21.06)	(-1.37)

PUTS (NEAR) 2007

Qspread for Volume	-0.0007	-0.0079	0.0224	-0.0069	-0.0057	-21.0900	1.5700	0.3239
	(-40.82)	(-37.29)	(-25.32)	(-3.00)	(-0.91)	(-81.53)	(3.71)	(13.38)
Qspread for Market Cap	-0.0007	-0.0007	-0.0127	-0.0071	-0.0194	-26.4800	4.5200	0.0000
	(-36.93)	(-14.77)	(-29.50)	(-15.28)	(-8.97)	(-89.64)	(6.68)	(11.92)
Qspread for GK Volatility	-0.0005	-0.0002	0.0004	-0.0009	-0.0008	-51.7400	-21.3000	0.8620
	(-3.68)	(-3.37)	(0.61)	(-13.78)	(-38.29)	(-56.49)	(-15.29)	(7.50)

PUTS (OUT) 2007

Qspread for Volume	-0.0019	-0.0242	-1.0000	-0.0141	-0.0092	77.1800	8.9500	1.0800
	(-40.14)	(-24.05)	(-14.33)	(-1.79)	(-0.23)	(-160.94)	(9.97)	(25.98)
Qspread for Market Cap	-0.0017	-0.0025	-0.0381	-0.0158	-0.1005	-81.4500	11.7900	0.0001
	(-30.92)	(-19.97)	(-15.02)	(-8.59)	(-3.97)	(-152.16)	(8.60)	(24.27)
Qspread forGK Volatility	-0.0011	-0.0011	-0.0008	-0.0030	-0.0026	-109.2100	-31.9200	7.7900
	(-3.49)	(-10.37)	(-6.96)	(-16.15)	(-35.20)	(-65.25)	(-10.42)	(20.07)

The Table regresses the quoted Spread (QSpread) on a proxy for algorithmic trading (message traffic) and the three control variables of market capitalization, Garman-Klass volatility of the underlying stock, and the dollar volume of the stock's options for the general sample for 2007. The control variable values given here are for quintile 1. The specification is: $l_{it} = \alpha_i + \beta_i A_{it} + \delta_{it} X_{it} + \epsilon_{it}$ where l_{it} is the liquidity variable (quoted spread in this case), A_{it} is the

message traffic representing algorithmic trading, and X_{it} is the set of control variables such as market capital, Garman-Klass volatility of the underlying stock, and the dollar volume of the option. Volume is the logarithm of the average volume per strike and per stock after dividing by 100.

Table 4: The Effect of Algorithmic Trading on Bid-Ask Spreads (2008, Calls)

CALL(IN)2008

Group/Sorting Criteria	Q1	Q2	Q3	Q4	Q5	Volume	Market Cap	GK Volatility
Qspread for Volume	-0.0003	-0.0015	-0.0027	-0.0128	0.0056	-3.3500	1.7700	0.0069
	(-27.05)	(-19.07)	(-4.72)	(-3.62)	(0.36)	(-16.11)	(7.52)	(8.59)
Qspread for Market Cap	-0.0004	-0.0005	-0.0013	-0.0010	-0.0077	-5.0100	2.0100	0.1516
	(-30.47)	(-31.04)	(-12.30)	(-22.64)	(-4.90)	(-19.65)	(4.34)	(44.10)
Qspread for GK Volatility	-0.0091	-0.0007	-0.0017	-0.0014	-0.0004	-2.7500	-17.2900	0.0535
	(-5.99)	(-13.34)	(-7.25)	(-10.12)	(-18.49)	(-0.91)	(-2.04)	(1.40)

CALL(NEAR)2008

Qspread for Volume	-0.0005	-0.0056	-0.0138	-0.0267	-0.0243	-14.3600	4.5300	0.0186
	(-54.71)	(-44.77)	(-28.56)	(-14.22)	(-5.18)	(-59.11)	(12.92)	(16.56)
Qspread for Market Cap	-0.0007	-0.0007	-0.0078	-0.0016	-0.0352	-22.6500	1.2900	0.1008
	(-58.71)	(-39.11)	(-33.69)	(-22.80)	(-18.37)	(-76.17)	(1.97)	(40.89)
Qspread for GK Volatility	-0.0111	-0.0012	-0.0011	-0.0015	-0.0008	-61.4200	-282.5700	-0.0889
	(-3.38)	(-11.94)	(-4.97)	(-15.94)	(-9.72)	(-11.86)	(-28.69)	(-1.55)

