Illiquidity Premia in the Equity Options Market*

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Standard option valuation models leave no room for option illiquidity premia. Yet we find that the risk-adjusted return spread for illiquid over liquid equity call options is 22 bps per day for at-the-money calls and 42 bps overall. These illiquidity premiums are computed using state-of-the-art option illiquidity measures for a large panel of US equities, and are robust to different empirical implementations. Results for puts are not economically or statistically significant. These findings are consistent with evidence that market makers in the equity options market hold large and risky net long positions in calls but much smaller net positions in puts.

1. Introduction

In positive net supply markets such as bond or stock markets, it is natural to expect a positive illiquidity premium (Amihud and Mendelson, 1986). In zero net supply derivatives markets, buying and selling pressures not only affect prices and expected returns, they also determine if the illiquidity premium is positive or negative. Market makers absorb net buying or selling pressure and need to be compensated for the costs and risks that this entails. This compensation depends not only on the risk preferences of buyers and sellers, the capital of the market maker, the stochastic properties of the derivative and underlying securities, but also on the market and search frictions that determine the ease by which the market maker can locate an offsetting trade. The search frictions interact with the other determinants of option supply and demand to determine bid-ask spreads and liquidity, and result in illiquidity premia that are not just functions of inventory or hedging costs.

Most option pricing models ignore the role of financial intermediaries, and thus the impact of supply and demand on option prices.[1] In response to this, Garleanu, Pedersen, and Poteshman (2009) develop a demand-based option theory involving market makers who incur unhedgeable risks, which results in an upward sloping supply curve. The steepness of the supply curve depends on the nature of the risks facing the market maker. While Garleanu, Pedersen, and Poteshman (2009) do not model bid-ask spreads and illiquidity, Deuskar, Gupta, and Subrahmanyam (2011) argue convincingly that higher illiquidity gives rise to a more positively sloped supply curve and thus a bigger price impact. The sign of the illiquidity premium in such markets depends on whether end users are net buyers or net sellers.

[1] Black and Scholes (1973), Hull and White (1987), and Heston (1993) are classic papers in this literature. See Jones (2006) for a detailed analysis of returns on S&P500 index options.

Lakonishok, Lee, Pearson, and Poteshman (2009) and Garleanu, Pedersen, and Poteshman (2009) document that in the equity option market, end-users are net sellers. We therefore expect that in equity option markets, market makers need to be compensated for the costs of being net long equity options by price discounts and higher expected returns, and that the size of the return premium will be partly determined by the illiquidity of the option.

This paper empirically investigates this prediction. We construct daily illiquidity measures from a new dataset on intraday option trades and quotes for S&P 500 firms during the 2004-2012 period. We confirm the existence of selling pressures from end-users, and find that expected option returns increase with illiquidity. We refer to the resulting differences in returns as illiquidity premiums. Selling pressures are much stronger for calls than for puts, which explains why we find an economically and statistically significant premium for calls but not for puts. We find that proxies for asymmetric information, hedging costs, stock illiquidity and inventory costs are significant drivers of the option illiquidity measures. These factors, which are often difficult to measure or even observe, thus indirectly determine option returns via the illiquidity premium, but illiquidity remains an important determinant of returns after directly including them in the return regressions.

To our knowledge, we are the first to use intraday trades and quotes to compute illiquidity using effective spreads for equity options on a large number of underlying firms. When sorting firms into quintiles based on option illiquidity, we find that the option spread portfolio that goes long the most illiquid calls and short the least illiquid calls earns a positive and significant premium across moneyness categories. Using daily returns, the average risk-adjusted option return spread for at-the-money (ATM) calls is 22 basis points (bps). The return spread is 42 bps for calls overall, and it is largest for out-of-the-money call options. Selling pressures from end-users are much lower for puts, and we find that the return spread is not significant in the single sorts. The results for weekly option returns–with a delta hedge that is rebalanced daily–are consistent with the daily results. While these average call return spreads are large, it is important to note that equity option spreads are wide.

We complement the results from portfolio sorts using cross-sectional Fama-MacBeth (1973) regressions for daily and weekly delta-hedged returns. We run multivariate regressions controlling for stock volatility and other firm characteristics. An increase in option illiquidity has a positive and significant impact on next period's option returns, confirming the existence of illiquidity premiums in the options market. The effect of illiquidity on option returns is substantial: for example, a one standard deviation positive shock to at-the-money (ATM) call option illiquidity would result in a 10 bps increase per day in the return on the call option. This can be compared with the average delta-hedged return on ATM calls, which is only 1 bps per day.

