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Options Illiquidity: Determinants and Implications for Stock Returns

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Options Illiquidity: Determinants and Implications for Stock Returns *

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Abstract

We study the determinants of options illiquidity measured with relative bid-ask spreads of intraday transactions for S&P 500 firms over an extended period. We find that market makers' hedging costs significantly impact options illiquidity with the future rebalancing cost dominating the initial delta-hedging cost. Inventory demand pressure and adverse selection also contribute to variations in options illiquidity, with the latter effect intensifying around information events. We find option-induced order flows predict their underlying stock returns only when options illiquidity simultaneously increases. This suggests that shocks to options illiquidity help distinguish abnormal order flows that contain private information from those induced by liquidity trading. We show a simple strategy that uses high-option-illiquidity stocks and yields 16.5% in risk-adjusted returns per year.

JEL Classification: G14; G12; G24.

Keywords: Market microstructure; Options; Liquidity; Market making.

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1 Introduction

The market microstructure literature has extensively studied the costs of market making in equity markets. It is well established that bid–ask spreads in the stock market increase with dealers' inventory risk (Amihud and Mendelson (1980), Ho and Stoll (1983), and Stoll (1989) and asymmetric information costs (Copeland and Galai (1983), Glosten and Milgrom (1985), and Easley and O'Hara (1987)). Besides understanding the market structure of traded securities, explaining economic sources behind illiquidity, which is conventionally measured by bid-ask spreads, has been the focus of a large body of research. The consensus is that illiquidity affects asset prices.[1]

Recent equity options market literature documents the impact of market frictions and trading costs on equity option prices. Bollen and Whaley (2004) find that option-induced order imbalances exert an impact on option-implied volatilities, suggesting that market makers are not able to absorb all order flows without moving prices. Garleanu, Pedersen and Poteshman (2009) argue that end-users' net demand pressures significantly affect option prices. Finally, Christoffersen et al. (2015) document the presence of illiquidity premium in individual equity option returns. Therefore, similar to the equity market, transaction costs in the options markets affect asset valuations.

This evidence demands closer examinations of the options market's illiquidity. While option bid-ask spreads reflect dealers' total costs for providing liquidity, little is known about the determinants affecting their dynamics. Further, because options illiquidity affects option valuations, it should have implications for pricing the underlying assets since the valuations of both securities are related. The implication of options illiquidity for the underlying return is particularly important because of increasing evidence that informed trading occurs in the options market.[2]

Unlike previous studies, we use a comprehensive data set of intraday option trades to empirically validate the economic significance of the determinants that have been theoretically argued to affect options illiquidity. We use the direct measure of options illiquidity, which is the relative (quoted as well as effective) bid-ask spreads obtained from intraday transactions.

All option exchanges must report their intraday trades for each option series via the Options Price Reporting Authority (OPRA). We obtain intraday option transaction-level data from LiveVol, a commercial data vendor who processes the OPRA data. This includes the

[1] To name a few, studies of illiquidity premia in the equity market include Amihud and Mendelson (1989), Eleswarapu and Reinganum (1993), Brennan and Subrahmanyam (1996), Amihud (2002), Jones (2002), Pastor and Stambaugh (2003), and Acharya and Pedersen (2005). Bond market studies include Warga (1992), Boudoukh and Whitelaw (1993), Kamara (1994), Krishnamurthy (2002), Longstaff (2004), Goldreich, Hanke, and Nath (2005), Bao, Pan, and Wang (2011), and Beber, Brandt, and Kavajecz (2009). The more extensive literature is surveyed in Amihud, Mendelson, and Pedersen (2012).

[2] For examples, see Easley, O'Hara and Srinivas (1998), and Pan and Poteshman (2006).

national best bid and offer (NBBO) quotes at the time of the trade, the execution price, and the trading volume. LiveVol data begins in January 2004, and therefore our sample period is from 2004 to 2013. The sample consists of 2,504 trading days. Our empirical analysis focuses on contracts written on firms that make up the S&P 500 index. This sample represents the most liquid and tradable option series in the equity options market. Overall, over 629 million option trades are used in our analyses.

Examining the determinants of options illiquidity, we find that market makers' cost of establishing initial delta-hedged positions for their contracts significantly widens option bid-ask spreads. Further, as shown by Leland (1985), maintaining the initial-hedged position is risky due to market frictions and because market makers must continually rebalance their positions. We empirically confirm Leland's (1985) theory that rebalancing costs significantly widen option bid-ask spreads. In fact, the economic significance of the rebalancing cost dominates the initial delta-hedging cost by about fourfold.

The existing literature has largely ignored or underestimated the effect of rebalancing costs on options bid-ask spreads. We believe the difference between our finding and those by previous studies is due to the inclusion of the recent 2009-2013 period, which we are among the first to empirically examine. Importantly, the options market over this sub-period has become more competitive and more liquid as measured by lower bid-ask spreads, lower effective-to-quoted spreads ratios, and higher trading volume.

We also find that options illiquidity significantly increases with the magnitude of option-induced order imbalance, which is used as a proxy for inventory-risk. The other important factor affecting options illiquidity is adverse selection cost, which increases with the amount of private-information-driven trading in the underlying security. We measure adverse selection cost facing option dealers using the probability of informed trading measure, PIN, introduced by Easley, Hvidkjaer and O'Hara (2002).

Our next set of empirical analyses focus on the economic role of options illiquidity in reflecting informed trading. First, we examine how option market makers revise their quotes in response to events that are well-known associates of significant information asymmetry. Motivated by Kim and Verrecchia (1994), we test the prediction that higher option trading volume on earnings announcement dates is accompanied by aggressive widening of option bid-ask spreads because dealers demand compensation for providing liquidity when they run the risk of trading against informed investors. Consistent with their theory, we find that higher abnormal option trading volume around earnings announcements is accompanied by a jump in option bid-ask spreads, often economically large one day before the earnings announcement. This finding holds for both positive and negative earnings surprises. Overall, options illiquidity and trading volume simultaneously spike when information-based trading in the options market significantly intensifies.

Second, we examine the implication of options illiquidity as a measure of informed trading activity. The market microstructure theories argue that dealers should widen their bid-ask quotes after observing an abnormal order flow (i.e., order imbalance) to compensate for the risk of providing liquidity to informed traders (see e.g., Glosten and Milgrom (1985)). However, as shown by Muravyev (2015), abnormal order flows calculated from option trades do not always signal the presence of informed trading. In particular, he finds that variations in options' order flows are due to inventory shocks and private information, but importantly, the former effect often dominates. Therefore, we expect option spreads to widen more quickly when abnormal order flows are motivated by informed option trades, and these order flows contain information about their underlying returns.

To test the above prediction, we calculate abnormal order flow induced by option trades using the option-induced order-imbalance (OOI) measure of Hu (2014), which has been shown to positively predict the underlying's next-day return. We verify the predictability of the OOI measure in our sample. Using the regression framework, we find the OOI measure positively and significantly predicts stock returns the next day. However, its predictive ability disappears when we add the cross-interaction term between the OOI measure and change in options illiquidity. In this case, the cross-interacted term becomes the leading variable that predicts the next-day return. Thus, higher OOI, associated with excess of synthetic long positions on the underlying, positively predicts stock returns when accompanied by increasing options illiquidity. Similarly, lower OOI, associated with excess of synthetic short positions on the underlying, negatively predicts stock returns when accompanied by increasing options illiquidity. These finding suggest that options' order flows predict their underlying returns only when the imbalance is driven by informed option trading as signaled by increasing options illiquidity. Therefore, shocks to options illiquidity help identify option-induced imbalances that are driven by private information from those that are liquidity-demand driven such as inventory shocks (Muravyev (2015)) and investors' disagreements (Choy and Wei (2012)).

We find that a daily long-short equity strategy that buys high-OOI stocks and sell low-OOI stocks from 2004–2013 earns a risk-adjusted return of 10% per year. However, the same strategy earns up to 16.35% per year if we focus only on a subset of stocks with aggressively widening option bid-ask spreads. The economic benefit of using options illiquidity to identify abnormal order flow containing private information improves over the recent period when the options market became more competitive, 2009–2013, for which the strategy generates an annualized alpha of 18.7%.[3]

The profits from the high-minus-low OOI strategy disappear on the second day after the

[3]An important regulatory change affecting the options market is the Penny Pilot project which were implemented in three phases beginning in 2007. The Penny Pilot project specifies that quoted tick size of certain option series reduces from five-cent to one-cent increments.

portfolio formation if we do not focus on stocks experiencing a significant increase in options illiquidity. This finding suggests that the predictive ability of option-induced order flow is transitory. However, we find a significant portfolio alpha of 6.3% per year when trades are executed on the second day after the portfolio formation for the strategy that focuses on high-options-illiquidity stocks. Overall, our portfolio-trading results show a sizable economic benefit of using changes in options illiquidity to identify option trades that are likely to contain private information.

The rest of the paper is organized as follows. Section 2 reviews literature and outlines our hypotheses. Section 3 describes the data and variable constructions. Section 4 reports results for the determinants of options illiquidity. Section 5 focuses on private information captured by options illiquidity and its implications for stock returns. Section 6 concludes.

2 Empirical predictions and related literature

The empirical literature on options illiquidity is relatively scarce due to the limited availability of comprehensive intraday transaction data necessary for a thorough analysis. This section identifies the main economic determinants affecting option trading costs and develops hypotheses for their empirical tests. Afterwards, we examine the implication of options illiquidity for their underlying stock returns.

2.1 Determinants of options illiquidity

In the Black-Scholes world, market frictions and execution costs associated with option trading are irrelevant since one can perfectly hedge option contracts with shares of the underlying asset. However, in the real world, a perfect hedge is not possible due to model risks (Cetin et al. (2006), Figlewski (1989)), as well as investors' inability to hedge continuously (Jameson and Wilhelm (1992)). Besides hedging costs, the costs associated with inventory risk (Muravyev (2015)), and information asymmetry between option dealers and informed investors (Easley et al. (1998)) have been recognized in the literature. As a result, we focus on three fundamental forces as potential determinants of options illiquidity: hedging cost, inventory risk, and private information.

2.1.1 Hedging

The option hedging literature is far from conclusive. Existing studies have largely focused on two hedging costs faced by option market makers. The first is the fixed cost of establishing the initial delta-hedged position (Cho and Engle (1999), and Kaul, Nimalendran and Zhang (2004)). The initial delta-hedged position, however, does not immunize market makers against future price changes in the underlying asset. Therefore, in order to keep their positions delta-neutral, market makers must continually rebalance them using the underlying security. This is referred to as the rebalancing cost (Leland (1985) and Engle and Neri (2010)). While the literature generally agrees that the initial delta-hedging cost substantially determines option bid-ask spreads, empirical evidence for the rebalancing cost is less conclusive.

George and Longstaff (1993) find that substantial variations in option bid-ask spreads can be attributed to the premiums for the risk of holding uncovered option positions, suggesting that options dealers cannot hedge completely. Jameson and Wilhelm (1992) show that bid-ask spreads of options increase with their delta and gamma, reflecting the initial hedging costs and the future rebalancing costs, respectively. In a similar vein, Cho and Engle (1999) and Engle and Neri (2010) find that hedging and rebalancing costs are the only important determinants of equity options spreads. On the other hand, De Fontnouvelle et al. (2003), and Kaul et al. (2004) do not find a strong relationship between options' effective spreads and their proxies for rebalancing cost. Chan et al. (2002) also argue that rebalancing cost should be relatively small.

Contrary to our paper, the aforementioned studies either focus on S&P 100 index options or on a few equity options covering short time spans.[4] Importantly, they do not examine equity options' bid-ask spread dynamics after 2002 when option exchanges became integrated.[5] Our paper contributes by providing comprehensive analyses of hedging costs in relation to options illiquidity for the modern-day options market.

Leland (1985) theoretically derives the rebalancing cost for replicating an option contract in the presence of transactions costs and shows that it is proportional to the product of option vega and bid-ask spread of the underlying security. Therefore, when quoting an option contract, market makers should account not only for the initial hedging cost, but also for the future rebalancing cost of their initial-hedged position. Thus, our first empirical prediction is as follows.

H 1 (Rebalancing cost) *If option dealers demand compensation for rebalancing their initially hedged position, then rebalancing cost (Leland (1985)) should positively affect option bid-ask spreads.*

The economic significance of rebalancing cost versus initial delta hedging cost is an empirical question that we also examine.

[4]De Fontnouvelle et al. (2003) use two month of data, August and September of 1999 for options on 28 stocks, and Kaul et al. (2004) use one month of data for February 1995 and only CBOE-listed options.

[5]In 2003, all option exchanges were linked via Linkage, and the National Best Bid and Offer (NBBO) rule was introduced.

2.1.2 Inventory

The market microstructure literature suggests that bid-ask spreads of a security should increase with its inventory risk (Amihud and Mendelson (1980), and Ho and Stoll (1981)). We empirically test whether this effect holds in the equity options market.

Muravyev (2015) advocates a significant inventory risk in the options market as measured by dealers' order imbalances and documents their effects on options returns. Bollen and Whaley (2004) find that order imbalances have a significant impact on option-implied volatilities because of liquidity providers' inability to costlessly absorb larger positions.

Garleanu et al. (2009) applied the inventory risk models (e.g., Ho and Stoll (1983), and Grossman and Miller (1988)) to the options market and show that end-user demand pressures contemporaneously affect options prices. Their main empirical prediction is that a net demand shock in option contracts increases option prices by an amount proportional to the variance of an unhedged part of the option. In other words, a net demand shock should have an additive effect on bid-ask spreads after accounting for hedging costs. We test this empirical prediction next.

H 2 (Inventory) *Options bid-ask spreads should increase with the magnitude of option-induced order imbalances (positive or negative).*

We calculate option-induced order imbalances (OOI) measure following Hu (2014), and use it as the proxy for an inventory shock.

2.1.3 Private information

The information asymmetry literature shows that security dealers widen bid-ask spreads to compensate for the risk of providing liquidity to investors with private information, i.e., adverse selection cost (Glosten and Milgrom (1985)). We test this empirical prediction in the options market.

H 3 (Private information) *Option bid-ask spreads should increase with the measure of adverse selection.*

We estimate the degree of private information in the underlying stock with the probability of informed trading measure, PIN, introduced by Easley, Hvidkjaer and O'Hara (2002). A higher level of PIN in the underlying stock should reflect a higher adverse selection cost for option dealers, and thus a wider bid-ask spread.[6]

[6] Option-induced order imbalance, arguably, proxies for inventory risk, as well as adverse selection concern to options dealers. Muravyev (2015) argues that in the daily data, option-induced order imbalances mainly capture inventory risks with economically insignificant adverse selection components. On the other hand, Hu (2014) advocates in favor of private information as the driver of option-induced order imbalance. We examine when changes in option-induced order imbalance are likely to reflect private information in Hypothesis 5.

2.2 Options illiquidity and Informed Trading

As liquidity providers, option market makers revise their quotes in response to trades initiated by informed and uninformed traders. However, when the market is dominated by informed traders, adverse selection arises as the primary concern of option dealers thereby pressuring them to widen their quotes more aggressively (Glosten and Milgrom (1985)). As a result, large positive changes to option bid-ask spreads may signal the arrival of informed trading activities. We develop two hypotheses examining to what extent options illiquidity reflects the level of informed trading and contribute to the debate on the presence, as well as the impact of informed trading in the options market.