CALL(OUT)2008

Qspread for Volume	-0.0022	-0.0158	-0.0308	-0.0640	0.0018	-97.3200	18.4100	0.0279
	(-83.72)	(-48.95)	(-20.89)	(-10.85)	(0.14)	(-210.46)	(23.40)	(14.57)
Qspread for Market Cap	-0.0020	-0.0023	-0.0222	-0.0049	-0.0047	-108.2300	0.1238	0.1357
	(-59.49)	(-50.95)	(-29.43)	(-29.57)	(-10.87)	(-197.49)	(0.08)	(40.87)
Qspread for GK Volatility	-0.0170	-0.0020	-0.0080	-0.0067	-0.0040	-123.3700	-232.1600	-0.1090
	(-3.07)	(-12.08)	(-10.08)	(-19.20)	(-13.40)	(-19.09)	(-18.84)	(-1.58)

Table 4: The Effect of Algorithmic Trading on Bid-Ask Spreads (2008, Puts) Continued…

PUT(IN)2008

	Q1	Q2	Q3	Q4	Q5	Volume	Market Cap	GK Volatility
Qspread for Volume	-0.0003	-0.0013	0.0007	0.0016	0.0171	-0.2.6700	-1.6200	0.0050
	(-34.50)	(-16.0)	(1.80)	(0.94)	(1.27)	(-16.80)	(-7.84)	(13.95)
Qspread for Market Cap	-0.0004	-0.0005	-0.0011	-0.0008	-0.0048	-4.2300	-5.5400	0.0139
	(-37.68)	(-36.23)	(-7.72)	(-22.41)	(-4.10)	(-21.67)	(-13.66)	(20.19)
Qspread for GK Volatility	-0.0025	-0.0008	0.0005	-0.0003	-0.0004	-26.5300	-21.3100	-0.0017
	(-1.92)	(-11.21)	(0.46)	(-6.27)	(-6.59)	(-10.23)	(-4.26)	(-0.42)

PUT(NEAR)2008

	Q1	Q2	Q3	Q4	Q5	Volume	Market Cap	GK Volatility
Qspread for Volume	-0.0003	-0.0045	-0.0095	-0.0210	-0.0263	-9.1900	3.3200	0.0083
	(-46.88)	(-38.59)	(-19.28)	(-10.58)	(-3.83)	(-47.72)	(11.61)	(9.40)
Qspread for Market Cap	-0.0005	-0.0005	-0.0073	-0.0016	-0.0120	-15.1500	-1.4600	0.0316
	(-50.82)	(-32.5)	(-28.36)	(-23.16)	(-8.94)	(-64.18)	(-2.72)	(15.43)
Qspread for GK Volatility	-0.0030	-0.0014	-0.0004	-0.0010	-0.0007	-54.4300	4.5400	0.2978
	(-1.37)	(-15.86)	(-2.56)	(-11.76)	(-9.36)	(-19.07)	(0.79)	(6.69)

PUT(OUT)2008

	Q1	Q2	Q3	Q4	Q5	Volume	Market Cap	GK Volatility
Qspread for Volume	-0.0015	-0.0077	-0.0336	-0.0185	-0.0319	-60.7000	2.7200	0.0096
	(-59.43)	(-25.84)	(-12.89)	(-2.81)	(-1.62)	(-139.72)	(3.89)	(4.57)
Qspread for Market Cap	-0.0014	-0.0018	-0.0203	-0.0047	-0.0373	-63.8900	-9.2000	0.3208
	(-41.43)	(-39.69)	(-17.14)	(-24.16)	(-5.37)	(-41.43)	(-6.55)	(28.61)
Qspread for GK Volatility	-0.0771	-0.0026	-0.0071	-0.0070	-0.0042	-90.0600	62.7100	0.3808
	(-3.36)	(-12.65)	(-11.89)	(-17.74)	(-10.41)	(-6.28)	(1.59)	(2.20)

The Table regresses the quoted Spread (QSpread) on a proxy for algorithmic trading (message traffic) and the three control variables of market capitalization, Garman-Klass volatility of the underlying stock, and the dollar volume of the stock's options for the general sample for 2008. The control variable values given here are for quintile 1. The specification is: $l_{it} = \alpha_i + \beta_i A_{it} + \delta_{it} X_{it} + \epsilon_{it}$ where l_{it} is the liquidity variable (quoted spread in this case), A_{it} is the

message traffic representing algorithmic trading, and X_{it} is the set of control variables such as market capital, Garman-Klass volatility of the underlying stock, and the dollar volume of the option. Volume is the logarithm of the average volume per strike and per stock after dividing by 100.