The existing empirical evidence on illiquidity premia and discounts in derivatives markets is very limited. Li and Zhang (2011) discuss the zero net supply case and find empirically that buying pressure combined with illiquidity creates price premiums for more liquid warrants relative to more illiquid options on the Hang Seng index. Deuskar, Gupta, and Subrahmanyam (2011) find an liquidity price discount in the market for interest rate caps and floors, where market makers have a net short position. Consistent with these findings, we show that the combination of selling pressures and illiquidity in equity options on a panel of 500 US firms generates a positive illiquidity premium in equity call option returns. If net demand from end-users is negative, then dealers are required to absorb it. Liquidity providers in equity option markets thus hold long positions and require higher compensation in more illiquid series, consistent with lower current prices and higher expected returns.[2] Stock illiquidity is positively related to option illiquidity and therefore indirectly impacts option returns.

In contrast to the limited evidence on illiquidity premia in derivatives markets, the empirical literature contains a wealth of evidence regarding illiquidity premia in stock and bond markets. It has been shown in both markets that illiquidity affects returns, with more illiquid assets having higher expected returns. The illiquidity premium was first documented for the equity market in Amihud and Mendelson (1986), and for the bond market in Amihud and Mendelson (1991).[3] There is also a growing body of evidence on the existence of significant illiquidity premia in other markets, see for instance Mancini, Ranaldo, and Wrampelmayer (2013) for the FX market, and Bongaerts, de Jong, and Driessen (2011) for the credit default swap market. Option spreads and their determinants have been analyzed in, for example, Vijh (1990), George and Longstaff (1993), and Wei and Zheng (2010).

The remainder of the paper is structured as follows: In Section 2 we develop our hypotheses and construct option return and illiquidity measures. In Section 3 we perform single and double sorts on option illiquidity and related variables. Section 4 contains our multivariate analysis based on Fama-MacBeth regressions. Section 5 investigates potential drivers of option illiquidity, and Section 6 concludes.

[2]For related results on trading activity and demand pressures in equity option markets, see Bollen and Whaley (2004), Easley, O'Hara, and Srinivas (1998), Mayhew (2002), Pan and Poteshman (2006), and Roll, Schwartz, and Subrahmanyam (2010).

[3]Other 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), Acharya and Pedersen (2005), and Lee (2011). 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).

2. *Illiquidity and Option Returns*

In this section we first develop our hypotheses regarding the relationship between option illiquidity and returns. We then construct daily stock and option illiquidity measures from intraday trades and quotes, and we discuss the data on option returns and option order imbalances.

i. Hypothesis Development

The standard Black and Scholes (1973) replication approach to option valuation leaves no room for illiquidity to impact option returns, because equity options can be perfectly replicated by continuously trading the perfectly liquid underlying stock. The supply curve for each option series is a horizontal line. But in reality market makers are forced to rebalance and incur trading costs. As a result replication is imperfect due to stock price jumps and stochastic volatility. Moreover, market makers may have changing attitudes toward risk and they sometimes face capital constraints.[4] Bollen and Whaley (2004) therefore argue that supply curves are upward sloping, and that option returns are determined by the interaction of the market maker's willingness to supply options with option demand. The slope of

[4]We think of option prices and spreads as being determined in something akin to a dealer market. In reality the structure of U.S. equity option markets is much more complex. See Battalio, Shkilko, and Van Ness (2011) for details.

the supply curve reflects unhedgeable risks. Garleanu, Pedersen, and Poteshman (GPP, 2009) develop a model of option dealers and end-users in which selling pressure in an option series decreases its price by an amount proportional to the steepness of the supply curve, and the steepness of the supply curve is determined by the variance of the unhedgeable part of the option.

GPP (2009) do not explicitly model the spread of the option.[5] However, there is a rich literature that models bid-ask spreads set by market makers. Option market makers face fixed order processing costs, asymmetric information costs (Glosten and Milgrom, 1985), inventory costs (Amihud and Mendelson, 1980, Ho and Stoll, 1983) and hedging costs (Cho and Engle, 1999, Engle and Neri, 2010). Along with Deuskar, Gupta, and Subrahmanyam (2011), we argue that the higher this endogenously determined illiquidity, the steeper the supply curve.