Black (1975) argues that informed investors are attracted to the options market because they can gain higher leverage. However, empirical evidence of informed trading in the options market is quite mixed. Vijh (1990) finds that trading in options is largely driven by differences of opinion rather than private information. Cho and Engle (1999) fail to find any link between options bid-ask spreads and trading volume, therefore, concluding in favor of the differences of opinion hypothesis. More recently, Muravyev, Pearson and Broussard (2013) find no economically significant price discovery in the options market.

In contrast, using a different methodology, Chakravarty, Gulen and Mayhew (2004) find that the options market significantly contributes to price discovery. Easley, O'Hara and Srinivas (1998) develop an asymmetric information model under which informed traders choose to trade in both the options and stock markets. The authors test their empirical prediction and show that signed options volume can predict stock returns.

The existing studies also differ in how to empirically identify trades that originated from informed option traders. Several studies advocate the use of metrics derived from directional option trading volume (e.g, Bollen and Whaley (2004), and Pan and Poteshman (2006)). However, Chan, Chung and Fong (2002) argue that information in the options market is reflected mostly via quote revisions rather than changes in volume.

2.2.1 Options illiquidity around information events

The existing literature argues that the benefits of trading in options are highest around corporate events when the value of private information is the largest.[7] Therefore, we apply the event-study methodology to examine how option bid-ask spreads change during the period when we are most likely to observe informed option trades. Our proxy for the information event is the date of the earnings announcement. Kim and Verrecchia (1994) argue that financial accounting disclosures such as earnings announcements induce higher information asymmetry

[7]See Cao, Chen, and Griffin (2005), Augustin, Brenner and Subrahmanyam (2014) for evidence of informed option trading ahead of mergers and acquisitions. Similarly, evidence of informed option trading in the IPO aftermarket is documented in Chemmanur, Ornthanalai, and Kadiyala (2015).

because they facilitate informed judgments. Their model predicts that on earnings releases dates, asset illiquidity should increase, i.e., wider bid-ask spreads, while trading volume rises sharply as well. This prediction starkly differs from inventory-risk models (see e.g., Amihud and Mendelson (1980), and Ho and Stoll (1983)), which argue that option trading volume and option spreads are negatively correlated.

Our event-study approach is similar to Amin and Lee (1997), who empirically examined option trading around earnings announcements. They find higher volume around earnings releases, but they also find economically insignificant increases in option bid-ask spreads which are inconsistent with the informed trading hypothesis. Choy and Wei (2012) argue against informed trading around earnings announcements and advocate that speculative trading and differences of opinion drive an increase in trading volume. The authors, however, do not analyze options bid-ask spreads. Motivated by Kim and Verrecchia (1994), our next empirical prediction is:

H 4 (Information events) *Around earnings announcements, higher trading volume is associated with a higher participation rate by informed traders and thus should be met by higher options bid-ask spreads.*

2.2.2 Implication for stock returns

If informed investors trade in the options market, their trades would reveal the direction of information and subsequent return pattern of the underlying stock. For example, buying a call or selling a put indicates a synthetic long position in the underlying and tends to convey positive information about future stock prices. Alternatively, selling a call or buying a put may signal negative information. Motivated by this intuition, there exists a growing literature that uses directional (i.e., "signed") option trades to infer future information about the underlying security.[8]

Using signed option trades, Bollen and Whaley (2004) show that the net option-buying pressure, defined as the difference between buy-initiated and sell-initiated option trades, has a contemporaneous price impact on the shape of option-implied volatility curve. Hu (2014) derives a slight variation of Bollen and Whaley's (2004) measure referred to as the option-induced order imbalance (OOI) and shows that it positively predicts stock returns the next day.[9] Hu (2014) argues that positive (negative) OOI reflects synthetic net buying (selling)

[8]Such studies include Easley, O'Hara and Srinivas (1998), Pan and Poteshman (2006), and Ge, Lin and Pearson (2015).

[9]Bollen and Whaley (2004) scale their daily option-induced demand pressure by the option trading volume, while Hu (2014) scales it by the number of shares outstanding of the underlying stock. In both studies, each option trade is weighted by the absolute value of its options delta to express demand in stock equivalent units.

pressure and thus positive (negative) private information, which explain the predictive ability of OOI for stock returns.

However, as argued by Chan, Chung and Fon (2002) and Muravyev (2015), the net demand pressure calculated using signed option trades (e.g., OOI) is an imperfect measure of informed-trading activity in the options market. Chan, Chung and Fong (2002) find support for the return predictability using option bid-ask quote revisions, but not with signed option volume. They argue that information in the options market is reflected mostly via quote revisions rather than changes in volume because informed investors often trade with limit orders due to high option trading costs. As a result, option bid-ask quotes rather than option trades reflect the extent of private information. Relatedly, Muravyev (2015) shows that option-induced demand pressure reflects the aggregate net demand of both informed and liquidity-driven trades, but importantly, the liquidity-driven component dominates with the information-driven component being economically insignificant.

This debate raises an important question as to why prior studies find that option-induced demand pressure (e.g., OOI) positively predicts the underlying stock returns. We argue that the return predictability due to option-induced demand pressures manifests when trading in the options market is predominantly motivated by private information, which can be identified using shocks to option bid-ask spreads (Chan, Chung and Fong (2002)). This occurs because as market makers suspect informed trading, they aggressively widen their securities' bid-ask spreads. Therefore, we expect changes in options illiquidity to proxy for the extent of private information embedded in current option trades, regardless of whether the signal is positive or negative.[10]

Following the argument above, we hypothesize that the positive relationship between option-induced demand pressure, OOI, and future stock returns emerges when option bid-ask spreads simultaneously and significantly widen, indicating that option trades during this period are dominated by private information. On the other hand, when changes to option bid-ask spreads are relatively small, the OOI measure should have little to no predictive power for the underlying stock returns because option trades during this period are mostly motivated by either disagreement or liquidity-driven demand. We summarize the empirical predictions of the last hypothesis below:

H 5 (Impact on stock returns) *Higher (lower) option-induced order imbalances accompanied by increasing options illiquidity identify informed trading on positive (negative) information and predict positive (negative) stock returns. Alternatively, higher (lower) option-induced*

[10]Roll, Schwartz and Subrahmanyam (2010) study the price impact of information content in option volume. Here, they use absolute stock return as the dependent variable because they do not have directional information on the option trading volume. Similar to them, we cannot "sign" option bid-ask spreads. We verify the absolute-return predictability using changes in options illiquidity in the appendix Table B1.

order imbalances accompanied by relatively lower options illiquidity identify disagreement or liquidity-demand-driven trades and have no information about future stock returns.

3 Data and variable constructions

3.1 Data and sample selection

The data used in this study are drawn from several sources. We obtain intraday option transactions data from LiveVol, intraday stock transactions from the NYSE's TAQ database, and daily stock return and volume data from CRSP.

Our sample covers exchange-listed option contracts written on firms that are included in the S&P 500 index from January 2004 to December 2013. There are a total of 2,504 trading days. The time period corresponds to the coverage of the available LiveVol data. The monthly history of the S&P 500 index constituents is drawn from COMPUSTAT. In any given month, we consider all firms that constitute the S&P 500 index, and keep all firm-day observations that also appear in the CRSP daily stock file.

Our main data source is the intraday option transactions data obtained from LiveVol. Similar to the NYSE TAQ database, the LiveVol data contains trades and quotes on each option series, which is uniquely identified by its underlying stock, option type (call or put), expiration date, and strike price. LiveVol provides national best bid and offer (NBBO) quotes associated with each transaction. Other intraday transaction-level information includes trade price and trade size (number of contracts) for each option series. We apply a list of filters to this data set. First, we focus on option series, whose daily closing mid-quote is at least 10 cents, and the quoted spread does not exceed 50% of the transacted price. Second, we remove trades that were canceled or recorded outside the regular trading hours (9:30 a.m. – 4:00 p.m. EST). Next, we retain option trades that meet all the following conditions: (1) trade price $\geq$ intrinsic value; (2) trade size > 0; (3) prevailing best quotes satisfy $0 <$ bid $<$ ask $< 5 \times$ bid; (4) trade price $\leq 2 \times$ mid–quote. After these filters, 626,348,046 out of the 678,159,426 raw trade transactions, or 92.4% of the raw data, remain.

In January 2007, major option exchanges such as CBOE and ISE initiated the Penny Pilot project. The exchange rules stipulate that for a participating underlying stock, any associated option series should be quoted in increments of 1¢ if below \$3.00 and in increments of 5¢ otherwise.[11] Whereas options written on a non-participating underlying stock should be quoted in increments of 5¢ if below \$3.00 and in increments of 10¢ otherwise. Therefore, we place an additional filter by checking whether option bid and ask quotes conform to this rule. After this additional screening, 626,298,280 trades remain.

[11] See CBOE Rule 6.42.

We obtain intraday trades and quotes on the underlying stocks from the NYSE TAQ database. In order to obtain bid and ask quotes associated with each stock trade, we merge the consolidated trade files with the NBBO data. We require that each trade recorded during the regular trading hours (9:30 a.m. – 4:00 p.m. EST) is matched with the prevailing NBBO quotes at least one second before the trade's timestamp. Next, we purge the merged intraday stock data by deleting records that are reported out-of-sequence or with special settlement conditions (condition code= Z, O, L, G, W). Finally, we place the following standard filters on the trade records: (1) $\$0.01 \leq \text{bid} < \text{ask}$; (2) $\text{ask} - \text{bid} \leq \$3.00$; and (3) $\$0.01 \leq \text{trade price} < 1.5 \times \text{mid-quote}$.

Using intraday LiveVol and TAQ data, we compute option-implied volatilities and option sensitivities, i.e., Greeks, which we use to measure hedging-related costs faced by option market makers. First, we match each time-stamped option trade with its underlying stock's prevailing NBBO quotes recorded in the TAQ database at least one second before. The option price and the underlying stock price used in the calculation are based on the option trade recorded in LiveVol and its underlying stock's prevailing mid quote from TAQ, respectively.

Second, we employ a binomial-tree option-pricing model and solve for the implied volatility of each option trade. To account for the effect of stock dividends, we use the dividend schedule of each underlying firm obtained from OptionMetrics.[12] Next, for each option transaction, we calculate option delta, gamma and vega based on the implied volatility obtained previously. Finally, for each option series, we aggregate the transaction-level implied volatility, delta, gamma, and vega at the daily level by calculating volume-weighted (number of contracts) averages of their respective intraday values.

On a given day, the number of option series on an underlying stock can be quite large. Therefore, we group options written on the same underlying stock into subsets indexed by option type, i.e., call vs. put, with our main tests focused on options with short-to-medium maturities defined as those with 30-182 calendar days to expiration. Options with extreme moneyness are deleted. We define moneyness as in Bollen and Whaley (2004), using options' average delta on day t and retaining calls with $1/8 < \text{delta} \leq 7/8$, and puts with $-7/8 < \text{delta} \leq -1/8$. The final sample size is 260,583,909 trades. For future reference, we define a unique firm-option-type combination as an *option class*.

[12]For details on the numerical procedure for computing the implied volatility of an American option, see Hull (2011) Ch.20.

3.2 Variable constructions

Options and stock illiquidity

We measure illiquidity in the options market using relative bid-ask spreads at the time of option trades. For each option transaction, we calculate two measures of relative bid-ask spreads: *relative effective spreads* and *relative quoted spreads*. The relative effective spread is defined as twice the absolute difference between the trade price and the mid-point of the prevailing NBBO quotes, divided by this mid-quote. The *relative quoted spread* is the quoted bid-ask spread divided by the mid-point of the prevailing NBBO quotes.

Because our main empirical analyses rely on cross-sectional regressions at the daily level, we construct options illiquidity measures (ILO) on a daily basis. For a given option class, we compute daily ILO as the dollar-volume-weighted average of the relative option effective (or quoted) spreads. Thus, the contribution to ILO from each option trade in the option class is proportional to its dollar trade amount. We use two measures of options illiquidity, ILO, throughout this paper: one calculated using effective spreads, and the other calculated using quoted spreads.

In addition to the options illiquidity measure, we compute $OptVolume$ as the total number of contracts traded in the option class during the day.

We measure stock illiquidity (ILS) using stock relative effective bid–ask spreads. The daily relative effective spread is calculated as the dollar-volume-weighted average of relative effective spreads of the underlying stock intraday trades.

Option trade imbalance

For each recorded option transaction, we classify its trade direction following the Lee and Ready (1991) algorithm. Trade records are first subject to the 'quote test' – assigned as buyer-initiated if it is executed above the mid-quote, and as seller-initiated if it is below the mid-quote. For trades where the 'quote test' is not applicable or inconclusive due to missing quotes or the trade price being equal to the mid-quote, we conduct the 'tick test' by looking back at the previously recorded trades.

In order to account for the size in each trade direction, we multiply each buyer-initiated (or seller-initiated) trade amount by its option delta to express it in the underlying stock equivalent units (see also Bollen and Whaley (2004)). We then aggregate buyer-initiated trades and seller-initiated trades at the daily level.

For each day, we calculate net option-induced demand pressure for each underlying stock as the difference between daily aggregate buyer-initiated and aggregate seller-initiated trades. We follow Hu (2014) and normalize daily option-induced demand pressure of each underlying stock by the number of shares outstanding and refer to it as the option-induced order imbalance, *OOI*. The *OOI* measure is calculated daily for each stock in our sample.

Option hedging costs

For a given option class on day t, we calculate two hedging cost variables. The first is the cost associated with initial hedging, i.e., a delta-hedged position. An option delta is the first partial derivative of option price with respect to the price of its underlying. It indicates the amount of shares in the underlying stock that the option writer must buy or sell in order to immunize the position against a small change in the price of the underlying. Similar to Cho and Engle (1999), among others, we measure delta-hedging cost using percentage delta, $\%DELTA$, which is defined as

$$\%DELTA \equiv \left|\frac{\partial C}{\partial S}\right| \frac{S}{C} = |\Delta| \frac{S}{C}, \tag{1}$$

where Δ is the daily volume-weighted average option delta, S is the closing price of the underlying, and C is the daily volume-weighted average option price. We use the percentage delta, rather than the raw delta, to have its magnitude economically comparable across different option price levels. A call option delta is always positive while a put option delta is always negative. We therefore apply the absolute sign in equation (1) in order to capture the magnitude. We can interpret $\%DELTA$ as the absolute option price elasticity with respect to the underlying stock price.

A delta-hedged option position provides immunity against changes in its value temporarily. Immunization against further changes in value requires continuous rebalancing of the hedged portfolio. Leland (1985) shows that the costs associated with continuous rebalancing could be very high, and depend on the option contract's sensitivity to changes in volatility, as well as the liquidity of the underlying. Specifically, Leland (1985) shows that the cost of future rebalancing of the initially hedged option position in dollar terms is proportional to $v \cdot ILS$, where $v \equiv \partial C/\partial \sigma$ is the option vega, and ILS is the underlying stock illiquidity.[13]

In order to apply the rebalancing cost to cross-sectional tests, we scale the dollar rebalancing cost by the volume-weighted average option price. This procedure allows us to measure rebalancing costs in percentage units ($\%RBC$) of the traded dollar amount, and makes it comparable to the percentage delta variable described previously. For our empirical analyses,

[13]Note that the rebalancing cost defined using option vega, v, is related to the cost of gamma hedging an option position. This is because option gamma, Γ, and vega, v, are related by the relationship $v = \Gamma S^2 \sigma^2 T$, where S is the underlying price, σ is the implied volatility, and T is the time-to-maturity of the option contract.

we calculate the rebalancing cost for each option class each day, which we define as

$$\%RBC = \frac{v}{C} ILS, \tag{2}$$

where v is the daily volume-weighted average option vega.