Table 5: The Effect of Algorithmic Trading on Depth (2007, Calls)

CALL(IN)2007								
Group/Sorting Criteria	Q1	Q2	Q3	Q4	Q5	Volume	Market Cap	GK Volatility
Qdepth for Volume	0.0036	-0.0006	-0.0023	-0.0005	0.0012	-15.5500	27.0500	-3.0200
	(27.30)	(-8.30)	(-8.92)	(-0.88)	(1.81)	(-8.79)	(12.30)	(-29.75)
Qdepth for Market Cap	0.0041	0.0094	0.0012	0.0012	0.0079	-4.2945	68.4400	-6.1800
	(29.38)	(43.00)	(9.12)	(11.87)	(10.06)	(-0.24)	(21.17)	(-31.94)
Qdepth for GK Volatility	0.0008	0.0008	0.0030	0.0008	0.0002	6.2269	3.6400	2.0100
	(19.94)	(36.52)	(51.23)	(10.076)	(13.75)	(1.48)	(5.61)	(30.030)
CALL(NEAR)2007								
Qdepth for Volume	-0.0010	-0.0006	-0.0010	-0.0001	0.0001	-90.1200	33.5800	-11.5300
	(-4.39)	(-6.28)	(-7.30)	(-0.88)	(0.07)	(-23.19)	(5.43)	(-32.06)
Qdepth for Market Cap	0.0031	0.0140	0.0025	-0.0005	0.0048	6.2000	-101.7600	-28.4900
	(10.64)	(57.55)	(20.36)	(-3.76)	(15.74)	(1.47)	(-10.50)	(-41.14)
Qdepth for GK Volatility	0.0004	0.0005	0.0033	-0.0006	-0.0048	-3.8693	35.5300	2.1400
	(5.83)	(19.48)	(46.17)	(-5.81)	(-15.83)	(-0.85)	(49.64)	(29.80)
CALL(OUT)2007								
Qdepth for Volume	0.0010	0.0001	-0.0001	-0.0002	0.0001	-104.0500	173.4600	-4.4200
	(4.09)	(0.60)	(-3.75)	(-1.34)	(0.68)	(-40.41)	(39.93)	(-22.54)
Qdepth for Market Cap	0.0034	0.0048	0.0073	0.0007	0.0026	-85.0300	224.0500	-12.1300
	(11.67)	(16.97)	(17.07)	(2.35)	(5.18)	(-28.75)	(29.84)	(-30.084)
Qdepth for GK Volatility	0.0003	0.0006	0.0012	0.0018	-0.0046	-3.6600	39.5800	0.87070
	(0.034)	(18.91)	(10.69)	(10.36)	(-10.09)	(-7.04)	(45.12)	(15.49)