Deuskar, Gupta, and Subrahmanyam (2011) and Li and Zhang (2011) empirically investigate the existence of illiquidity premia and discounts in derivatives markets. Both papers convincingly argue that it is not obvious ex-ante whether one should expect a liquidity premium or discount in derivatives markets. The *size* of the liquidity premia and discounts depends on partly unobservable factors such as the risk-aversion of the marginal trader, the ability of traders to efficiently replicate the option using the underlying stock, and the nature and magnitude of the unhedgeable risks. As emphasized by Deuskar, Gupta, and Subrahmanyam (2011), the *sign* of the illiquidity risk premium should depend on whether the market is characterized by net buying or net selling pressure. Higher illiquidity will be associated with higher expected returns in derivatives markets where end-users are net sellers, while the correlation will be negative in markets where end-users are net buyers.

The empirical evidence in Deuskar, Gupta, and Subrahmanyam (2011) and Li and Zhang (2011) is consistent with the theoretical predictions. Deuskar, Gupta, and Subrahmanyam (2011) find an liquidity price discount in the market for interest rate caps and floors, where market makers have a net short position. Li and Zhang (2011) use data on options and derivative warrants on the Hang Seng index and find price discounts in the more illiquid options.

Our empirical analysis focuses on U.S. individual equity options. Using data on 303 firms from 1996 to 2001, GPP find that dealers in U.S. equity option markets face selling pressures. We obtain data on S&P500 firms from 2005 through 2012. We confirm the existence of these selling pressures. Our first and most important testable hypothesis is therefore

- $H_0(1A)$: If market makers on average face strong selling pressures then more illiquid options will have higher expected returns.[6]

We find that selling pressures for calls are much stronger than for puts. This leads to our next hypothesis:

- $H_0(1B)$: If selling pressures are stronger for calls than for puts then we expect to find a larger and more robustly estimated illiquidity premium for calls than for puts.

If $H_0(1A)$ is confirmed by the data, and we find below that it is, then it becomes of first-order importance to investigate which factors determine option illiquidity, which we denote IL^O. We conjecture that factors driving IL^O include

[5] See Duffie, Garleanu, and Pedersen (2005) for a search model in which market makers set bid and ask prices.

[6] Similar to the analysis in Li and Zhang (2011), we do not think of this excess return as an illiquidity *risk* premium in the sense of, for example, Pastor and Stambaugh (2003).

those that can be quantified relatively easily, such as option Gamma and Vega, but also risks that are much harder to quantify, such as asymmetric information about the future price and volatility of the underlying stock. This leads to the following hypotheses:

- $H_0(2A)$: Option Gamma and Vega capture unhedgeable risks left over after delta-hedging. Higher Gamma and Vega will increase IL^O and therefore option returns in the presence of selling pressures.
- $H_0(2B)$: Higher values of proxies for asymmetric information will increase IL^O.
- $H_0(2C)$: Higher underlying stock illiquidity will increase IL^O.
- $H_0(2D)$: Increased option imbalance magnitudes will lead to an increase in IL^O.

These determinants of IL^O affect option returns indirectly through their impact on illiquidity. Studying the determinants of IL^O therefore aids our understanding of the sources of illiquidity and illiquidity premiums in option markets, which may be quite different from illiquidity in the stock market for several reasons. Most importantly, even if option markets do not strictly operate as over-the-counter markets, the role of market makers is important in equity option markets. When option market makers are unable to quickly re-sell illiquid series, they will incur higher hedging and rebalancing costs.

Note also that in equity option markets, both sides retain exposure to the asset until the position is closed. Equity option end-users often sell covered calls and hold their position to maturity (see Lakonishok, Lee, Pearson, and Poteshman, 2007), and illiquidity may be less of a concern for these investors.[7] However, market makers who absorb negative demand pressure wish to unload their positions as soon as possible. Inability to do so due to high illiquidity in options leads to higher inventory, asymmetric information and hedging costs, and ultimately to an illiquidity premium.[8]

ii. Option Returns and Stock Returns

In the standard Black-Scholes (1973) model, the option price, O, for a non-dividend paying stock with price S is a function of the strike price, K, the risk-free rate, r, maturity, T, and constant volatility, σ, which can be written as

$$O = BS\left(S, K, r, T, \sigma\right) \tag{1}$$

Coval and Shumway (2001) show that in this basic model with constant risk-free rate and constant volatility, the expected instantaneous return on an option $E\left[R^O\right]$ is given by

$$E\left[R^O\right] = \left(r + (E\left[R^S\right] - r)\frac{S}{O}\frac{\partial O}{\partial S}\right) dt \tag{2}$$

where $E\left[R^S\right]$ is the expected return on the stock. The sensitivity of the option price to the underlying stock price (the option delta), denoted by $\frac{\partial O}{\partial S}$, will depend on the variables in equation (1). The delta is positive for call options and negative for puts. Thus the expected excess return on call options is positive and the expected excess return on put options is negative.