PIN

We use the intraday stock data to calculate the probability of the information-based trading (PIN) measure developed by Easley, Kiefer, O'Hara, and Paperman (1996). We first aggregate the number of market buy and sell orders on each day by using the Lee and Ready (1991) algorithm to determine the trade direction for each stock trade. The resulting daily buy and sell order counts are then used to estimate the probability of information-based trading (PIN). We explain the details of the PIN model and its estimation procedure in Appendix A.

4 Determinants of Options Illiquidity

4.1 Sample descriptive statistics

Table 1 presents summary statistics of options illiquidity and trading activity variables. Panel A reports the time-series averages of the cross-sectional distribution of relative effective and quoted spreads and other key variables for calls and puts. Effective spreads (ILOE), on average, are wider for a representative call (6.5%) compared to a representative put (5.8%). Consistent with trades taking place inside the quotes, quoted spreads (ILOQ) are higher (8% and 7.2% for call and put options, respectively). On average, ILOE and ILOQ are slightly higher for calls compared to puts. The average trading volume (number of option contracts) and number of trades per day for calls significantly exceed those for puts. For example, the average daily call volume is 2,208 contracts, and the put volume is 1,546 contracts, a difference of approximately 30%. Overall, call options are more actively traded.

Figure 1 plots daily cross-sectional averages of options illiquidity calculated using effective spreads (ILOE) and quoted spreads (ILOQ). For comparison, we also plot daily cross-sectional averages of illiquidity measure of the underlying stocks in the bottom panel. Overall, we observe a gradual improvement in options liquidity, especially for effective spreads, from the start to the end of our sample with a common spike during 2008–2009 crisis. The illiquidity of the underlying stocks, on the other hand, remains fairly stable through our sample period outside the 2008–2009 crisis.

In order to compare the time-series dynamics of option-effective versus quoted spreads, we plot the daily aggregate effective-to-quoted spread ratio in the top panels of Figure 2.

We define effective-to-quoted ratio as the ratio of option effective spreads to option quoted spreads. The ratio below one would suggest that option trades, on average, are executed within the quoted bid-ask spreads. The top-left and top-right panels of Figure 2 represent the daily volume-weighted averages across firms for calls and puts, respectively. In the beginning of our sample, this ratio is approximately one for both calls and puts, suggesting that almost all transactions occur at the quoted spreads. However, by the end of our sample this ratio decreases to below 0.8. This finding suggests that increasing competition among market makers forces them to trade at more competitive prices.

Alternatively, the quality of trades' execution can be observed by looking at the fraction of trades executed within the quoted spreads. Any trades executed outside the quoted bid-ask spreads can be considered non-competitive, perhaps due to inability of liquidity providers to absorb excess demands. The bottom panels of Figure 2 plot daily fractions of option trades that are executed within the quoted spreads for puts and calls. The results show that the fraction of trades that occur within quoted spreads gradually increases towards the end of the sample, yet remained below 80%. Overall, we find that the quality of trading in the options market gradually improves through our sample.

We compute daily cross-sectional average option volume, measured as the number of contracts for each option type on each day. Figure 3 plots its time-series dynamic. As we move towards the end of the sample, trading volume increases significantly. One of the highest spikes in volume is observed in the second half of 2008 after the Lehman Brothers' collapse. Overall, we observe higher trading volume for both calls and puts in the second half of the sample, 2009-2013. For the remaining analyses, we use the natural log transformation of *OptVolume*.

Panel B of Table 1 reports summary statistics for stock illiquidity averaged across firms in the S&P 500 index. The average effective spread is 8 basis points. The maximum of 1.36% is reached during the 2008 financial crisis (see the bottom panel of Figure 1).

Table 2 reports time-series averages of the cross-sectional pairwise correlations for the main variables. ILOE and ILOQ are highly positively though not perfectly correlated with the magnitude of 0.88 for calls and 0.85 for puts. Although ILOQ is indicative of the bid and ask prices at which dealers are willing to trade, it is not always binding. In fact, certain trades do occur outside the bid-ask quotes. We therefore include both ILOE and ILOQ in our analyses throughout the paper for completeness.

Focusing on options illiquidity calculated using effective spreads, ILOE, we find that it is positively and significantly correlated with the two hedging cost variables $\%DHC$ and $\%RBC$. For call (put) options, their correlations reach 0.30 (0.29) and 0.47 (0.41), respectively. Option-induced order imbalance, OOI, has very little to no correlation with ILOE. The stock illiquidity measure, ILS, significantly correlates with ILOE, although the magnitude is small, ranging between 0.13 for puts and 0.16 for calls. The low correlation between ILOE and ILS suggests that the options illiquidity is not largely driven by the underlying stock illiquidity. Table 2 also shows that *OptVolume* is negatively and significantly correlated with ILOE. This is expected since higher trading volume leads to lower order processing costs for dealers, and thus lower bid-ask spreads. We find that PIN has a positive and significant correlation with ILOE of 0.13 for both calls and puts, suggestive of informed trading being an important concern facing option dealers.

As expected, we find the correlations between ILOQ and various variables in Table 2 carry the same sign and are comparable to those calculated for ILOE. This finding suggests that factors influencing quoted and effective bid-ask spreads in the options market are fairly similar.

4.2 Hedging costs, Inventory and Private Information

We run the Fama-Macbeth regressions for 1,134,312 firm-day observations for each of the two option types: calls and puts. Table 3 reports regression results. The dependent variable in Panel A is options illiquidity calculated using quoted spreads (ILOQ), while for Panel B, the dependent variable is options illiquidity calculated using effective spreads (ILOE). Our main variables of interest are $\%DHC$, which captures the initial hedging cost; $\%RBC$, which is the measure of future rebalancing cost (Leland (1985)); $|OOI|$, which is the absolute value of option-induced order imbalance and captures inventory shocks, either positive or negative, to option dealers (Chordia, Roll and Subrahmanyam (2002)); and PIN, which measures the level of private information on the underlying stock.

Among other control variables, we include lagged options spreads, ILO(t-1), to account for persistence in options illiquidity, and *OptVolume* to control for cross-sectional differences of option trading activity. We also control for trading activity in the underlying market by including stock return, lagged stock return, and 5-day moving average absolute stock return, $MA5|RET|$. The latter controls for the volatility of the underlying stock.

First, consider call options and ILOQ, Panel A. Here, $\%DHC$, $\%RBC$, $|OOI|$ and PIN have positive and significant impact on quoted spreads. Combining the coefficients in Panel A with the standard deviations of these variables reported in Table 1, suggests that one standard deviation shock to $\%DHC$ results in 0.9% increase in ILOQ, and a similar shock to $\%RBC$ leads to a 3.7% increase in ILOQ, i.e., more than four times the magnitude of initial delta hedge impact. Similar magnitudes are observed for puts, and for ILOE (see Panel B). Different from De Fontnouvelle et al. (2003) and Kaul et al. (2004), we find that rebalancing costs are not only statistically significant but their impact substantially exceeds those of delta-hedging. This new evidence highlights the role of rebalancing cost as one of the leading concerns for market makers in the modern U.S. equity options market. It also provides overwhelming support to our Hypothesis 1.

Further, after controlling for hedging costs, we observe a significant impact of both option-induced order imbalance and private information on options spreads. Here, a one standard deviation shock to $|OOI|$ and PIN leads to 0.57% and 0.32% increase in ILOQ, respectively. Although smaller but comparable to the initial delta-hedge in economic magnitudes, these variables add to bid-ask spreads variability after accounting for all hedging costs. Therefore, the hedging cost theories of Cho and Engle (1999), and Engle and Neri (2010) do not fully explain variations in options illiquidity as shown by the data. Further, our findings confirm that inventory shocks (Muravyev (2015)) as well as private information (Easley et al. (1998)) significantly contribute to the costs of market making. These results are consistent with Garleanu et al. (2009) net demand pressures effect on options prices, and also support our Hypotheses 2 and 3.

Among the control variables in Table 3, we find that returns of the underlying stocks affect put and call options differently. Call option bid-ask spreads decrease when their underlying stock prices increase, while put bid-ask spreads decrease when their underlying stock prices decrease. Interestingly, we find that options illiquidity is negatively related to its stock illiquidity. The coefficients on ILS are negative and significant across puts and calls. This finding suggests that investors use the options market as an alternative trading venue for the underlying stocks experiencing high illiquidity.

Table 4 presents predictive regressions results for changes in options illiquidity.[14] Comparing the results against the estimates in Table 3, we find the coefficients on hedging variables, and order imbalance flip signs from positive to negative. This finding suggests the impact of hedging costs and inventory risk on options illiquidity is transitory, and the negative coefficients that we observe are due to the mean-reverting characteristics of their variables. However, we find that coefficients on PIN remain positive and significant. In other words, asymmetric information appears to be a long-lasting concern for option dealers, forcing them to continue widening their bid-ask spreads.

Among other variables, we find that options volume is negative and significant. This too supports the information theory of Easley et al. (1996) that higher trading volume decreases information asymmetry. It is also consistent with order-processing costs hypothesis which predicts that transactions costs are lower when trading volume increases.

While the volatility of the underlying stock, MA5$|RET|$, has a positive and significant impact on options spreads in Table 3, this effect is reversed in Table 4. This finding is consistent with the mean-reverting nature of volatility; a high volatility period is followed by a decrease in volatility.

Table 4 shows that past returns predict options illiquidity differently for puts and calls. The coefficients on RET(t-1) and RET(t-2) are negative for call options, suggesting that call

[14]Similar to Chordia, Roll and Subrahmanyam (2002), in predictive regressions we use changes in illiquidity.

option liquidity improves when the underlying stock is performing well. On other other hand, for put options, the coefficients on RET(t-1) and RET(t-2) are positive suggesting that put option liquidity improves when the underlying stock price is falling. We conjecture that an increasing share price generates interest in the synthetic long position, i.e., buying call and selling puts, leading to higher end-user demand for call options, but lower end-user demand for put options. As a result, order-processing cost decreases for call options resulting in narrower bid-ask spreads, while for puts, we observe the opposite effect.

Notice that adjusted R^2 values in our Table 3 range between 45% and 55%, suggesting that a significant variation of option bid-ask spreads are explained by hedging, inventory, private information, and other controls we use. Overall, the rebalancing cost dominates all other variables in terms of economic magnitude on a day-to-day basis. This result suggests that a substantial portion of options illiquidity reflects the premium for the risk that options market makers must continually hedge their positions after they have initiated option contracts. We also conclude from Tables 3 and 4 that the effects of hedging costs and inventory risk on options illiquidity are short-lived, while for private information, it has a lasting impact.

In the next section we first directly test the private information hypothesis and then its application for stock returns.

5 Private information

5.1 The impact of information events

Kim and Verrecchia (1994) argue that market participants use their private informed judgements to process earnings announcements. This stimulates their willingness to engage in trading activity and exacerbates the information asymmetry between traders and market makers. As a result, during earnings news releases, the market becomes less liquid, i.e., wider bid–ask spreads, even though we observe significant increases in trading volumes.

Empirical evidence on the behavior of option bid-ask spreads around earnings announcements is rather limited. Amin and Lee (1997) examine option volume and bid-ask spread behavior for 1988–1989 sample for 141 firms and find significant abnormal volume preceding earnings announcements and on the announcement day, but no economically meaningful changes in option bid-ask spreads. Therefore, while their evidence on trading volume supports informed trading, their finding on bid-ask spread changes is not consistent with the Kim and Verrecchia's (1994) theory.

We use S&P 500 firms' earnings announcements with available options traded from January 2004 to December 2013. We obtain earnings announcement information from I/B/E/S unadjusted files. We define an event window as [–10,10], with date 0 as the event day.[15] We identify the pre-event window [–42,–21] relative to the announcement date. All variables of interest are reported in abnormal values by subtracting the estimate on day t with its corresponding average value computed over the pre-event window.

We classify earnings announcements as either a negative or a positive surprise based on cumulative abnormal returns (CAR) to the earnings announcement. We calculate CAR over the three-day window [–1,1] as:

$$CAR_j = \sum_{t=-1}^{+1} \left(R_{jt} - R_{mt}\right),$$

where R_{jt} is the raw return of stock j on day t, and R_{mt} is CRSP NYSE/AMEX/NASDAQ value-weighted index return on day t. We then use standardized cumulative abnormal return (SCAR), computed as $SCAR_j = CAR_j/\sqrt{3}\sigma_j,$, where the standard deviation σ_j of abnormal returns in the denominator is computed over the [–42,–10] pre-event window.

We quintile-sort stock price reactions to earnings announcements based on SCAR, with the fifth quintile identified as a positive earnings surprise and the first quintile identified as a negative earnings surprise.[16]

Figure 4 plots event-study results for abnormal option trading volume (left panels) and abnormal stock trading volume (right panels) around earnings announcements. We plot results separately for call options (solid line) and put options (dotted line). The top panel reports results averaged across all earnings announcements. The middle (bottom) panel reports results for positive (negative) earnings surprises, respectively.

Confirming the results reported in previous studies, we find that trading volume spikes several days before the earnings announcement date for options as well as for their underlying stocks. The highest abnormal trading volume is observed on the day of earnings releases. In term of magnitude, we find that changes in abnormal trading volume is much larger for stocks than for put and call options.

Figure 5 presents event-study results of abnormal option bid-ask spreads (both ILOQ and ILOE), as well as stock bid-ask spreads (ILS) around earnings announcements. For both call and put options, we find that on the event day 0, option spreads increase substantially. We also observe a large increase in spreads on the pre-event day -1, suggesting informed trading one day before an announcement. This pattern holds for both positive and negative earnings surprises, i.e., option bid-ask spreads widen regardless of whether the signal is positive or neg-

[15] If an earnings announcement takes place after trading hours, then the event date is the next trading day.

[16] As a robustness check, we verify our results are qualitatively similar when classifying earnings surprise using SUE (standardized unexpected earnings). SUE is defined as the difference between actual earnings per share (EPS) and consensus EPS forecast (median), normalized by the standard deviation of analyst forecasts.

ative. Looking at abnormal stock illiquidity, we find an economically small increase in stock bid-ask spreads on the days before and on earnings announcements. Therefore, despite observing a tremendous change in abnormal stock trading volume around earnings announcements (see Figure 4), stock bid-asks spreads to do no widen substantially.

Table 5 tabulates the economic and statistical significance of the results reported in Figure 1. Consider Panel A, which reports the results for all earnings announcements. Both quoted $ILOQ$ and effective spreads $ILOE$ significantly increase on the day of earnings announcements. In terms of economic magnitude, the increase in abnormal quoted bid-ask spreads ranges between 74 bps for call options to 81 bps for put options. These values indicate relative increases of approximately 11% and 14% for $ILOQ$ and $ILOE$, respectively, on the event day. Importantly, Table 5 shows that option bid-ask spreads significantly increases one day preceding the announcements. On the event day -1, the relative option quoted spreads increase by 22 bps for calls, and by 31 bps for puts, which translate to 3.4% and 5.3% incremental increases above the mean. This finding evidently supports the presence of informed trading in the options market in anticipation of announcement news. Looking at abnormal stock bid-ask spreads(ILS), Panel A of Table 5 shows that changes in stock bid-ask spreads are economically trivial relative to changes in option bid-ask spreads, confirming the results illustrated in Figure 5.