Table 5: The Effect of Algorithmic Trading on Depth (2007, Puts) Continued…

PUT(IN)2007								
Group/Sorting Criteria	Q1	Q2	Q3	Q4	Q5	Volume	Market Cap	GK Volatility
Qdepth for Volume	0.0032	-0.0015	-0.0016	0.0009	0.0045	-30.8100	24.9500	-2.0400
	(27.62)	(-11.58)	(-5.60)	(1.76)	(5.50)	(-18.11)	(10.91)	(-24.58)
Qdepth for Market Cap	0.0040	0.0059	0.0011	0.0015	0.0063	-1.9800	119.8600	-3.7700
	(32.34)	(24.40)	(5.72)	(8.79)	(7.92)	(-1.15)	(33.84)	(-24.53)
Qdepth for GK Volatility	0.0004	0.0007	0.0039	0.0011	-0.0008	7.6400	8.1900	0.7930
	(7.37)	(24.69)	(44.68)	(11.73)	(-0.54)	(14.96)	(10.90)	(15.28)
PUT(NEAR)2007								
Qdepth for Volume	-0.0065	-0.0006	-0.0006	0.0001	0.0003	55.0500	3.7600	-14.2200
	(-23.57)	(-5.32)	(-3.41)	(0.83)	(0.61)	(13.26)	(0.055)	(-36.58)
Qdepth for Market Cap	-0.0039	0.0087	0.0027	-0.0002	0.0051	129.8600	-250.6500	-36.1600
	(-11.37)	(31.04)	(16.08)	(-1.38)	(11.27)	(27.11)	(-22.85)	(-46.40)
Qdepth for GK Volatility	0.0004	0.0003	0.0028	-0.0010	-0.0133	-0.99600	38.1900	1.2800
	(5.12)	(12.88)	(30.93)	(-7.25)	(-38.00)	(-1.87)	(47.02)	(19.07)
PUT(OUT)2007								
Qdepth for Volume	-0.0033	0.0002	0.0064	0.0007	0.0022	-77.3100	176.6200	-10.0700
	(-9.63)	(0.84)	(10.43)	(0.02)	(2.61)	(-22.72)	(27.73)	(-34.14)
Qdepth for Market Cap	0.0003	0.0049	0.0047	-0.0006	0.0271	-55.6000	115.4400	-23.7500
	(0.89)	(10.16)	(8.06)	(-1.62)	(6.82)	(-14.11)	(11.43)	(-43.58)
Qdepth for GK Volatility	0.0005	0.0003	0.0008	0.0012	-0.0136	-6.5000	46.3800	25.4000
	(4.72)	(9.50)	(5.89)	(4.82)	(-24.09)	(-10.41)	(40.59)	(17.55)

The Table regresses the quoted depth (Qdepth) on a proxy for algorithmic trading (message traffic) and the three control variables of market capitalization, Garman-Klass volatility of the underlying stock, and the dollar volume of the stock's options for the general sample for 2007. The control variable values given here are for quintile 1. The specification is: $l_{it} = \alpha_i + \beta_i A_{it} + \delta_{it} X_{it} + \epsilon_{it}$ where l_{it} is the liquidity variable (quoted spread in this case), A_{it} is the

message traffic representing algorithmic trading, and X_{it} is the set of control variables such as market capital, Garman-Klass volatility of the underlying stock, and the dollar volume of the option. Volume is the logarithm of the average volume per strike and per stock after dividing by 100.

Table 6: The Effect of Algorithmic Trading on Depth (2008, Calls)

CALL(IN)2008								
Group/Sorting Criteria	Q1	Q2	Q3	Q4	Q5	Volume	Market Cap	GK Volatility
Qdepth for Volume	0.0004	-0.0000	0.0000	-0.0000	-0.0001	-23.1000	6.7500	-0.0332
	(71.29)	(-0.35)	(0.87)	(-0.63)	(-0.44)	(-20.26)	(5.24)	(-7.30)
Qdepth for Market Cap	0.0003	0.0000	0.0000	0.0002	0.0004	-16.9600	4.9400	-0.3830
	(60.58)	(50.68)	(10.01)	(74.84)	(9.79)	(-15.99)	(2.56)	(-26.76)
Qdepth for GK Volatility	0.0001	0.0000	0.0001	0.0001	0.0002	3.8400	13.9200	-0.0144
	(10.50)	(12.25)	(8.42)	(19.18)	(22.16)	(1.68)	(2.18)	(-0.50)
CALL(NEAR)2008								
Qdepth for Volume	0.0002	-0.0002	-0.0000	0.0000	-0.0000	-67.1600	-15.1800	-0.0661
	(58.08)	(-21.18)	(-8.72)	(2.31)	(-0.76)	(-63.08)	(-9.89)	(-13.43)
Qdepth for Market Cap	0.0003	0.0001	0.0002	0.0005	0.0001	-44.4800	-61.8900	-0.1959
	(86.76)	(36.32)	(24.85)	(148.02)	(12.01)	(-41.84)	(-26.47)	(-22.23)
Qdepth for GK Volatility	-0.0002	0.0001	-0.0000	0.0001	0.0002	46.8200	-73.8700	-0.1554
	(-7.08)	(23.51)	(-0.00)	(12.91)	(23.77)	(7.65)	(-6.35)	(-2.29)
CALL(OUT)2008								
Qdepth for Volume	0.0002	0.0000	-0.0000	0.0001	-0.0000	-65.9800	27.0300	-0.0537
	(49.13)	(0.99)	(-2.29)	(6.40)	(-1.16)	(-67.27)	(16.20)	(-13.20)
Qdepth for Market Cap	0.0006	0.0001	0.0001	0.0006	0.0001	-69.6600	-76.7800	-0.1389
	(85.02)	(21.15)	(9.50)	(71.07)	(5.12)	(-61.18)	(-24.70)	(-20.14)
Qdepth for GK Volatility	-0.0001	0.0001	-0.0001	0.0002	0.0002	24.7400	-45.2200	-0.0657
	(-3.87)	(15.28)	(-4.28)	(14.22)	(13.20)	(6.63)	(-6.36)	(-1.64)