The presence of $E\left[R^S\right]$ and $\frac{\partial O}{\partial S}$ on the right-hand side of equation (2) shows that it is critical to properly control for the return on the underlying stock when regressing option returns on illiq-

[7] Moreover, Jensen and Pedersen (2015) recently show that an American call on a stock that does not pay dividends may nevertheless get exercised early rather than sold if the option bid-ask spread is sufficiently large, which may reduce the impact of illiquidity.

[8] We are grateful to Yakov Amihud for suggesting this interpretation.

uidity measures. We implement this control by using delta-hedged returns computed as

$$\tilde{R}^O_{t+1,n} = R^O_{t+1,n} - R^S_{t+1} S_t \frac{\Delta_{t,n}}{O_{t,n}} \qquad (3)$$

where the stock return, R^S_{t+1}, includes dividends and $R^O_{t+1,n}$ is the daily raw rate of return on option n. The option $\Delta_{t,n} = \frac{\partial O_{t,n}}{\partial S_t}$ is computed by OptionMetrics using the Cox, Ross, and Rubinstein (1979) binomial tree model, thus allowing for early exercise, and further assuming a constant dividend yield. We obtain daily stock returns, prices, and the number of outstanding shares from the Center for Research in Securities Prices (CRSP).

We now discuss the computation of the raw option returns $R^O_{t+1,n}$, from which we can compute the delta-hedged option returns, $\tilde{R}^O_{t+1,n}$. Raw option returns are constructed for all S&P500 index constituents using OptionMetrics, which includes daily closing bid and ask quotes on American options, as well as their implied volatilities and deltas.

To compute raw option returns, we follow Coval and Shumway (2001) and use quoted end-of-day bid-ask midpoints if quotes are available on the respective days.[9] We compute equally-weighted average daily returns on a firm-by-firm basis for different moneyness categories by averaging option returns for all available series. For each option moneyness category and for each firm, the delta-hedged return is then computed from equation (3) as

$$\tilde{R}^O_{t+1} = \frac{1}{N} \sum_{n=1}^{N} \frac{O_{t+1}(K_n, T_n - 1) - O_t(K_n, T_n)}{O_t(K_n, T_n)} - R^S_{t+1} S_t \frac{1}{N} \sum_{n=1}^{N} \frac{\Delta_t\,(K_n, T_n)}{O_t(K_n, T_n)} \qquad (4)$$

where N is the number of available series in the particular category at time t with legitimate quotes at time $t+1$. $O_t(K_n, T_n)$ is the midpoint quote, (ask+bid)/2, for an option with strike price K_n and maturity T_n.[10] While our benchmark returns are thus equal-weighted we consider open-interest weighted returns below as well. In a robustness exercise, we also consider ask-to-ask returns instead of returns based on midpoints.

The weekly firm-specific option returns for each option category are computed in a similar fashion, using daily rebalancing of the delta hedge

$$\tilde{R}^O_{t:t+5} = R^O_{t:t+5} - \sum_{j=1}^{5} \frac{R^S_{t+j} S_{t+j-1} \Delta_{t+j-1}}{O_t}. \qquad (5)$$

The daily rebalancing of the delta hedge is designed to capture the nonlinear (Gamma) effect from the underlying stock which otherwise must be hedged via option positions that potentially incur much larger trading costs. Weekly option returns are constructed using Tuesday-to-Tuesday quotes wherever possible, and alternatively using a minimum of two daily returns. Our weekly return data contains just over three trading days on average. Although potentially interesting, we do not consider holding periods longer than a week due to data limitations arising from option series expirations and missing observations.

Our sample period is from January 2004 to December 2012, because for this period we have intraday option prices and quotes from LiveVol.[11] We control for the index composition on a

[9] This allows us to compare returns across the largest possible number of options and stocks.

[10] When computing returns we use the adjustment factor for splits and other distribution events provided by OptionMetrics.

[11] Battalio, Hatch, and Jennings (2004) document structural changes in option markets until 2002, after which the market more closely resembles a national market.

monthly basis. The last month of a firm in the index corresponds to the last month of the firm in our sample. We focus on S&P500 firms for reasons of data availability and because of their high liquidity, which biases our results towards not finding evidence of the importance of illiquidity.