Panels B and C of Table 5 present results for positive and negative earnings surprises, respectively. On average, we find that relative option bid-ask spreads started increasing on the day before earnings announcements, with the highest level reached on the announcement date, except for calls. For positive earnings surprises (see Panel B), relative quoted spreads for calls are highest on the day before the event, i.e., event day -1, with the magnitude of 25 bps. The second highest value is realized on the announcement day, i.e., event day 0, with the magnitude of 17 bps. For put options, we find that the highest increase in $ILOQ$ and $ILOE$ is observed on the event day, with magnitudes of 101 bps and 90 bps, respectively. The substantially larger increase in put option spreads than call option spreads in Panel B is consistent with our finding in Table 3 that put bid-ask spreads are positively related to their underlying returns. On positive earnings announcement days, stock prices respond positively and strongly to the news. Given the evidence that, on average, investors are net-sellers of equity options (see e.g., Garleanu et al. (2009), and Christoffersen et al. (2015)), the higher abnormal put spreads in response to positive stock returns are consistent with increased selling activity of put options by investors to create synthetic-long positions on the underlying stocks.

Conversely, for negative earnings surprises (see Panel C), the highest increase in options illiquidity is observed for calls. Here, abnormal increases in relative quoted and effective spreads are 120 bps and 107 bps, respectively. This finding can be attributed to investors taking a synthetic short position in the underlying by increasingly selling calls, resulting in higher call bid-ask spreads. Interestingly, we observe abnormally high call spreads persisting up to 5 days after the announcement date.

Table 5 also reports results for abnormal effective spreads of underlying stocks, *ILS*, around earnings announcements. Similar to the options market, *ILS* increases on the announcement day, but the economic magnitude is trivial relative to changes in options bid-ask spreads.

Overall, we find an empirical support for Kim and Verrecchia's (1994) theory in the options market, which supports the empirical prediction of our Hypothesis 4. By looking at changes in options illiquidity, we find evidence of informed trading in the options market before and on earnings announcement dates.

5.2 Options Illiquidity and Stock Returns

This section examines the implications of options illiquidity for their underlying returns, which addresses Hypothesis 5 of the paper.

Existing studies find that option-induced demand pressure, e.g., Hu's (2014) OOI, by capturing private information positively predicts the underlying stock returns. However, Muravyev (2015) finds that variations in option net-buying pressure, on average, are due to liquidity-driven trades and not due to private information, which raises the question of the source of its ability to predict future returns of the underlying. We address this question by showing that the documented predictive power of option-induced demand pressure comes mostly from circumstances where order flow is influenced by trading activities of informed investors. In other words, while fluctuations in option net-buying pressure, on average, are due to liquidity-driven trades or investors' disagreements, for certain periods, trading by informed investors intensifies, leading the net-buying demand pressure to contain information about the underlying.

Specifically, we use changes in options illiquidity to identify the underlying securities for which the adverse selection issue arises as the leading concern for option market makers. This approach is motivated by the market microstructure theories of information asymmetry (see e.g., Glosten and Milgrom (1985), and Copeland and Galai (1983)). In these models, the securities' dealers infer the risk of trading against informed traders by observing traders' quotes and in response, widen their bid-ask spreads to compensate for potential losses on informed trades.

5.2.1 Portfolio Sorting Results

We measure option-induced demand pressure using Hu's (2014) order imbalance measure, OOI.[17] The summary statistics in Table 1 show that OOI is, on average, negative but close to zero. The magnitude of OOI measure is almost identical across calls and puts. Similar to Hu (2014) and Bollen and Whaley (2004), we aggregate the OOI measure across calls and puts in order to capture the aggregate net-buying demand on the underlying stock.

A higher level of OOI measure indicates an excess demand for synthetic long positions relative to short positions on the underlying stock. Alternatively, a lower OOI level suggests that the selling pressure dominates, which points towards an excess demand for synthetic short positions.

Hu (2014) finds that the OOI measure positively predicts return of the underlying on the next day. We confirm this finding using a portfolio-sorting strategy. Panel A of Table 6 reports the results. On each day t, we tercile-sort S&P 500 stocks in the sample based on their OOI level, from low (portfolio 1) to high (portfolio 3). Then, on the next day $t+1$, we calculate the value-weighted average returns for these three portfolios. We repeat this analysis for the full sample period from 2004 to 2013. Table 6 reports portfolio alphas calculated using the Fama-French-Carhart four-factor model.

As expected, we find that high OOI portfolio has a positive and significant next-day risk-adjusted alpha of 2.38 bps ($t = 4.85$), while low OOI portfolio has a negative and significant alpha of -1.65 bps ($t = 3.25$). A self-financing high-minus-low strategy based on sorted OOI portfolios yields an alpha of 4.02 bps ($t = 6.72$) per day, or equivalent of about 10% annually.

We next consider a double-sorting portfolio strategy based on OOI and changes in options illiquidity. Panels B and C of Table 6 report the results for options illiquidity measure calculated using quoted spreads (ILOQ), and effective spreads (ILOE), respectively. We use changes in options illiquidity to alleviate its persistence and to account for the fact that information in the options market is also revealed via quote revisions (Chan et al. (2002)). According to Hypothesis 5, we expect that directional change in OOI measure to contain information about the underlying when accompanied by increasing options illiquidity. Alternatively, when there is little change in options illiquidity, the directional change in OOI measure is likely due to liquidity-driven trades and contains little information about the future underlying stock price.

Focusing on the results with ILOQ in Panel B, we find the highest portfolio alpha of 3.37 bps ($t = 2.12$) for the high-OOI portfolio with the largest increase in ILOQ. The alpha of the High-OOI portfolio with the smallest change in ILOQ is significant but very small economically, i.e., 1.5 bps ($t = 2.04$). The difference in portfolio alphas of the largest and the

[17] We verify that our conclusions are qualitatively similar when we use other variations of net-buying pressure calculated from signed option trades. For instances, the options' order imbalance measure, OIB, of Bollen and Whaley (2004), and the raw option net-buying pressure (i.e., order flow).

smallest $\Delta ILOQ$ portfolios for the high-OOI category is statistically significant at the 5% level. This finding suggests the positively large return following a high OOI day is observed mostly among stocks with higher probability of informed trading as measured by changes in their options illiquidity. We find a consistent set of results when looking at the low OOI portfolios in Panel B; these are stock portfolios with excess demand for synthetic short positions. The alpha for the double-sorting portfolio with the largest $\Delta ILOQ$ is -3.13 ($t = 4.08$), while for the lowest $\Delta ILOQ$, the alpha is near zero and statistically insignificant.

Overall in Panel B, we find the OOI measure has the best predictive ability for the next-day return when we focus on portfolios with the largest increase in options illiquidity, i.e., among stocks with the highest likelihood of informed trading. The alphas of the portfolio in the lowest $\Delta ILOQ$ group (Column A) do not monotonically increase with the OOI measure. However, we find that portfolio alphas of the largest $\Delta ILOQ$ group (Column C) monotonically increase with the OOI measure. A long-short strategy based on OOI measure that uses only stocks with the largest $\Delta ILOQ$ earns a daily alpha (see $\text{Alpha}_{\text{OOI}\times\text{ILO}}$) of 6.5 bps ($t = 6.55$), or equivalently 16.5% per year. This portfolio alpha is larger than the 4.02 bps (see $\text{Alpha}_{\text{OOI}}$ in Panel A) earned from the long-short strategy based on single-sorting the OOI measure that uses all underlying stocks; the p-value for the difference is 0.007. Collectively, the findings in Table 6 confirm the prediction of Hypothesis 5 that the return predictability due to option-induced demand pressure is confined to stocks experiencing an increased of informed option trading.

Panel C reports alphas from the double-sorting portfolio strategy based on OOI and $\Delta ILOE$. We find that the results in Panels B and C are qualitatively similar.

5.2.2 Options Illiquidity and Stock Returns: Regression Analysis

Portfolio sorting results reported above provide univariate estimates of the economic magnitude of informed trading captured by changes in options illiquidity. However, they do not allow us to control for other variables such as underlying stock illiquidity, firm size, volatility, and other variables which have been shown to explain daily stock returns. In this section, we apply the regression analysis to further verify the prediction of Hypothesis 5.

Table 7 reports the Fama-MacBeth regression results examining the predictability of stock returns using the ILO measure and the change in options illiquidity. The dependent variable here, $Ret_{i,t+1}$, is the one-day ahead return on stock i. Our independent variables of interest include the current level of option-induced order imbalance, $OOI_{i,t}$; the tercile-ranked change in options illiquidity, $\Delta ILO\_\text{ranked}_{i,t}$. We use the daily cross-sectionally ranked change in ILO instead of the raw daily change in ILO in order to mitigate the effect of outliers found in the ILO variables as shown in Table 1. Importantly, Figure 1 shows the liquidity in the options market improved throughout our sample period. Therefore, raw changes in the ILO measure are not meaningfully comparable between the beginning and end of our sample. The other independent variable of interest that we focus on is the cross-interaction term $OOI_{i,t} \times \Delta ILO\_\text{ranked}_{i,t}$. This interacted variable captures the predictive ability of the OOI measure at different levels of $\Delta ILO\_\text{ranked}_{i,t}$ when changes in the underlying stock's options illiquidity are lowest, average, and largest.

We include a host of control variables in the regressions. We control for changes in the underlying stocks' illiquidity using $\Delta ILS\_\text{ranked}_{i,t}$, which is calculated by ranking cross-sectional changes in ILS daily into three increasing groups. We use ranked change in ILS in order to stay consistent with our change in the options illiquidity variable, $\Delta ILO\_\text{ranked}_{i,t}$. We control for lagged stock returns using $Ret_{i,t}$, and stock return momentum using $Ret_{i,[-5,-1]}$. In addition, we control for uncertainties in the stock market and in the options market using realized volatility, $RRV_{i,t}$, and option-implied volatility, $IV_{i,t}$, respectively. $RRV_{i,t}$ is a daily range-based proxy for the realized volatility of the underlying stock, defined as the difference of the underlying stocks intraday high and low price divided by the closing stock price. $IV_{i,t}$ is the implied volatility for the underlying stock, calculated as the average implied volatilities of the call-put pair with 30 calendar days to maturity reported in the standardized option file from OptionMetrics. The remaining control variables include firm size and option trading volume.

The first regression specification in Table 7, Column (I), examines the predictive ability of the raw OOI measure for the underlying returns. This finding confirms the results in Hu (2014) that option-induced demand pressure positively predicts one-day ahead return of the underlying stock. In Columns (II) and (III), we examine the predictive ability of the change in options illiquidity calculated using quoted spreads (ILOQ), while in Columns (IV) and (V) we examine the predictive ability of the change in options illiquidity calculated using effective spreads (ILOE).

The regression specifications in Columns (II) and (IV) examine the predictive ability of the $\Delta ILO\_\text{ranked}_{i,t}$ variable. As expected, we do not find that $\Delta ILO\_\text{ranked}_{i,t}$ predicts the underlying return. This finding is consistent with the market microstructure theory of information asymmetry (see e.g., Glosten and Milgrom (1985)), and our results in Table 5 which show that option bid-ask spreads widen with the arrival of positive and negative news about the underlying firm. As a result, the positive and negative information effects cancel each other out resulting in an insignificant predictive coefficient for $\Delta ILO\_\text{ranked}_{i,t}$.

Columns (III) and (V) of Table 7 present results for the regression specification with the cross-interacted variable, $OOI_{i,t} \times \Delta ILO\_\text{ranked}_{i,t}$. In these two specifications, we find that $OOI_{i,t} \times \Delta ILO\_\text{ranked}_{i,t}$ is positive and highly significant, while $\Delta ILO\_\text{ranked}_{i,t}$ is negative and highly significant. These findings are consistent with the double-sorting portfolio strategy results reported in Table 6. First, by looking at the positive coefficient on $OOI_{i,t} \times \Delta ILO\_\text{ranked}_{i,t}$, we observe that $OOI_{i,t}$ positively predicts the next-day return of the underlying stock that has a large increase in options illiquidity, $\Delta ILO\_\text{ranked}_{i,t}$. This confirms the prediction of our Hypothesis 5.

Second, the coefficient on $\Delta ILO\_\text{ranked}_{i,t}$ can be interpreted as the predictive ability of changes in options illiquidity for the baseline case when $OOI_{i,t}$ level is very low, i.e, there is an excess demand for synthetic short positions on the underlying. The negative coefficient on $\Delta ILO\_\text{ranked}_{i,t}$ suggests that when there is an aggregate synthetic net-selling pressure in the underlying stock, increasing options bid-ask spreads would indicate that the selling pressure is driven by informed trades which convey negative information about the underlying stock. This finding is consistent with the double-sorted portfolio results in Panels B and C of Table 6. Looking specifically at the rows labeled (1) where we observe "low OOI" levels, we find that portfolio alphas decrease with increasing ΔILO_ranked.

In Table 7, we find the coefficient on $OOI_{i,t}$ in Columns (III) and (V) is not significant when the cross-interacted variable $OOI_{i,t} \times \Delta ILO\_\text{ranked}_{i,t}$ is included in the regressions. For these two specifications, the coefficient on $OOI_{i,t}$ can be interpreted as the predictive ability of the OOI measure when option bid-ask spreads of the underlying stock decreases, i.e., lowest $\Delta ILO\_\text{ranked}_{i,t}$ tercile. This finding is consistent with Hypothesis 5, which predicts that variations in the OOI measure contains information about the underlying stock only when options illiquidity increases, i.e., when option dealers aggressively widen their spreads to compensate for the risk of trading against informed investors.

5.3 Subperiods

Table 8 summarizes the economic profits from trading on the simple high-minus-low OOI-sorted portfolios (Strategy I), versus the high-minus-low OOI-sorted portfolios that utilize only stocks in the highest $\Delta ILOQ$ tercile, (Strategy II). Column (I) reports portfolio alphas of the Strategy I, $\text{Alpha}_{\text{OOI}}$, while Column (II) reports portfolio alphas of the Strategy II for various subperiods and specifications.

The first row of Table 8 reports the high-minus-low alphas from the two strategies for the full 2004–2013 sample period, which are replicated from Table 6. The difference between the two strategies is 2.48 bps per day (or 6.25% per year) and significant at the one percent level. We next divide our sample into two supberiods with equal length: 2004–2008, and 2009–2013. The second row reports results for the 2004–2008 subperiod, which overlaps with the sample of Hu (2014). Here, the gain of using Strategy II vs. Strategy I is only marginal, 5.67 bps (t = 3.85) vs. 4.40 bps (t = 4.92). However, for the later subperiod, i.e., 2009–2013, the difference is striking. Strategy I results in daily alpha of 3.47 bps (t = 4.35), while Strategy

II yields daily alpha of 7.42 bps ($t = 5.62$) or 18.7% per year. This strong performance of Strategy II that we observe after 2008 is likely due to the fact that the options market became significantly more liquid, due to increasing competition among options market makers, as well as regulatory effects of the Penny Pilot project.[18] The reduction in options trading cost likely push informed traders to increasingly use the options market as trading venue for their private information instead of the equity market. As a result, changes in option bid-ask spreads increasingly signal trades that contain private information. This could explain why the double-sorting strategy that uses change in *ILO* performs significantly well in the latter half of the sample relative to the single-sorted strategy that relies on OOI alone.