Table 6: The Effect of Algorithmic Trading on Depth (2008, Puts) Continued…

PUT(IN)2008								
Group/Sorting Criteria	Q1	Q2	Q3	Q4	Q5	Volume	Market Cap	GK Volatility
Qdepth for Volume	0.0003	-0.0000	-0.0000	-0.0000	-0.0001	-17.9800	9.2044	-0.0120
	(62.76)	(-6.13)	(-3.71)	(-1.33)	(-1.07)	(-18.65)	(0.73)	(-5.45)
Qdepth for Market Cap	0.0002	0.0005	0.0001	0.0002	0.0001	-14.7700	26.08	0.0739
	(50.12)	(66.79)	(12.76)	(53.57)	(5.25)	(-15.14)	(12.86)	(21.45)
Qdepth for GK Volatility	0.0005	0.0001	0.0000	0.0001	0.0001	18.2700	-28.02	-0.00411
	(5.68)	(12.03)	(0.28)	(16.02)	(21.19)	(10.06)	(-8.00)	(-1.38)
PUT(NEAR)2008								
Qdepth for Volume	0.0002	-0.0002	-0.0000	0.0000	-0.0003	-60.5100	-28.7300	-0.0595
	(56.51)	(-17.02)	(-10.31)	(3.02)	(-0.73)	(-52.97)	(-16.95)	(-11.33)
Qdepth for Market Cap	0.0004	0.0001	0.0002	0.0005	0.0017	-43.7000	-98.9400	-0.1910
	(84.84)	(24.12)	(19.19)	(109.73)	(11.54)	(-37.81)	(-37.56)	(-19.00)
Qdepth for GK Volatility	-0.0002	0.0001	-0.0000	0.0000	0.0020	-25.2000	-13.5700	-0.0803
	(-1.83)	(18.80)	(-4.62)	(6.71)	(16.41)	(-1.83)	(-4.20)	(-3.21)
PUT(OUT)2008								
Qdepth for Volume	0.0002	0.0000	0.0013	-0.0000	0.0002	-71.0400	-15.2700	-0.0479
	(39.54)	(3.39)	(5.85)	(-0.66)	(0.16)	(-58.48)	(-7.82)	(-8.13)
Qdepth for Market Cap	0.0005	0.0000	0.0014	0.0006	0.0013	-67.1700	-229.1100	-1.0800
	(60.85)	(11.91)	(4.37)	(50.42)	(2.43)	(-45.04)	(-58.38)	(-34.29)
Qdepth for GK Volatility	0.0002	0.0000	-0.0011	0.0002	0.0052	-3.2500	29.9000	-0.0203
	(6.52)	(3.53)	(-3.99)	(11.18)	(16.04)	(-1.69)	(5.64)	(-0.88)

The Table regresses the quoted depth (Qdepth) on a proxy for algorithmic trading (message traffic) and the three control variables of market capitalization, Garman-Klass volatility of the underlying stock, and the dollar volume of the stock's options for the general sample for 2008. The control variable values given here are for quintile 1. The specification is: $l_{it} = \alpha_i + \beta_i A_{it} + \delta_{it} X_{it} + \epsilon_{it}$ where l_{it} is the liquidity variable (quoted spread in this case), A_{it} is the

message traffic representing algorithmic trading, and X_{it} is the set of control variables such as market capital, Garman-Klass volatility of the underlying stock, and the dollar volume of the option. Volume is the logarithm of the average volume per strike and per stock after dividing by 100.