For each firm, we consider put and call options with maturity between 30 and 180 days which are the most actively traded. Puts and calls are further divided into moneyness categories, and we report on at-the-money (ATM), and out-of-the-money (OTM) options. We follow Driessen, Maenhout, and Vilkov (2009) and Bollen and Whaley (2004) and define moneyness according to the option delta from OptionMetrics, which we denote by Δ. OTM options are defined by $0.125 < \Delta \leq 0.375$ for calls and $-0.375 < \Delta \leq -0.125$ for puts and ATM options correspond to $0.125 < \Delta \leq 0.375$ for calls and $-0.625 < \Delta \leq -0.375$ for puts. The ALL option category includes all moneyness categories, including in-the-money (ITM) options and is defined by $0.125 < \Delta \leq 0.875$ for calls and $-0.875 < \Delta \leq -0.125$ for puts.[12]

Following Goyal and Saretto (2009), Cao and Wei (2010), and Muravyev (2014) we apply filters to the option data, eliminating the following series: (i) prices that violate no-arbitrage conditions; (ii) observations with ask price lower than or equal to the bid price; (iii) options with open interest equal to zero; (iv) options with missing prices, implied volatilities or deltas; (v) options with quoted bid-ask spread above 50% of the mid-quote; (vi) options with mid-point prices below $0.10.

For options that are not part of the penny-pilot program we remove series with prices lower than $3 *and* bid-ask spread below $0.05, or prices equal to or higher than $3 *and* bid-ask spread below $0.10, on the grounds that the bid-ask spread is lower than the minimum tick size, which signals a data error. For penny-pilot options we remove series with prices equal to or higher than $3 *and* bid-ask spreads below $0.05.

We merge four datasets in our empirical analysis: CRSP, OptionMetrics, TAQ and LiveVol. An additional filter is therefore that a firm should have data available across all four data sources. Finally, we include only firm/day observations with positive volume reported in OptionMetrics. For calls this yields on average 487 firms for the daily data, and 440 firms in the weekly data, for puts we have 423 and 407 firms for daily and weekly data, respectively.

Using equal-weighted returns across firms, Figure 1 plots the daily delta-hedged call and put option returns, $\tilde{R}^O_{t+1}$, over time. All the option returns display volatility clustering and strong evidence of non-normality. As is typical of daily speculative returns, the mean is completely dominated by the dispersion. Outliers are clearly visible as well. Below, we therefore run robustness checks, eliminating the most extreme option returns.

Table 1 reports summary statistics for daily and weekly delta-hedged option returns. We first compute the respective statistics for each firm and report the average across firms. The delta-hedged return averages are close to zero except for OTM options. The option returns exhibit positive skewness and excess kurtosis in all categories, which is expected due to the option payoff convexity. Returns on OTM options are more variable than returns on ATM options. The option returns display mixed evidence of serial dependence judging from the first-order autocorrelation. The absolute return autocorrelation is positive for all categories and nontrivial for the daily returns in Panels A and B, confirm-

[12] Note that these sample selection criteria eliminate deep ITM and OTM options, which are less actively traded (see Harris and Mayhew, 2005).

ing the volatility clustering, apparent in Figure 1. The average number of observations refers to the number of option series per day (or week) in each moneyness category in the sample.

To put the option return moments in perspective, Table 1 reports sample statistics for daily (Panel E) and weekly (Panel F) stock returns. We have again averaged the sample statistics across firms. Not surprisingly, volatility and skewness are both much lower for stock returns than for option returns. Kurtosis is quite high for stock returns although it is again much lower than for option returns. Volatility persistence, as measured by the absolute return autocorrelation, is generally higher for stocks than for options.

iii. *Illiquidity Measures from Trades and Quotes*

We document the impact of option illiquidity on option returns, but also investigate if illiquidity in the underlying stock market affects option returns. We rely on the relative effective spread which is a conventional measure of illiquidity that measures the direct costs that dealers charge for transactions, reflecting dealers' costs of market making.