To further separate the transitory effect from the private information effect, the last row, row (4), reports results for high-minus-low alphas assuming that investors can only enter to buy or sell the underlying stocks on day $t+1$, i.e., on the second day after portfolio formation. The results for Strategy I are no longer significant. Consistent with private information story, Strategy II still provides significant spreads of 2.5 bps ($t = 2.55$), or 6.3% per year. The results are qualitatively similar for ILOE, but not reported here for brevity.

Muravyev (2015) shows that order flows are persistent in the options market. That is, if we observe an excess demand for a synthetic long position today, we will likely observe it again tomorrow. As a result, the persistence of options' order flow mechanically generates return predictability on the underlying because it is well known that contemporaneously, order flows and stock returns are positively correlated. In other words, the predictive ability of the OOI measure on stock returns is merely transitory and should not persist beyond the first day. Our findings that the OOI measure does not predict the underlying return beyond the next day is consistent with the results of Murayev (2015). However, the fourth row in Table 8 shows that if we form high-minus-low OOI-sorted portfolios that utilize stocks with increasing options illiquidity, the return predictability persists beyond the first day. This finding suggests that changes in options illiquidity can help identify a subset of underlying securities where informed option trading is most likely to take place.

Table 9 further explores the 2009–2013 sub-sample results for double-sorting strategy reported in Table 6. As we already mentioned, this second half of our sample experiences significantly improvements in option liquidity. The improvement in options liquidity can be partly attributed to the Penny pilot program which was implemented in three phases beginning in 2007 and ending in 2008, representing about 50% of industry trading volume. The Penny Pilot program significantly reduce options trading cost by specifying quoting increments of one cent for options trading at less than \$3.00 and increments of five cents for options trading at \$3.00 or more. In 2009, the SEC expanded the pilot project to additional 500 securities.

[18] The Penny Pilot project begins in three phases starting in 2007. It's intention is to decrease the tick size of option quotes trade below \$3 from five-cent increment to one-cent increment

We identify that 40% of stocks in our sample is a part of Penny Pilot program. Thus from 2009 and on-wards, almost half of our sample experiences significant improvement in liquidity. Further, Amihud,Mendelson and Lauterbach (1997) documented that there are positive externalities that spillover from the pilot stocks (i.e, those subject to trading increment reduction) to non-pilot stocks. This positive liquidity spillover effects likely explain the overall options liquidity improvement across all S&P500 stocks in the second half of our sample (2009–2013). This sub-sample, both in terms of cross-sectional selection and time span, differs from Hu (2014) sample and can further explain the differences in the results we find.

Panel A of Table 9 reports double-sorting results using $\Delta ILOQ$, and Panel B uses $\Delta ILOE$. Concider first Panel A. Here, the highest OOI portfolio and the highest $\Delta ILOQ$ portfolio has risk adjusted alpha of 4 bps ($t = 4.05$) per day, and the lowest OOI and the highest $\Delta ILOQ$ portfolio has the risk-adjusted alpha of -3.4 bps ($t = -3.27$) per day, Panel A. Note that for the low and medium $\Delta ILOQ$ portfolios, we do not largely observe any significant results. The high-minus-low OOI difference for the medium $\Delta ILOQ$ portfolio, although is statistically significant, it is economically very small, approximately 2 bps ($t = 2.09$). The results are qualitatively similar in Panel B. Thus, the predictive ability of OOI on stock returns, as hypothesised in H5, is driven by stocks with significantly increasing options illiquidity.

6 Conclusion

Using intraday transactions data of individual equity options written on the S&P 500 index constituents from 2004 to 2013, we empirically examine two research questions. First, we analyze the determinants of options dealers' market making costs, measured by relative effective and quoted spreads. Unlike previous literature, we use the largest cross-section and the longest time-series of options intraday transactions data to conduct our analyses and highlight the economic and statistical significance of variables affecting options illiquidity. Second, we study and explain the implications of options illiquidity for the return predictability of the underlying stock.

We find that hedging costs are the largest component of options bid-ask spreads in terms of economic magnitudes with future rebalancing cost dominating the initial delta hedging costs. This finding contributes to a deeper understanding of the market microstructure of the US options market. Besides hedging costs, we find that option-induced demand pressure and private information are other sources of risks for options market makers, which they normally absorb by quoting wider bid-ask spreads.

Finally, we study the implications of private information captured by options illiquidity for stock returns. Consistent with market microstructure theories of asymmetric information, we find that higher option-induced order imbalance (excess demand for synthetic long positions) and higher options illiquidity positively predict next day stock returns. On the other hand, lower option-induced order imbalance (excess demand for synthetic short positions) and higher options illiquidity negatively predict stock returns.

We do not find that option-induced order imblance contains information about the underlying stock when options illiquidity decreases. This finding suggests that option-induced net buying pressure reflects trades of informed investors only when option dealers aggresively widen their spreads in response to the increased likelihood that they are trading against informed investors.

Table 1: Summary statistics

We report time–series averages of cross-sectional statistics of the main variables used in our study. The sample consists of S&P 500 index firms with exchange-listed options from January 2004 to December 2013 (2,504 trading days). Intraday option trades and quotes are obtained from LiveVol. We focus on transactions on option contracts with maturity of 30–182 calendar days. Intraday stock data are obtained from NYSE's TAQ database. Panel A reports descriptive statistics for option-related variables separately for call and put options. *ILOQ* is the daily options illiquidity measure defined as the dollar-volume-weighted average relative quoted spreads of intraday option trades. *ILOE* is the daily options illiquidity measure defined as the dollar-volume-weighted average relative effective spreads of intraday option trades. $\%DHC$ is the daily percentage initial hedging cost associated with delta-hedging an option contract. $\%RBC$ is the daily percentage rebalancing cost of for maintaining the initially hedged option position (Leland(1985)). *OOI* is the daily option-induced order imbalance measure calculated following Hu(2014). *OptVolume* is the daily number of option contracts traded (in thousands). *Num of trades* is the daily number of option transactions executed in each option category. Panel B reports descriptive statistics of stock-related variables used in our study. *ILS* is the daily underlying stock illiquidity measure defined as the average relative effective spreads of intraday stock trades. *RET* is the return on the underlying stock. $MA5|RET|$ is the average absolute stock return over the past 5 trading days. *PIN* is the probability of information–based trading in the underlying stock computed on a quarterly basis for each firm (Easley et al (1996)).

Panel A: Option-related variables for call and put options

Variable	Call options (472 Firms)				Put options (443 Firms)			
	Mean	Stdev	Min	Max	Mean	Stdev	Min	Max
ILOE	6.5%	6.8%	0.2%	66.6%	5.8%	6.1%	0.1%	61.7%
ILOQ	8.0%	7.7%	1.1%	68.7%	7.2%	7.0%	1.1%	64.7%
%DHC	11.04	4.76	2.75	44.75	10.33	4.39	2.45	41.01
%RBC	0.003	0.002	0.000	0.028	0.003	0.002	0.000	0.025
OOI	0.0000	0.0002	-0.0025	0.0022	0.0000	0.0002	-0.0024	0.0022
OptVolume	2,208	7,367	1	106,993	1,546	4,630	1	61,539
Num. of trades	120	376	1	6,299	76	218	1	3,355

Panel B: Underlying stock variables

Variable	Mean	Stdev	Min	Max	# firm count
ILS	0.08%	0.09%	0.02%	1.36%	500
RET	0.05%	1.74%	-10.12%	11.10%	
MA5|RET|	1.49%	0.85%	0.15%	7.66%	
PIN	9.1%	3.4%	0.6%	42.4%	

Table 2: Cross correlation matrix of the main variables.

We report time-series averages of daily cross–sectional pairwise correlation coefficients of the main variables used in this paper. Panels A and B report results for variables calculated using call options and put options, respectively. $ILOQ$ is the daily options illiquidity measure defined as the dollar-volume-weighted average relative quoted spreads of intraday option trades. $ILOE$ is the daily options illiquidity measure defined as the dollar-volume-weighted average relative effective spreads of intraday option trades. $\%DHC$ is the daily percentage initial hedging cost associated with delta-hedging an option contract. $\%RBC$ is the daily percentage rebalancing cost of for maintaining the initially hedged option position (Leland(1985)). OOI is the daily option-induced order imbalance measure calculated following Hu(2014). $OptVolume$ is the natural logarithm of the daily number of option contracts traded. ILS is the daily underlying stock illiquidity measure defined as the average relative effective spreads of intraday stock trades. RET is the return on the underlying stock. $MA5|RET|$ is the average absolute stock return over the past 5 trading days. PIN is the probability of information-based trading in the underlying stock computed on a quarterly basis for each firm (Easley et al (1996)). ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively, based on Newey-West adjustment for autocorrelation up to 45 lags.

Panel A: Call Options

	ILOQ	ILOE	%DHC	%RBC	OOI	OptVolume	ILS	RET	MA5|RET|
ILOE	0.88***								
%DHC	0.32***	0.30***							
%RBC	0.48***	0.47***	0.29***						
OOI	0.01***	0.01***	-0.00***	0.01***					
OptVolume	-0.43***	-0.38***	-0.20***	-0.16***	0				
ILS	0.16***	0.16***	-0.32***	0.60***	0.01***	0.03***			
RET	-0.01***	-0.01***	0.02***	-0.01***	0.08***	0.02***	-0.01***		
MA5|RET|	-0.07***	-0.06***	-0.45***	-0.06***	0	0.20***	0.29***	-0.01**	
PIN	0.13***	0.12***	-0.05***	0.09***	-0.00***	-0.16***	0.17***	0	0.07***

Panel B: Put Options

	ILOQ	ILOE	%DHC	%RBC	OOI	OptVolume	ILS	RET	MA5|RET|
ILOE	0.85***								
%DHC	0.31***	0.29***							
%RBC	0.43***	0.41***	0.24***						
OOI	0	-0.00***	0.00*	0.01***					
OptVolume	-0.38***	-0.33***	-0.19***	-0.13***	0				
ILS	0.13***	0.13***	-0.32***	0.59***	0.01***	0.03***			
RET	0.00***	0.00***	0.01***	0.02***	0.08***	0.02***	-0.01***		
MA5|RET|	-0.08***	-0.07***	-0.44***	-0.06***	0	0.20***	0.29***	-0.01**	
PIN	0.13***	0.11***	-0.06***	0.08***	-0.00***	-0.16***	0.16***	0	0.07***

Table 3: Determinants of ILO.

This table reports coefficient estimates from daily Fama-MacBeth cross-sectional regressions. The dependent variables are the daily options illiquidity measures *ILOQ* and *ILOE*. The sample consists of S&P 500 index firms with exchange-listed options from January 2004 to December 2013 (2,504 trading days). Intraday option trades and quotes are obtained from LiveVol. We focus on transactions on option contracts with maturity of 30182 calendar days. Intraday stock data are obtained from NYSE's TAQ database. Panels A and B report results for *ILOQ* and *ILOE* regressions, respectively. The independent variables include proxy for the probability of informed trading, market-making costs, and option-induced demand pressure faced by options' dealers, as well as control variables. We consider two hedging cost variables affecting option market makers. $\%DHC$ is the daily percentage initial hedging cost associated with delta-hedging an option contract. $\%RBC$ is the daily percentage rebalancing cost of for maintaining the initially hedged option position (Leland(1985)). $|OOI|$ is the daily absolute value of option-induced order imbalance calculated following Hu(2014). PIN is the probability of information-based trading in the underlying stock (Easley et al (1996)) calculated at the quarterly frequency. *OptVolume* is the natural logarithm of the number of option contracts traded. *ILO(t-1)* is the one-day lagged measure of options illiquidity (ILOQ or ILOE). *RET* is the return of the underlying stock. *RET(t-1)* is the return of the underlying stock on the previous trading day. *MA5*$|RET|$ is the average absolute stock return over the past 5 trading days; it proxies for the stock volatility level. *Day Count* reports the number of daily cross-section regressions used for calculating the Fama-MacBeth coefficient estimates. *Avg. cross section* is the average sample size of daily cross-sectional regressions. Newey-West t-statistics adjusted for autocorrelation up to 45 lags are reported in square brackets below each estimate. ***, **, and * indicate significance at the 1, 5, and 10 percent confidence levels.

Table 3: (Continued...)

	Panel A. Relative quoted spreads: *ILOQ(t)*		Panel B. Relative effective spreads: *ILOE(t)*	
	Call	Put	Call	Put
Hedging costs				
%DHC	0.0019***	0.0023***	0.0017***	0.0019***
	[17.64]	[21.27]	[16.22]	[18.31]
%RBC	16.1051***	14.4994***	14.3471***	12.4025***
	[30.29]	[33.59]	[32.32]	[35.65]
Demand pressure				
|OOI|	23.7549***	20.7614***	22.6028***	19.0965***
	[31.52]	[36.25]	[31.81]	[37.33]
Private information				
PIN	0.0945***	0.0934***	0.0851***	0.0865***
	[9.55]	[10.06]	[9.17]	[9.96]
Other controls				
OptVolume	-0.0037***	-0.0030***	-0.0026***	-0.0019***
	[-10.50]	[-8.66]	[-10.17]	[-7.81]
ILS	-20.2360***	-16.3433***	-17.3962***	-13.3172***
	[-14.37]	[-13.08]	[-14.09]	[-12.57]
ILO(t-1)	0.3639***	0.3581***	0.2929***	0.2874***
	[46.63]	[40.50]	[74.14]	[56.44]
RET	-0.0323***	0.0139***	-0.0181***	0.0102**
	[-6.75]	[2.85]	[-3.39]	[2.41]
RET(t-1)	-0.0223***	-0.0174***	-0.0174***	-0.0127***
	[-4.63]	[-4.86]	[-4.32]	[-4.16]
MA5|RET|	0.7988***	0.6760***	0.6833***	0.5538***
	[23.55]	[23.10]	[20.25]	[18.22]
Day Count	2504	2504	2504	2504
Avg. cross section	453	413	453	413
Adj. R^2	0.531	0.471	0.4492	0.3841

Table 4: Determinants of change in ILO.

This table reports coefficient estimates from daily Fama-MacBeth cross-sectional regressions. The dependent variables are changes in the equity options illiquidity measures: $\Delta ILOQ$ and $\Delta ILOE$ on day t. The sample consists of S&P 500 index firms with exchange-listed options from January 2004 to December 2013 (2,504 trading days). Intraday option trades and quotes are obtained from LiveVol. We focus on transactions on option contracts with maturity of 30182 calendar days. Intraday stock data are obtained from NYSE's TAQ database. Panels A and B report results for $\Delta ILOQ$ and $\Delta ILOE$ regressions, respectively. The independent variables include proxy for the probability of informed trading, market-making costs and demand pressures faced by options' dealers, as well as control variables. $\%DHC(t-1)$ is the one-day lagged percentage initial hedging cost associated with delta-hedging an option contract. $\%RBC(t-1)$ is the one-day lagged percentage rebalancing cost of for maintaining the initially hedged option position (Leland(1985)). $|OOI(t{-}1)|$ is the one-day lagged absolute value of option-induced order imbalance calculated following Hu(2014). PIN is the probability of information-based trading in the underlying stock (Easley et al (1996)). *OptVolume(t-1)* is the natural logarithm of the number of option contracts traded on day $t-1$. $\Delta ILS(t-1)$ is the change in the underlying stock illiquidity measure on day $t-1$. $\Delta ILO(t-1)$ is the change in the equity options illiquidity measure on day $t-1$. $RET(t-1)$ and $RET(t-2)$ are daily returns of the underlying stock on day $t-1$ and $t-2$, respectively. $MA5|RET|(t-1)$ is the lagged average absolute stock return over the past 5 trading days. *Day Count* reports the number of daily cross–section regressions used for reporting the Fama-MacBeth regression estimates. *Avg. cross section* is the average sample size of daily cross-sectional regressions. Newey-West t-statistics adjusted for autocorrelation up to 45 lags are reported in square brackets below each estimate. ***, **, and * indicate significance at the 1, 5, and 10 percent confidence levels.