Table 7: Summary Statistics for the Penny Quote Sample

		CALLS	PUTS
Quoted Spread			
	in	0.0213	0.0348
	near	0.0989	0.1050
	out	0.6063	0.5353
Quoted Depth			
	in	692	584
	near	1,322	1,447
	out	1,126	1,593
Messages			
	in	37,958	37,689
	near	42,756	39,396
	out	22,561	18,696
GK Volatility			
	in	5.4287	5.4287
	near	5.4287	5.4287
	out	5.4287	5.4287
Market Cap			
	in	16.9911	16.9911
	near	16.9911	16.9911
	out	16.9911	16.9911
Volume			
	in	556.5453	708.1939
	near	1767.2345	1960.4648
	out	367.3980	358.2757

Based on the option code we divide the data into call and put options and then into in-, near-, and out-of-the-money options. The above table provides the averages for the call and put options for the penny quote sample for 2007 and 2008 for the variables of interest. Dollar option volume is the average per strike price for each stock in the category and then divided by 100 (the strikes include those without a trade but with a quote).

Table 8: The Effect of Algorithmic Trading on Bid-Ask Spreads for the Penny Quote Sample (Calls)

CALL(IN)2007

	Messages	GK Volatility	Market Cap	Volume
Qspread for phase1	-0.0000	0.0006	-0.0024	0.0002
	(-0.06)	(0.04)	(-0.09)	(0.01)
Qspread for phase2	-0.0001	0.0006	-0.0036	0.0006
	(-0.09)	(0.12)	(-0.18)	(0.03)
Qspread for phase3	0.0000	-0.0004	-0.0088	-0.0013
	(0.07)	(-0.05)	(-0.07)	(-0.04)

CALL(NEAR)2007

Qspread for phase1	-0.0002	0.0029	0.0115	-0.0230
	(-5.45)	(2.36)	(2.21)	(-2.58)
Qspread for phase2	-0.0002	0.0030	0.0013	-0.0218
	(-10.47)	(8.65)	(0.82)	(-11.16)
Qspread for phase3	-0.0000	0.0034	0.0350	-0.0206
	(-10.54)	(10.95)	(10.47)	(-6.18)

CALL(OUT)2007

Qspread for phase1	-0.0001	0.0567	-0.0061	0.0258
	(-6.40)	(7.63)	(-0.68)	(0.92)
Qspread for phase2	-0.0000	0.0079	0.0107	-0.0720
	(-9.67)	(11.16)	(2.75)	(-16.65)
Qspread for phase3	-0.0000	0.0070	0.0954	-0.0206
	(-16.60)	(15.15)	(20.18)	(-2.98)

Table 8: The Effect of Algorithmic Trading on Bid-Ask Spreads for the Penny Quote Sample (Puts)

PUT(IN)2007

	Messages	GK Volatility	Market Cap	Volume
Qspread for phase1	0.0000	-0.0070	0.0001	0.0005
	(0.03)	(-0.03)	(0.00)	(0.01)
Qspread for phase2	-0.0000	0.0006	-0.0006	-0.0048
	(-0.58)	(0.49)	(-0.16)	(-1.54)
Qspread for phase3	0.0000	-0.0031	-0.0465	-0.0019
	(0.47)	(-0.46)	(-0.47)	(-0.36)

PUT(NEAR)2007

Qspread for phase1	-0.0000	0.0034	0.0066	0.0065
	(-5.55)	(1.18)	(1.77)	(0.64)
Qspread for phase2	-0.0000	0.0021	0.0022	-0.0209
	(-9.32)	(6.89)	(1.68)	(-10.62)
Qspread for phase3	-0.0000	0.0025	0.0293	-0.0119
	(-8.13)	(7.03)	(6.88)	(-3.63)

PUT(OUT)2007

Qspread for phase1	-0.0002	0.0961	-0.0236	0.1049
	(-4.39)	(4.43)	(-1.80)	(2.18)
Qspread for phase2	-0.0000	0.0050	0.0042	-0.0482
	(-12.07)	(9.78)	(1.32)	(-13.41)
Qspread for phase3	-0.0000	0.0032	0.0548	0.0266
	(-13.88)	(8.85)	(13.99)	(3.24)

The Table regresses the quoted spread on a proxy for algorithmic trading (message traffic) and various controls such as market capitalization, the Garman-Klass volatility of the underlying stock, dollar trading volume of the stock's options and a dummy variable which takes the value of 1 if it is after the penny quote introduction. The specification is: $l_{it} = \alpha_i + \gamma_t + \beta_i A_{it} + \delta_{it} X_{it} + \epsilon_{it}$ where l_{it} is the liquidity variable (either spread or depth), A_{it} is the message traffic representing algorithmic trading, and X_{it} is the set of control variables such as market capital, Garman-Klass volatility of the underlying stock, and the trading volume of the option. The equation includes an additional variable γ_t to represent the time dummy for before and after the penny quotes were introduced. Volume is the logarithm of the average volume per strike and per stock after dividing by 100.