We follow the convention in the literature, and compute stock illiquidity as the effective spread obtained from high-frequency intraday TAQ (Trade and Quote) data. Specifically, for a given stock, the TAQ effective spread on the trade is defined as

$$IL_k^S = \frac{2|S_k^P - S_k^M|}{S_k^M}, \tag{6}$$

where S_k^P is the price of the k^{th} trade and S_k^M is the midpoint of the consolidated (from different exchanges) best bid and offer prevailing at the time of the k^{th} trade. The daily stock's effective spread, IL^S, is the dollar-volume weighted average of all IL_k^S computed over all trades during the day

$$IL^S = \frac{\sum_k DolVol_k IL_k^S}{\sum_k DolVol_k}$$

where the dollar-volume, $DolVol_k$, is the stock price multiplied by the trading volume. Below, we compute IL^S on each day during the 2004-2012 sample for each stock.

Intraday options trading data are reported by all equity options exchanges via the Options Price Reporting Authority (OPRA). We obtain data from LiveVol, a commercial data vendor that uses the raw OPRA data to create files for each company on each day with information about each option trade during the day, including the national best bid and offer quotes prevailing at the time of the trade, execution price, trading volume, and option delta of each trade. The LiveVol data start in January 2004 and our sample goes through the end of 2012.

Our sample contains all trades and matched quotes for all option series on S&P500 firms. Using intraday data we compute the effective relative option spread as

$$IL_k^O = \frac{2|O_k^P - O_k^M|}{O_k^M},$$

where O_k^P is the price of the k^{th} trade and O_k^M is the midpoint of the consolidated (from different exchanges) best bid and offer prevailing at the time of the k^{th} trade. The daily effective option spread, IL^O, is the volume-weighted average of all IL_k^O computed over all trades during the day

$$IL^O = \frac{\sum_k Vol_k IL_k^O}{\sum_k Vol_k}$$

where the volume, Vol_k, is the number of contracts transacted in the kth trade.[13] For every

[13]Following Bollen and Whaley (2004), we weigh IL_k^O by the number of contracts and not by dollar volume in order to avoid the mechanical effect from option moneyness.

day in the sample, we compute IL^O for all series traded on any of the available 500 firms in the sample. The IL^O measure is then averaged across series within the same moneyness category for each firm, using equal weights. To the best of our knowledge we are the first to construct option illiquidity measures from TAQ-type data on an extensive sample of firms for an extended time period.

Panel A of Table 2 presents summary statistics of our liquidity measures for calls and puts across different moneyness categories. Relative effective spreads are higher on average for calls, at 8.03% (ALL), compared with puts, at 7.01%. OTM options have the highest effective spreads for both calls and puts. Note that the average effective spread on stocks is much smaller at 0.09%.

Panel A of Table 2 also contains information on option trading volume and the number of trades. We report the average number of trades per firm per day as well as the average number of contracts traded per firm per day. Call trading volume exceeds put trading volume overall and for each moneyness category as well. While ATM call trading volume averages 759 contracts per day, ATM put volume is only 453 contracts per day. This difference in trading volume is also reflected in the frequency of trading which is lower for puts.

Figure 2 shows the time series of relative effective spreads for each moneyness category averaged across firms. OTM options exhibit the most variation in effective spreads for both calls and puts. All spreads spike up significantly during the 2008-2009 credit crisis, and less so during the European debt crisis in 2010-2011. All series are trending down throughout the sample, as the option markets get more efficient.

The top panel of Figure 3 plots stock illiquidity over time. There is no obvious downward trend, because liquidity in stock markets had already increased significantly prior to the beginning of our sample. Figure 3 also plots the S&P500 index level (middle panel) and the VIX volatility index (bottom panel). Note that when illiquidity spikes in the recent financial crisis, the S&P500 drops and the VIX also increases.

Panels B (for calls) and C (for puts) in Table 2 report cross-sectional correlations between IL^O for OTM, ATM, and ALL options as well as IL^S. We compute the cross-sectional correlations between the illiquidity measures on each day and report the time-series averages of these correlations. The correlation of different option illiquidity categories with stock illiquidity ranges between 12% and 18%. The correlation between OTM and ATM illiquidity is 48% for calls and 45% for puts. The correlation between ALL illiquidity and the illiquidity of the separate moneyness categories is also positive.

While we will rely on relative effective spreads throughout this paper, it is of interest to assess how the distribution of dollar spreads varies with the bid size of the option. Figure 4 follows de Fontnouvelle, Fishe, and Harris (2003) and reports the volume weighted effective dollar option spreads for five categories of options defined by the option bid price. Call options are in the left-side panels and put options are in the right-side panels. Note that for low-bid options, the dollar effective spreads exhibit a slight downward trend over time, whereas for bids above $5 the dollar spreads do not contain a trend. Figure A.1 in the appendix contains the same plot for ATM options only.