Table 4: (Continued...)

	Panel A: *Change in relative quoted spreads: Δ ILOQ(t)*		Panel B. *Change in relative effective spreads: Δ ILOE (t)*	
	Call	Put	Call	Put
Hedging costs				
%DHC(t-1)	-0.0014***	-0.0014***	-0.0010***	-0.0008***
	[-20.23]	[-20.04]	[-14.65]	[-12.58]
%RBC(t-1)	-5.1568***	-3.4600***	-3.4600***	-3.6214***
	[-25.15]	[-29.83]	[-25.57]	[-28.44]
Demand pressure				
|OOI (t-1)|	-2.3500***	-1.6416***	-2.7565***	-1.7651***
	[-6.92]	[-6.30]	[-7.63]	[-6.64]
Private information				
PIN	0.0060*	0.0087**	0.0037**	0.0059**
	[1.89]	[2.15]	[1.99]	[2.33]
Other controls				
OptVolume (t-1)	-0.0003***	-0.0001	-0.0003***	-0.0001**
	[-3.05]	[-1.56]	[-3.83]	[-2.08]
Δ ILS (t-1)	8.6090***	8.9325***	5.9937***	6.1237***
	[24.13]	[21.10]	[22.15]	[22.20]
Δ ILO (t-1)	-0.3343***	-0.3228***	-0.4557***	-0.4529***
	[-60.77]	[-49.50]	[-148.6]	[-147.6]
RET (t-1)	-0.0339***	0.0511***	-0.0433***	0.0432***
	[-6.72]	[8.86]	[-10.27]	[10.09]
RET (t-2)	-0.0001	0.0315***	-0.0109***	0.0241***
	[-0.03]	[7.95]	[-2.86]	[7.84]
MA5|RET| (t-1)	-0.3895***	-0.3490***	-0.2627***	-0.2188***
	[-18.53]	[-18.08]	[-15.19]	[-14.06]
Day Count	2497	2497	2497	2497
Avg. cross section	441	395	441	395
Adj. R^2	0.1859	0.174	0.2707	0.2679

Table 5: Options and stock illiquidity around earnings announcement
We report event-study results for abnormal *ILOQ*, *ILOE*, and *ILS* over [–5,+5] trading-day windows around earnings announcement dates. The sample consists of S&P 500 index firms with exchange-listed options from January 2004 to December 2013 (2,504 trading days). Abnormal options illiquidity is calculated by subtracting daily *ILOQ* (*ILOE*) from its time–series average calculated over the [–42,–21] days relative to the event date, i.e. pre–event window. We consider option series with maturity between 30–182 calendar days. *ILOQ* is the daily option illiquidity measure defined as the dollar-volume-weighted average relative quoted spreads of intraday option trades. *ILOE* is the daily option illiquidity measure defined as the dollar-volume-weighted average relative effective spreads of intraday option trades. Abnormal stock illiquidity is calculated similarly by subtracting daily *ILS* from its time-series average calculated over the [–42,–21] days relative to th event date. *ILS* is the daily average relative effective spreads of intraday stock trades. Panel A reports event-study results for all earnings announcements. Panels B and C report event-study results for positive earnings surprises and negative earnings surprises, respectively. In each panel, we report results for abnormal *ILOQ*, *ILOE*, and *ILS* in basis points (bps). Results for options are reported separately for call and put options. We measure the magnitude of earnings surprises using the standardized cumulative abnormal returns of the underlying stock over the window [–1,1] relative to the event. The t-statistics, reported in square brackets, are based on the Hall (1992) skewness-corrected transformed normal test.

Panel A: All earnings announcements

Event day	Abnormal Option quoted spread (bps)		Abnormal Option effective spread (bps)		Abnormal Stock effective spread (bps)
	Call options	Put options	Call options	Put options	
-5	0.38 [0.14]	1.70 [0.64]	-0.60 [-0.22]	0.16 [0.07]	-0.09 [-2.32]
-4	0.50 [0.17]	0.08 [0.03]	3.52 [1.25]	-0.16 [-0.06]	0.02 [1.76]
-3	-2.32 [-0.82]	-1.07 [-0.38]	-0.05 [-0.01]	0.93 [0.37]	0.04 [0.86]
-2	2.06 [0.74]	1.97 [0.74]	2.98 [1.16]	1.56 [0.65]	0.05 [1.30]
-1	21.73 [7.78]	31.01 [12.21]	17.64 [7.13]	28.69 [12.53]	0.04 [1.27]
0	74.43 [28.83]	81.43 [36.04]	67.83 [29.18]	74.35 [36.67]	2.45 [73.68]
1	6.59 [2.28]	7.05 [2.67]	5.78 [2.17]	12.1 [5.08]	0.65 [18.59]
2	-4.56 [-1.50]	-5.30 [-1.92]	-5.31 [-1.83]	-5.96 [-2.43]	-0.13 [-2.64]
3	-3.28 [-1.11]	-7.17 [-2.54]	-3.55 [-1.30]	-7.04 [-2.76]	-0.26 [-5.09]
4	-7.26 [-2.39]	-14.00 [-4.88]	-6.91 [-2.53]	-12.2 [-4.82]	-0.35 [-7.23]
5	-10.13 [-3.47]	-6.23 [-2.18]	-10.20 [-3.68]	-3.03 [-1.17]	-0.28 [-6.50]

Table 5: (Continued...)

Panel B: Positive earnings announcements surprises

Event day	Abnormal Option quoted spread (bps)				Abnormal Option effective spread (bps)				Abnormal Stock effective spread (bps)	
	Call options		Put options		Call options		Put options			
-5	-6.1	[-0.97]	-11.06	[-1.88]	-5.12	[-0.88]	-5.38	[-1.03]	0.01	[0.16]
-4	-5.93	[-0.91]	-13.54	[-2.30]	-0.36	[-0.04]	-4.57	[-0.83]	0.04	[1.46]
-3	2.78	[0.45]	-2.02	[-0.31]	10.48	[1.77]	0.88	[0.16]	0.16	[1.95]
-2	3.64	[0.60]	-6.15	[-1.07]	4.62	[0.85]	-0.6	[-0.11]	0.30	[3.49]
-1	24.93	[4.28]	24.2	[4.40]	20.39	[3.92]	27.4	[5.31]	0.22	[3.56]
0	16.89	[3.07]	101.12	[20.51]	26.45	[5.30]	90.49	[21.07]	2.79	[49.72]
1	-52.03	[-7.29]	15.67	[2.70]	-39.92	[-5.96]	25.48	[5.03]	0.71	[10.15]
2	-67.39	[-10.15]	-18.35	[-3.07]	-54.43	[-7.61]	-11.2	[-2.14]	0.06	[0.56]
3	-59.82	[-9.85]	-20.82	[-3.51]	-50.38	[-8.89]	-13.3	[-2.54]	-0.31	[-2.07]
4	-60.62	[-9.24]	-17.21	[-2.59]	-46.32	[-6.52]	-14.6	[-2.62]	-0.48	[-2.52]
5	-58.17	[-9.15]	-15.61	[-2.33]	-43.93	[-5.38]	0.67	[0.12]	-0.38	[-2.91]

Panel C: Negative earnings announcements surprises

Event day	Abnormal Option quoted spread (bps)				Abnormal Option effective spread (bps)				Abnormal Stock effective spread (bps)	
	Call options		Put options		Call options		Put options			
-5	-0.36	[-0.04]	10.99	[1.90]	2.18	[0.37]	4.07	[0.79]	-0.03	[-0.37]
-4	1	[0.16]	7.66	[1.27]	8.75	[1.49]	8.12	[1.52]	0.03	[0.83]
-3	-0.88	[-0.13]	2.23	[0.39]	5.75	[0.96]	2.78	[0.53]	0.11	[1.83]
-2	-0.27	[-0.04]	4.03	[0.70]	9.09	[1.62]	2.04	[0.40]	0.13	[1.76]
-1	17.83	[3.02]	34.72	[6.29]	22.6	[4.25]	29.85	[6.15]	0.19	[3.26]
0	120.18	[22.55]	58.24	[12.19]	107.46	[22.70]	61.96	[14.17]	3.43	[82.19]
1	54.31	[8.90]	-12.26	[-2.31]	47.66	[8.61]	0.09	[0.03]	1.19	[18.71]
2	27.9	[4.47]	-18.99	[-3.08]	22.88	[4.02]	-17.9	[-3.14]	0.28	[4.65]
3	33.09	[5.27]	-18.88	[-3.24]	27.44	[4.86]	-17.8	[-3.40]	0.26	[3.90]
4	32.02	[4.97]	-37.24	[-5.30]	25.98	[4.92]	-27.1	[-4.31]	0.13	[1.77]
5	16.36	[2.58]	-14.39	[-2.21]	17.26	[3.11]	-19.8	[-3.92]	0.19	[2.98]

Table 6: Portfolio strategies: Order flow and changes in options illiquidity
The sample consists of S&P 500 index firms that have options traded on their underlying from January 2004 to December 2013 (2,504 trading days). This table reports the risk-adjusted returns or alphas, in basis points per day, on the equally weighted portfolios of stocks ranked by their respective daily option-induced order imbalances OOI (Hu(2014)), and daily change in options illiquidity $\Delta ILOQ$ (or $\Delta ILOE$). At the market close of each day, stocks are sorted into portfolios by their OOI value and held for the next trading day. Panel A reports results from a single-sorting portfolio strategy based on OOI. Panel B reports results from a double-sorting portfolio strategy: First, stocks are sorted into three groups by OOI, and then are independently sorted into three groups by options illiquidity measure ($\Delta ILOQ$). All resulting nine (3 X 3) portfolios are to be held for the next trading day. Panel C repeats the strategy in Panel B using $\Delta ILOE$. The risk-adjusted returns are reported in the form of Fama-French-Carhart four-factor adjusted returns. The square brackets contain the t-statistics. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Portfolio alpha (t+1) sorted by OOI_t

OOI_t rank		α_{t+1}	t-stat
(3)	High OOI_t	2.38 ***	[4.85]
(2)		1.06 ***	[2.68]
(1)	Low OOI_t	-1.65 ***	[-3.25]
(3)–(1)	$\text{Alpha}_{\text{OOI}}$	4.02 ***	[6.72]

Panel B: Portfolio alpha (t+1) double-sorted by OOI_t and $\Delta ILOQ_t$

		$\Delta ILOQ_t$ rank						(A) – (C)
		(A) Low		(B) Mid		(C) High		
OOI_t rank		α_{t+1}	t-stat	α_{t+1}	t-stat	α_{t+1}	t-stat	t-stat
(3)	High OOI_t	1.48 **	[2.04]	2.30 ***	[3.15]	3.37 ***	[2.12]	[2.02]
(2)		1.54 ***	[2.88]	0.79	[1.48]	0.74	[1.32]	[-1.33]
(1)	Low OOI_t	-0.42	[-0.57]	-1.38 *	[-1.94]	-3.13 ***	[-4.08]	[-2.98]
(3)–(1)	$\text{Alpha}_{\text{OOIxILO}}$	1.91 **	[1.99]	3.68 ***	[4.13]	6.49 ***	[6.55]	

Panel C: Portfolio alpha (t+1) double-sorted by OOI_t and $\Delta ILOE_t$

		$\Delta ILOE_t$ rank						(A) – (C)
		(A) Low		(B) Mid		(C) High		
OOI_t rank		α_{t+1}	t-stat	α_{t+1}	t-stat	α_{t+1}	t-stat	t-stat
(3)	High OOI_t	1.59 **	[2.16]	1.94 ***	[2.67]	3.60 ***	[4.79]	[2.10]
(2)		1.59 ***	[2.96]	0.53	[1.05]	0.98 *	[1.73]	[-0.98]
(1)	Low OOI_t	-0.75	[-1.00]	-1.79 **	[-2.46]	-2.31 ***	[-3.14]	[-1.70]
(3)–(1)	$\text{Alpha}_{\text{OOIxILO}}$	2.34 **	[2.35]	3.73 ***	[4.13]	5.91 ***	[6.08]	

Table 7: Order flow, options illiquidity, and stock return: Regression analysis
This table reports results for the stock return predictability using daily Fama–MacBeth cross-sectional regressions. The dependent variable is the 1-day ahead return on the underlying stock i, $Ret_{i,t+1}$. The predictors include: Option-induced order imbalance on day t ($OOI_{i,t}$), cross-sectional rank of daily change in ILO ($\Delta ILO\_\text{ranked}_{i,t}$), and an interaction term between OOI and ΔILO_ranked ($OOI_{i,t} \times \Delta ILO\_\text{ranked}_{i,t}$). Control variables are also included. For stock i on day t, ΔILS_ranked is the cross-sectional rank of daily change in *ILS*. *RET* is the daily return on the underlying stock. *RET[-5,-1]* is the cumulative return on the underlying stock from day $t-5$ to day $t-1$. *RRV* is a daily range-based proxy for the realized volatility of the underlying stock, defined as the difference of the underlying stocks intraday high and low price divided by the closing stock price. *IV* is the implied volatility for the underlying stock, calculated as the average implied volatilities of the call-put pair with 30 calendar days to maturity reported in the standardized option file from OptionMetrics. *ln(OptVolume)* is the natural logarithm of the number of option contracts traded. *ln(size)* is the natural logarithm of the market value of the underlying stock. *Day count* reports the number of daily cross-section regressions used for reporting the Fama-MacBeth regression estimates. *Avg.cross section* is the average sample size of daily cross–sectional regressions. Newey-West t-statistics adjusted for autocorrelation up to 45 lags are reported in square brackets below each estimate. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

	Dependent variable: $Ret_{i,t+1}$ (%)				
		Quoted bid-ask spreads		*Effective bid-ask spreads*	
	(I)	(II)	(III)	(IV)	(V)
$OOI_{i,t}$	0.0211***		0.0017		0.0072
	[7.70]		[0.30]		[1.28]
Δ ILO $\text{ranked}_{i,t}$		-0.0006	-0.0077***	0.0001	-0.0048**
		[-1.03]	[-3.49]	[0.21]	[-2.50]
$OOI_{i,t} \times \Delta$ ILO $\text{ranked}_{i,t}$			0.0035***		0.0024**
			[3.39]		[2.54]
Control variables					
Δ ILS_$\text{ranked}_{i,t}$	-0.0012*	-0.0012*	-0.0012*	-0.0012*	-0.0013*
	[-1.72]	[-1.74]	[-1.80]	[-1.81]	[-1.86]
$RET_{i,t}$	-0.0055*	-0.0041	-0.0055*	-0.0041	-0.0054
	[-1.68]	[-1.23]	[-1.65]	[-1.22]	[-1.62]
$RET_{i,[-5,-1]}$	-0.0038***	-0.0038***	-0.0038***	-0.0038***	-0.0038***
	[-2.82]	[-2.86]	[-2.78]	[-2.85]	[-2.78]
$RRV_{i,t}$	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	[-5.80]	[-5.58]	[-5.60]	[-5.65]	[-5.59]
$IV_{i,t}$	0.0002	0.0002	0.0002	0.0002	0.0002
	[1.24]	[1.17]	[1.19]	[1.20]	[1.22]
$\ln(\text{OptVolume})_{i,t}$	0.0005	0.0001	0.0002	0.0000	0.0001
	[0.26]	[0.03]	[0.10]	[0.02]	[0.08]
ln(size)	-0.0058	-0.0055	-0.0055	-0.0053	-0.0052
	[-1.14]	[-1.05]	[-1.04]	[-1.02]	[-0.98]
Intercept	0.0656	0.1070*	0.1040*	0.1010*	0.0852
	[1.08]	[1.74]	[1.69]	[1.67]	[1.35]
Day Count	2,491	2,469	2,469	2,469	2,469
Avg. cross section	483	470	470	471	471
Adj. R^2	10.30%	10.27%	10.35%	10.26%	10.35%