Table 9: The Effect of Algorithmic Trading on Depth for the Penny Quote Sample (Calls)

CALL(IN)2007

	Messages	GK Volatility	Market Cap	Volume
Qdepth for phase1	-0.0002	-0.0440	-0.5286	0.2054
	(-12.92)	(-3.19)	(-16.86)	(8.69)
Qdepth for phase2	-0.0000	-0.0302	-0.0089	0.0581
	(-4.62)	(-6.23)	(-0.54)	(2.67)
Qdepth for phase3	0.0000	-0.0111	-0.1160	-0.0250
	(1.36)	(-1.27)	(-1.04)	(-0.78)

CALL(NEAR)2007

Qdepth for phase1	-0.0007	-0.4652	-1.5322	2.2927
	(-13.14)	(-21.78)	(-16.98)	(12.40)
Qdepth for phase2	-0.0000	-0.0659	0.0565	0.2299
	(-31.37)	(-27.81)	(6.67)	(20.29)
Qdepth for phase3	-0.0000	0.0254	0.4499	0.3652
	(-38.63)	(25.52)	(33.76)	(36.99)

CALL(OUT)2007

Qdepth for phase1	-0.0009	0.1309	-0.2900	0.8277
	(-2.01)	(1.03)	(-1.78)	(1.65)
Qdepth for phase2	-0.0001	-0.0189	0.0960	0.4000
	(-26.22)	(-2.86)	(7.08)	(22.88)
Qdepth for phase3	-0.0001	0.0038	0.1571	0.4254
	(-17.52)	(1.92)	(9.32)	(16.16)

Table 9: The Effect of Algorithmic Trading on Depth for the Penny Quote Sample (Puts) Continued…

PUT(IN)2007

	Messages	GK Volatility	Market Cap	Volume
Qdepth for phase1	0.0007	-0.3993	0.0963	0.0276
	(0.43)	(-0.46)	(0.31)	(0.15)
Qdepth for phase2	-0.0000	-0.0272	0.0153	0.0355
	(-3.24)	(-5.61)	(0.58)	(1.54)
Qdepth for phase3	0.0002	-0.0924	-1.3156	-0.0490
	(3.09)	(-3.19)	(-3.12)	(-1.78)

PUT(NEAR)2007

Qdepth for phase1	-0.0007	-0.3434	-0.9793	2.7788
	(-9.45)	(-5.57)	(-13.37)	(10.60)
Qdepth for phase2	-0.0000	-0.0581	0.1101	0.3246
	(-40.61)	(-35.32)	(15.71)	(31.10)
Qdepth for phase3	-0.0000	0.0210	0.4320	0.2901
	(-6.65)	(3.05)	(4.89)	(5.53)

PUT(OUT)2007

Qdepth for phase1	-0.0053	1.6353	-1.3258	3.8893
	(-4.75)	(4.23)	(-5.88)	(4.41)
Qdepth for phase2	-0.0000	-0.0333	0.1247	0.6238
	(-34.71)	(-6.75)	(13.64)	(34.68)
Qdepth for phase3	-0.0000	0.0037	0.1642	0.5181
	(-13.09)	(1.70)	(8.45)	(12.33)

The Table regresses the quoted depth on a proxy for algorithmic trading (message traffic) and various controls such as market capitalization, the Garman-Klass volatility of the underlying stock, dollar trading volume of the stock's options and a dummy variable which takes the value of 1 if it is after the penny quote introduction. The specification is: $l_{it} = \alpha_i + \gamma_t + \beta_i A_{it} + \delta_{it} X_{it} + \epsilon_{it}$ where l_{it} is the liquidity variable (either spread or depth), A_{it} is the message traffic representing algorithmic trading, and X_{it} is the set of control variables such as market capital, Garman-Klass volatility of the underlying stock, and the trading volume of the option. The equation includes an additional variable γ_t to represent the time dummy for before and after the penny quotes were introduced. Volume is the logarithm of the average volume per strike and per stock after dividing by 100.