While Figures 4 and A.1 plot time series of the average dollar spreads by bid level, Panel D of Table 2 reports various cross-sectional descriptive statistics. Not surprisingly, on average the cross-sectional variation is quite wide. Panel D also shows that while the average number of trades tends to increase with the bid size, the average trading volume does not. Finally, Panel D shows that the average number of firms available is largest for bids below \$10. This simply reflects the cross-sectional distribution of the underlying stock price levels and strongly suggests that relying on relative effective spreads, as we do below, is sensible.

iv. Order Imbalances

We obtain data from the CBOE and the ISE, the two largest option exchanges which capture more than 60% of overall trading volume. We obtain data on open and close positions, and buy versus sell orders from end users, that is, non-market-makers, from these two exchanges. The exchanges split the orders into firm and customer orders, and provide open-buy, open-sell, close-buy and close-sell volume for each series. We use these data to construct an option order imbalance measure for each firm and moneyness category, in the spirit of Bollen and Whaley (2004):

$$IMBAL = \frac{\sum_k |\Delta_k| \big(OpenBuy_k + CloseBuy_k - OpenSell_k - CloseSell_k\big)}{\sum_k \big(OpenBuy_k + CloseBuy_k + OpenSell_k + CloseSell_k\big)} \quad (7)$$

where for each component in equation (7) we sum across institutional and customer orders.

This measure has several advantages: (i) it provides signed volume so that we do not need to use the otherwise prevalent Lee and Ready (1991) algorithm to sign trades; (ii) the data does not include dealer volume, which allows us to directly observe the aggregate inventory pressures on dealers.[14]

Panel A of Table 2 reports the average option order imbalance for each moneyness category. We report both delta-weighted imbalances as in equation (7) and simple sums. In the analysis below we use delta-weighted imbalances throughout. Note that in either case imbalances are strongly negative on average, particularly for call options.

Figure 5 plots the delta-weighted order imbalances averaged across firms and days of the week. For each of the six option categories, order imbalances are persistent. Note also that the order imbalances for calls are strongly negative throughout the period, confirming that end-users consistently are net sellers of equity call options. For put options the picture is more mixed. Put order imbalances are mostly negative throughout the sample, but often close to zero or even positive. Order imbalances are also more clearly negative for OTM puts than for ATM puts. In our empirical results below we document how these patterns affect returns, bid-ask spreads, and the cross-sectional relation between returns and IL^O.

3. Illiquidity and the Cross-Section of Option Returns

We now investigate the cross-sectional relationship between option illiquidity and expected option returns. We first discuss simple univariate portfolio sorts on option illiquidity. We then run a number of robustness checks. Finally, we implement double-sorts on option illiquidity and several potential determinants of this illiquidity.

i. Sorting on Option Illiquidity

Perhaps the simplest approach to analyzing illiquidity effects is to sort firms into illiquidity portfolios, and investigate the resulting patterns in portfolio returns. This approach reduces the noise in returns on the individual series.

Following Amihud (2002) and French, Schwert, and Stambaugh (1987), we use ex-post re-

[14] Hu (2014) uses a similar measure to study predictability of the underlying stock returns.

alized returns as a measure of expected returns. In order to remove the first-order effects from the underlying asset, we transform the ex-post returns to delta-hedged returns using equation (4) for the daily horizon and equation (5) for the weekly horizon. To alleviate potential asynchronicity biases, we follow Goyal and Saretto's (2009) analysis of option returns and skip one day between the computation of illiquidity measures and the computation of returns.[15] Our analysis thus requires that an option series is available on four consecutive days.

Table 3 reports our main results. The table reports portfolio sorting results for delta-hedged call and put returns. The sample period is from January 2004 to December 2012 which corresponds to the availability of LiveVol data. We sort firms into quintiles based on lagged option illiquidity. For each quintile, we report the percentage average return as well as the corresponding alpha from the Carhart model.[16] We compute t-statistics using a Newey-West correction for serial correlation, using 8 lags for daily returns and 3 lags for weekly returns.

Panel A of Table 3 reports the results for daily delta-hedged returns on calls. Daily put option returns are in Panel B. We report average returns and alphas for all call or put options jointly, as well as for the two moneyness categories (ATM and OTM) separately. In Panel A, the 5-1 portfolio that goes long the most illiquid calls and short the least illiquid calls earns a positive and significant premium in all categories. The Carhart alphas are not very different from the average returns. The daily alpha spread is 22 bps for ATM calls and 109 bps for OTM calls.