Table 8: Portfolio alphas from daily trading strategies: Subperiods analysis
This table reports the risk-adjusted returns or alphas, in basis points per day, on the equally weighted portfolios of stocks ranked by their respective daily options order imbalance OOI(Hu(2014)), and/or daily change in options illiquidity measures $\Delta ILOQ$ for different subperiods as well as the results for the skip-one-day trading strategy for the entire time sample. The sample consists of S&P 500 index firms with exchange-listed options from January 2004 to December 2013 (2,504 trading days). At the market close of each day, stocks are sorted into portfolios by their OOI value and held for the next trading day. Column (I) reports results from a single-sorting portfolio strategy based on OOI. Column (II) reports results from a double-sorting portfolio strategy based on OOI and $\Delta ILOQ$. The risk-adjusted returns are calculated using the Fama-French-Carhart four-factor adjusted returns. The square bracket underneath each estimate reports the t-statistics. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

	Portfolio alpha				(II) − (I)	
	(I)		(II)			
	$\text{Alpha}_{\text{OOI}}$		$\text{Alpha}_{\text{OOIxILOQ}}$			
	Value	t-stat	Value	t-stat	Diff	t-stat
(1) Full sample 2004−2013	4.02 ***	[6.72]	6.49 ***	[6.55]	2.47***	[3.16]
(2) Subsample: 2004−2008	4.40 ***	[4.92]	5.67 ***	[3.85]	1.27*	[1.69]
(3) Subsample: 2009−2013	3.47 ***	[4.35]	7.42 ***	[5.62]	3.95***	[3.85]
(4) Skipping one-day: R_{t+2} strategy	0.59	[1.03]	2.49 **	[2.55]	1.90**	[2.42]

Table 9: 2009–2013 Portfolio strategies: Order flow and changes in *ILO*

The sample consists of S&P 500 index firms that have options traded on their underlying from January 2009 to December 2013 (1,252 trading days). This table reports the risk-adjusted returns or alphas, in basis points per day, on the equally weighted portfolios of stocks ranked by their respective daily option-induced order imbalances OOI (Hu(2014)), and daily change in options illiquidity $\Delta ILOQ$ (or $\Delta ILOE$). At the market close of each day, stocks are sorted into portfolios by their OOI value and held for the next trading day. Panel A reports results from a single-sorting portfolio strategy based on OOI. Panel B reports results from a double-sorting portfolio strategy: First, stocks are sorted into three groups by OOI, and then are independently sorted into three groups by options illiquidity measure ($\Delta ILOQ$). All resulting nine (3 X 3) portfolios are to be held for the next trading day. Panel C repeats the strategy in Panel B using $\Delta ILOE$. The risk-adjusted returns are reported in the form of Fama-French-Carhart four-factor adjusted returns. The square brackets contain the t-statistics. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Portfolio alpha (t+1) sorted by OOI_t

OOI_t rank		α_{t+1}	t-stat
(3)	High OOI_t	2.00 ***	[3.07]
(2)		1.25 **	[2.49]
(1)	Low OOI_t	-1.47 **	[-2.13]
(3)–(1)	$\text{Alpha}_{\text{OOI}}$	3.47 ***	[4.35]

Panel B: Portfolio alpha (t+1) double-sorted by OOI_t and $\Delta ILOQ_t$

		$\Delta ILOQ_t$ rank						(C) – (A)
		(A) Low		(B) Mid		(C) High		
OOI_t rank		α_{t+1}	t-stat	α_{t+1}	t-stat	α_{t+1}	t-stat	t-stat
(3)	High OOI_t	1.08	[1.31]	1.19	[1.29]	3.99 ***	[4.05]	[2.29]
(2)		1.43 *	[1.96]	0.69	[0.93]	1.47 **	[2.07]	[0.05]
(1)	Low OOI_t	0.45	[0.47]	-1.21	[-1.30]	-3.43 ***	[-3.27]	[-3.19]
(3)–(1)	$\text{Alpha}_{\text{OOIxILO}}$	0.83	[0.67]	2.40 **	[2.09]	7.42 ***	[5.62]	

Panel C: Portfolio alpha (t+1) double-sorted by OOI_t and $\Delta ILOE_t$

		$\Delta ILOE_t$ rank						(C) – (A)
		(A) Low		(B) Mid		(C) High		
OOI_t rank		α_{t+1}	t-stat	α_{t+1}	t-stat	α_{t+1}	t-stat	t-stat
(3)	High OOI_t	0.84	[0.83]	1.94 **	[2.05]	3.35 ***	[3.49]	[2.02]
(2)		1.37 *	[1.92]	0.95	[1.43]	1.36 *	[1.80]	[-0.01]
(1)	Low OOI_t	0.45	[0.46]	-2.04 **	[-2.22]	-2.36 **	[-2.30]	[-2.37]
(3)–(1)	$\text{Alpha}_{\text{OOIxILO}}$	0.39	[0.30]	3.98 ***	[3.34]	5.70 ***	[4.33]	

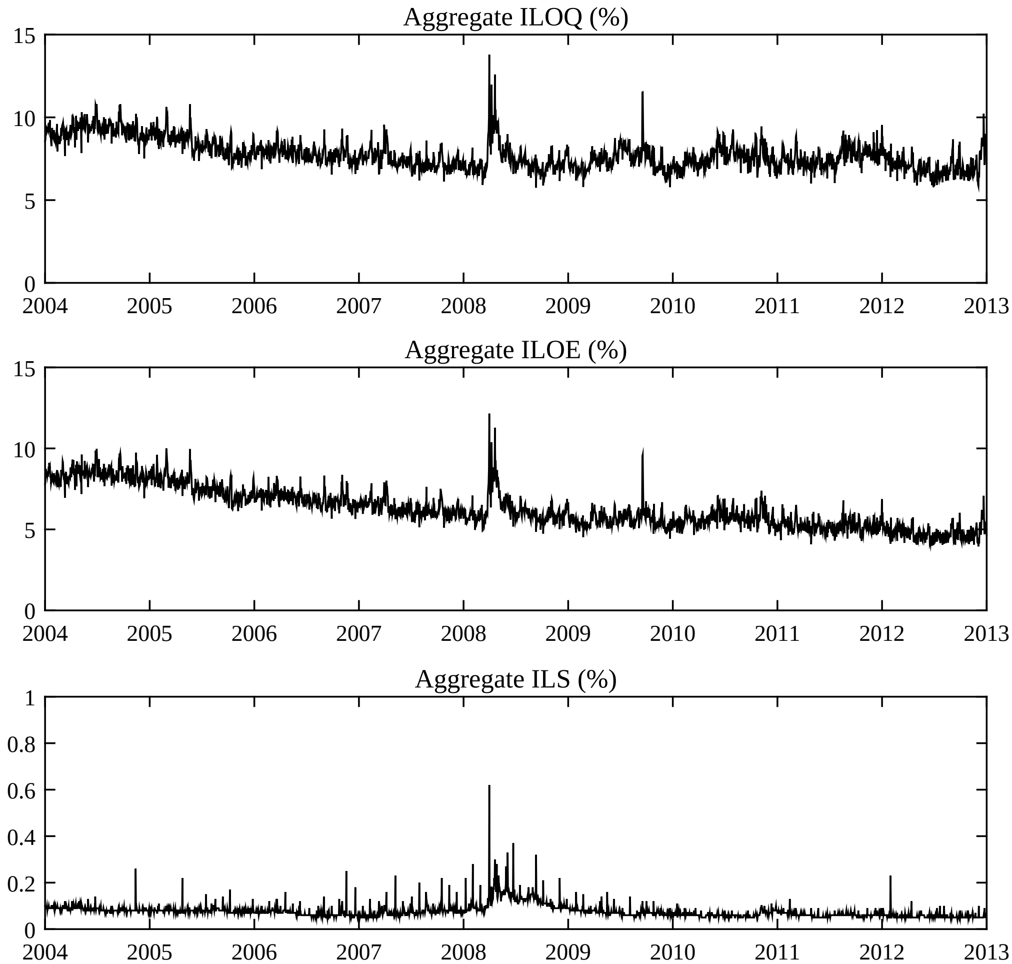

Figure 1: Aggregate option illiquidity (ILO)
We plot daily cross-sectional averages of the option illiquidity measures *ILOQ* and *ILOE* and the daily cross-sectional averages of underlying stock illiquidity measure *ILS* (bottom panel). For an individual firm, *ILS* is defined as the daily average relative effective spreads of intraday stock trades. The sample consists of S&P 500 index firms that have options traded on their underlying from January 2004 to December 2013 (2,504 trading days). Intraday option trades and quotes are obtained from LiveVol. We focus on transactions on option contracts with maturity of 30–182 calendar days. Intraday stock data are obtained from NYSE's TAQ database.

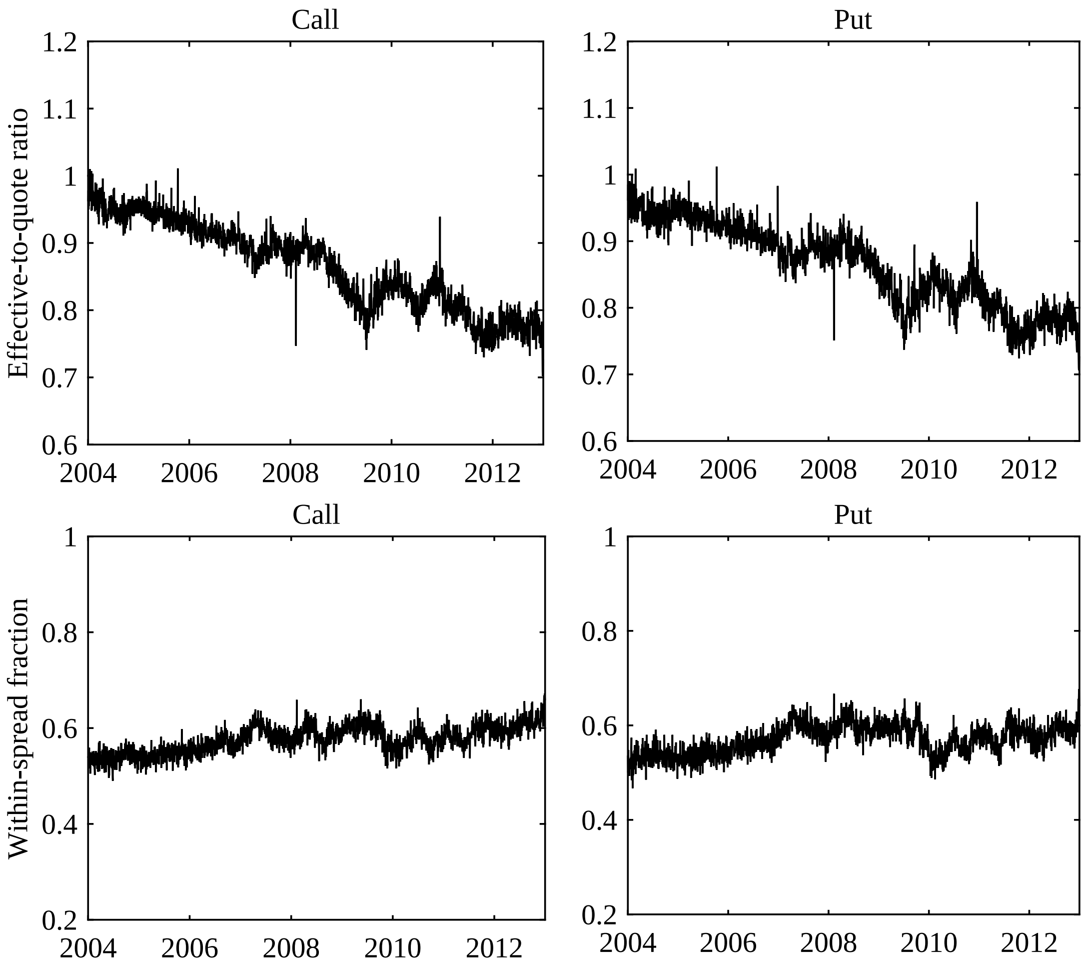

Figure 2: Option effective spreads v.s. quoted spreads by option type
The top row shows daily cross-sectional averages of the ratio of effective–to–quoted options spreads separately for calls and puts. A ratio below one indicates that trades are executed well within the quotes. The bottom row shows daily fraction of option trades that are executed within the quoted bid–ask spreads separately for calls and puts. The sample consists of S&P 500 index firms with exchange-listed options from January 2004 to December 2013 (2,504 trading days). Intraday option trades and quotes are obtained from LiveVol. We focus on transactions on option contracts with maturity of 30–182 calendar days. Intraday stock data are obtained from NYSE's TAQ database.

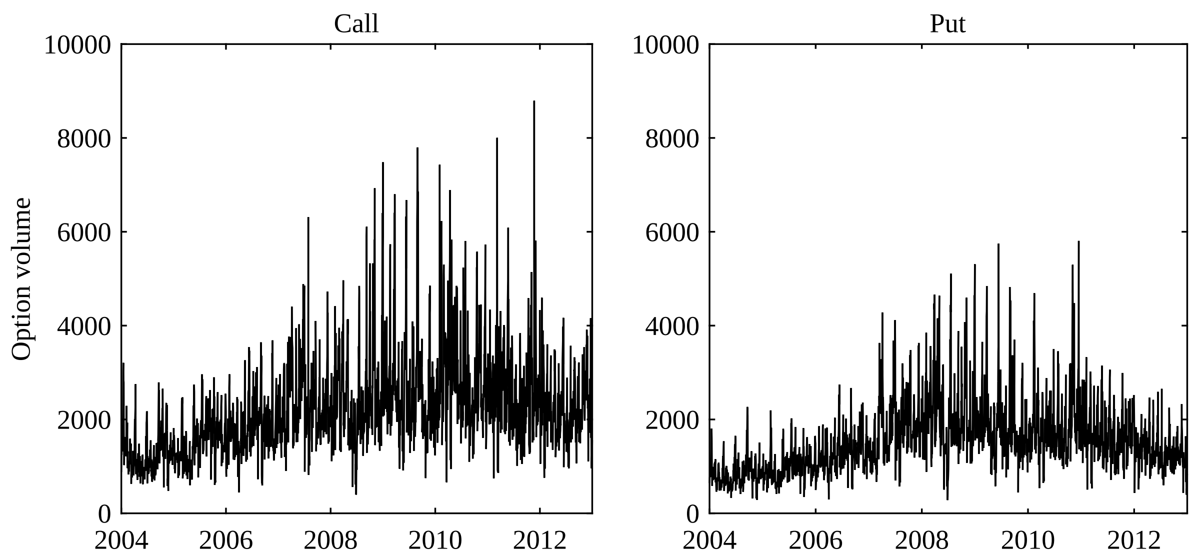

Figure 3: Option volume
We plot daily average option volume separately for calls and puts. Daily average volume is calculated by summing transaction volumes in each option category. The sample consists of S&P 500 index firms with exchange-listed options from January 2004 to December 2013 (2,504 trading days). Intraday option trades and quotes are obtained from LiveVol. We focus on transactions on option contracts with maturity of 30–182 calendar days. Intraday stock data are obtained from NYSE's TAQ database.

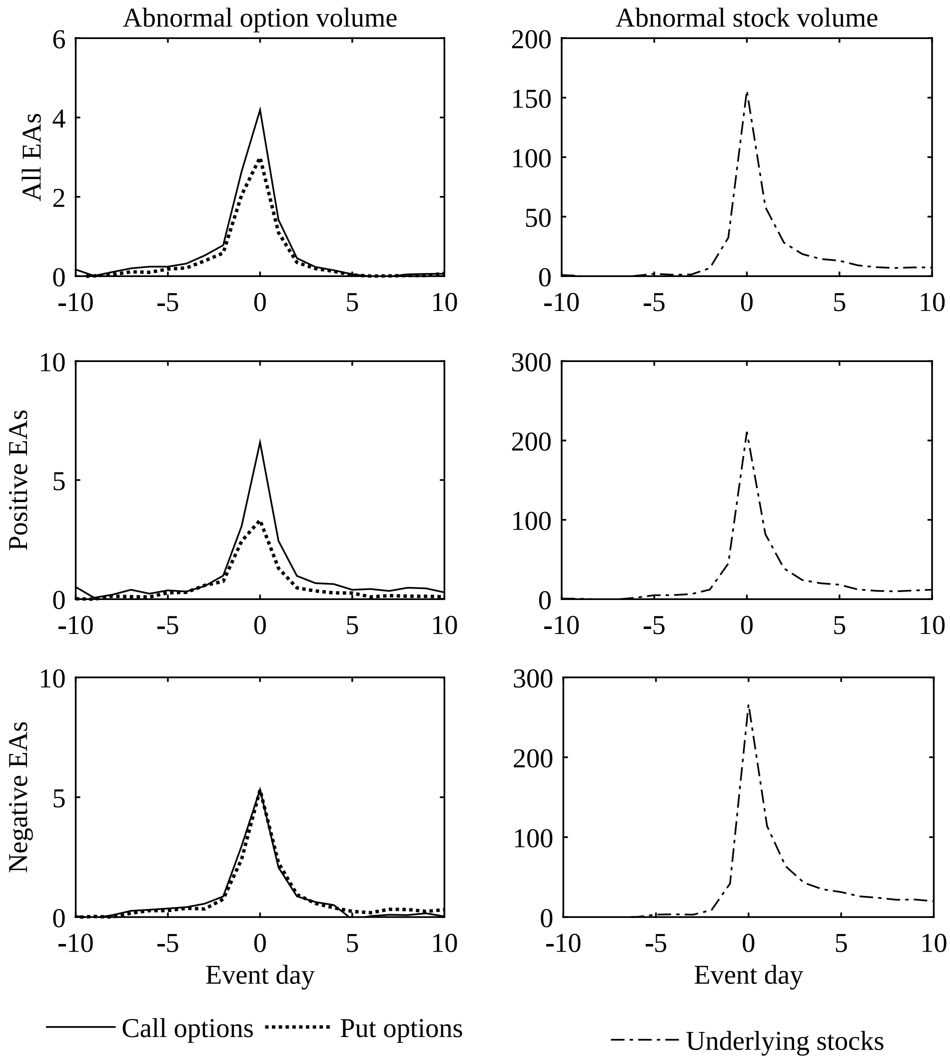

Figure 4: Abnormal volume around earnings announcements
This figure plots event-study results of option and stock abnormal trading volumes over the [–10,+10]–day window around earnings announcements. The left-hand and right-hand panels plot the results for option and stock trading volumes, respectively. Option trading volume is measured as the number of contracts traded (in thousandth units). Stock trading volume is measured as the level of shares turnover (trading volume over the number of shares outstanding). Abnormal option (or stock) volume is calculated as the daily average volume less its time-series mean over the pre-event window [–42,–21]. For option trading volume, we report results separately for call (solid line) and put (dotted line) options. The top panel plots event-study results for all earnings announcements news. The middle- and bottom-panels plot results for earnings announcements that are classified as positive surprises, and negative surprises, respectively. We measure the magnitude of earnings surprise using the standardized cumulative abnormal returns of the underlying stock over the three-day window [–1,1] relative to the event date. The sample consists of S&P 500 index firms that have options traded on their underlying from January 2004 to December 2013 (2,504 trading days). Intraday option trades and quotes are obtained from LiveVol. We focus on transactions on option contracts with maturity of 30–182 calendar days. Intraday stock data are obtained from NYSE's TAQ database.

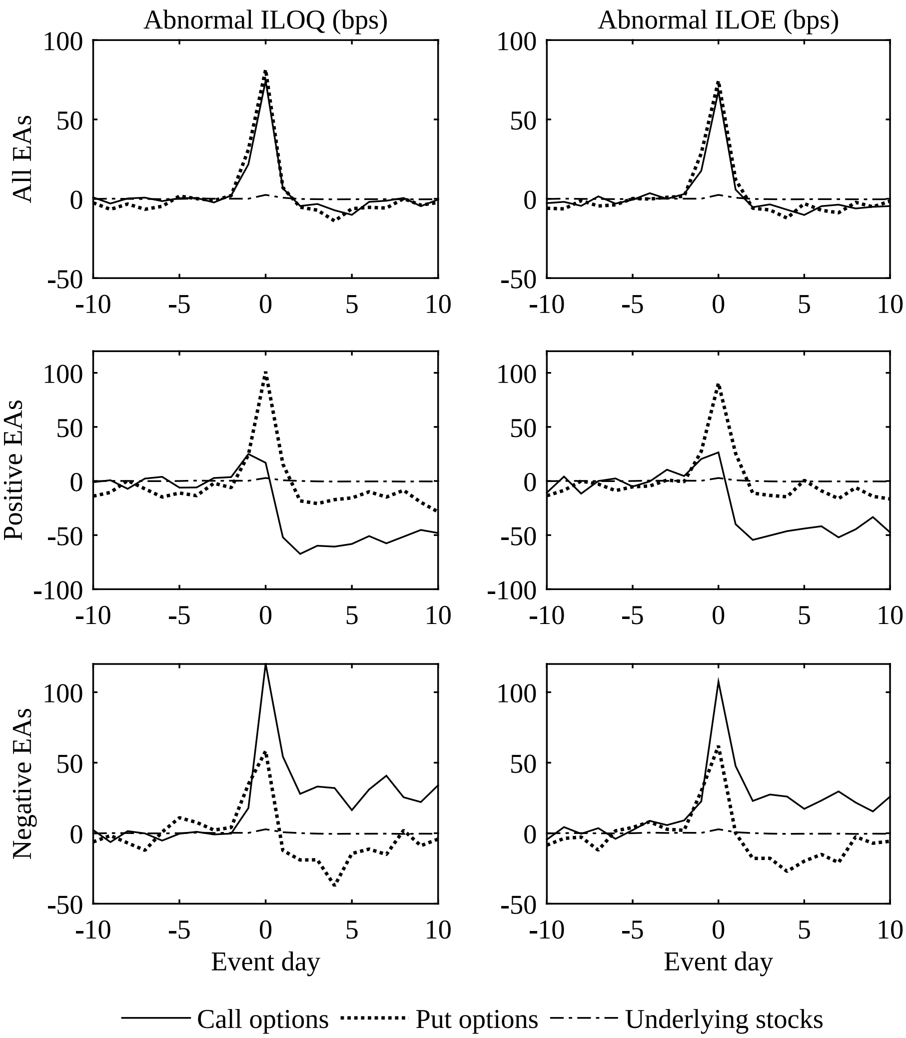

Figure 5: Abnormal option and stock illiquidity around earnings announcements This figure plots event–study results for options illiquidity (ILO) and stock illiquidity (ILS) over the [–10,+10] days window relative to earnings announcement dates. *ILOQ* is the daily option illiquidity measure defined as the dollar-volume-weighted average relative quoted spreads of intraday option trades. *ILOE* is the daily option illiquidity measure defined as the dollar-volume-weighted average relative effective spreads of intraday option trades. Abnormal option (or stock) illiquidity measure is calculated as its the daily level less its time-series mean over the pre-event window [–42,–21]. Results are reported separately for call options (solid line), put options (dotted line), and underlying stocks (dashed-dotted line). The top panel plots event-study results for all earnings announcements news. The middle- and bottom-panels plot results for earnings announcements that are classified as positive surprises, and negative surprises, respectively. We measure the magnitude of earnings surprise using the standardized cumulative abnormal returns of the underlying stock over the three-day window [–1,1] relative to the event date. The sample consists of S&P 500 index firms that have options traded on their underlying from January 2004 to December 2013 (2,504 trading days). Intraday option trades and quotes are obtained from LiveVol. We focus on transactions on option contracts with maturity of 30–182 calendar days. Intraday stock data are obtained from NYSE's TAQ database.

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Appendix A Calculation for PIN

In this subsection, we explain how PIN is estimated with intraday stock data. Details about the underlying market microstructure model can be found in Easley, Kiefer, O'Hara and Paperman (1996) and Easley, Hvidkjaer, and O'Hara (2002). Assuming that the market buy and sell orders arrive according to a Poisson process, the model implies that on any given day t, the likelihood of observing the number of buy trades B_t and the number of sell trades S_t is given by

$$\begin{aligned} L(\theta|Bt, S_t) &= \alpha(1-\delta)e^{-(\mu+\epsilon_b)}\frac{(\mu+\epsilon_b)^{B_t}}{B_t!}e^{-\epsilon_s}\frac{\epsilon_s^{S_t}}{S_t!} \\ &\quad +\alpha\delta e^{-\epsilon_b}\frac{\epsilon_b^{B_t}}{B_t!}e^{-(\mu+\epsilon_s)}\frac{(\mu+\epsilon_s)^{S_t}}{S_t!} + (1-\alpha)e^{-\epsilon_b}\frac{\epsilon_b^{B_t}}{B_t!}e^{-\epsilon_s}\frac{\epsilon_s^{S_t}}{S_t!}, \end{aligned} \tag{3}$$

where the parameter vector $\theta = (\alpha, \delta, \mu, \epsilon_b, \epsilon_s)$ represents the structural parameters of the model, and α denotes the probability of a private information event on the day. Given an information event day, the probability of a bad news is δ, and the probability of good news is $1-\delta$. Informed traders submit orders only on information event days with the arrival rate μ and act to their informational advantage. Uninformed investors trade every day and submit buy orders with the arrival rate ϵ_b and sell orders with the arrival rate ϵ_s.

Under the assumption of independence between days, the joint likelihood of observing a daily time series of buy and sell order counts $M = \{(Bt, S_t),\ t = 1, ..., T\}$ is then the product of the individual likelihoods:

$$L(\theta|M) = \prod_{t=1}^{T} L(\theta|Bt, S_t). \tag{4}$$

The PIN measure is then defined by

$$PIN = \frac{\alpha\mu}{\alpha\mu + \epsilon_b + \epsilon_s}, \tag{5}$$

which equals the probability that the opening trade comes from an informed trader.

To estimate the structural parameters, we maximize the joint likelihood in 4 over the parameter space numerically. The daily time series of buy and sell order counts are gathered and PIN estimates are produced for the subsample of firms which are listed on NYSE and AMEX because the specialist market structure is close to the PIN model feature. (see Easley, Kiefer, O'Hara and Paperman 1996). Vega (2006), Lin and Ke (2011) and Yan and Zhang (2012) express concerns about estimating the parameters by using optimization software packages. The optimization solution is sensitive to the initial values fed into the search algorithm and may yield boundary solutions frequently. Depending on the magnitude of the buy and sell counts, the likelihood function 4 may not be computed because of numerical overflow. Generally speaking, the larger the number of trades, the more difficult it is to obtain MLE estimates for PIN.

We employ the estimation method developed by Yan and Zhang (2012) who run the optimization procedure using a grid search algorithm.[19] These authors show that their method increases the probability of delivering valid PIN estimates, and generally makes the estimates more reliable. We run the estimation procedure for an underlying stock every calendar quarter, requiring that there are at least 50 days of trading on that stock during the quarter. Hence, for each firm, PIN is updated every quarter.

Appendix B Additional Tables

This appendix reports a series of additional results that are not part of the main paper.

[19]We greatly acknowledge the help from Yuxing Yan and Shaojun.Zhang who provided us with their computer code for estimating PIN.

Table B1: Options illiquidity and the magnitude of future stock returns

This table reports results for the absolute stock return predictability using daily Fama-MacBeth cross-sectional regressions. The dependent variable is the 1-day ahead absolute stock return on the underlying stock i , $|Ret_{i,t+1}|$. The main variable of interest is $\Delta ILO\_\text{ranked}_{i,t}$, which proxies for the change in options illiquidity (ILO) from time $t-1$ to time t. On each day, we cross-sectionally rank changes in ILO into 10 deciles from the lowest change, i.e., $\Delta ILO\_\text{ranked}_{i,t} = 1$, to the largest change, $\Delta ILO\_\text{ranked}_{i,t} = 10$. We include host of control variables in the regression specification. For stock i on day t, ΔILS_ranked is the cross-sectional rank of daily change in stock illiquidity, ILS; we use decile sort for consistent with $\Delta ILO\_\text{ranked}_{i,t}$. RET is the return on the underlying stock. RRV is a daily range-based proxy for the realized volatility of the underlying stock, defined as the difference of the underlying stocks intraday high and low price divided by the closing stock price. IV is the implied volatility for the underlying stock, calculated as the average implied volatilities of the call-put pair with 30 calendar days to maturity reported in the standardized option file from OptionMetrics. *ln(OptVolume)* is the natural logarithm of the number of option contracts traded. *ln(size)* is the natural logarithm of the market value of the underlying stock. The row labeled *Day count* reports the number of daily cross-section regressions used for reporting the Fama-MacBeth regression estimates. The row labeled *Avg.cross section* reports the average sample size of daily cross-sectional regressions. Newey-West t-statistics adjusted for autocorrelation up to 45 lags are reported in square brackets below each estimate. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

	Dependent variable: $\|Ret_{i,t+1}$ (%)$\|$	
	Quoted bid-ask spreads	*Effective bid-ask spreads*
	(I)	(II)
Δ ILO ranked$_{i,t}$	0.0012**	0.0010**
	[2.42]	[2.40]
Control variables		
Δ ILS_ranked$_{i,t}$	-0.0003	-0.0003
	[-0.40]	[-0.42]
RET $_{i,t}$	0.3860*	0.3890**
	[1.95]	[1.97]
RRV$_{i,t}$	0.0009***	0.0009***
	[23.34]	[23.36]
IV$_{i,t}$	0.0058***	0.08846***
	[23.36]	[23.47]
ln(OptVolume)$_{i,t}$	0.0122***	0.0124***
	[39.93]	[39.70]
ln(size)	-0.0059	-0.0060
	[3.83]	[3.73]
Intercept	0.0585	0.0623
	[-1.06]	[-1.04]
Day Count	2,469	2,469
Avg. cross section	470	471
Adj. R^2	16.79%	16.78%