Panel B of Table 3 reports the results for daily delta-hedged returns on puts. In sharp contrast to the results for daily calls in Panel A, we do not find significant alpha spreads for puts.

Panels C and D of Table 3 report the results for weekly delta-hedged returns on call and put options. The alpha spread is 43 bps per week for ATM calls and 307 bps for OTM calls.[17]

While the OTM call alphas in Table 3 may appear to be unrealistically large, it is important to remember from Table 2 that OTM option bid-ask spreads are very large. Therefore, the alphas computed from midpoint returns are not readily earned by investors who must pay the spread. Note finally from Panel A and C that for call options, the portfolio returns and alphas are very close to being monotonically increasing with illiquidity.

Overall we conclude that the illiquidity premium is strong for calls but not for puts. This confirms hypotheses $H_0(1A)$ and $H_0(1B)$.

ii. Robustness Checks on Option Illiquidity Sorts

It is natural to ask if the single-sort results for calls in Table 3 are robust to various permutations in the empirical design. To this end consider Table 4. Panels A and B contain the results for daily calls and puts, respectively. Panels C and D contain the weekly returns. To save space we only report the results for the 5-1 quintile spread returns.

[15] See Avramov, Chordia, and Goyal (2006) and Diether, Lee, and Werner (2009) for examples of studies that use the skip-day methodology when studying equity returns. We have verified that our results are robust when skipping two days as well.

[16] Additional risk factors could be considered, in particular liquidity risk factors. However, because we study daily and weekly returns, it is not obvious that standard equity liquidity factors, such as Pastor and Stambaugh (2003), are applicable. Furthermore, we will see below that stock illiquidity does not seem to be a significant driver of the delta-hedged option returns.

[17] Due to missing series, weekly returns are constructed from just over three trading days on average. Note also that weekly returns for each firm are computed from a potentially slightly different set of option series than daily returns. Finally, the sort and therefore the portfolio composition of weekly and daily portfolios is by definition somewhat different.

Consider first the daily returns in Panels A and B. The first column in Table 4 contains the base case sorting results from Table 3. They are repeated here just for convenience.

The second column in Table 4 contains the results when option returns are weighted by the open interest (OI), rather than by equal weights as in the base case. The results are similar to the first column. Call spread returns are significantly positive for all categories and put spread returns are insignificant. This shows that our results for calls are not driven by thinly traded series.

The third column in Table 4 computes option returns using ask prices rather than midpoint prices, as is done in the base case. Notice that the ask-to-ask results for calls are very close to the base case results in the first column of Table 4. The spread for OTM puts is now significantly positive.

The fourth column in Table 4 computes option returns using bid prices rather than midpoint prices. The spreads are now much larger for calls and they are also significant for puts. Demand pressures appear to have a stronger impact on bid than ask prices, thus generating a larger average return in column four.

The fifth column in Table 4 shows the results for only nonfinancial firms. In the financial crisis, which is part of our sample, there was a temporary short-sale ban on many financial firms. It is therefore pertinent to provide a robustness check using only nonfinancials. In the fifth column, we thus remove firms with SIC codes between 6200 and 6299 as well as between 6700 and 6799, corresponding to financials, insurance, and real estate companies. We conclude that the call option liquidity premium is significant for nonfinancial firms.

Note that the alphas in Table 4 are close to the raw returns. This also matches the base case results from Table 3.

The final two columns in Table 4 show the return spreads and alphas when using bid-to-ask and ask-to-bid returns, respectively. The bid-to-ask long-short illiquidity returns can be viewed as a market maker's profits from buying illiquid options today at the bid from an end-user who wants to sell and selling tomorrow at the ask to an end-user who wants to buy (Q5 return) minus the return from selling liquid options today at the ask to an end-user who wants to buy and closing the position tomorrow by buying at the bid from an end-user who wants to sell (Q1 return). The market maker thus earns the spread twice plus the long-short illiquidity spread. The effective option spreads are large and so the return spreads and alphas are very large in this case.

The ask-to-bid spreads in the last column can be viewed as the long-short illiquidity returns to an end-user who must pay the spread twice to earn the illiquidity premium. These returns are negative and large in magnitude again because the effective spreads are large. In this context it is very interesting to note the findings of Muravyev and Pearson (2014), who argue that because option prices tend to move slower than the underlying stock price, investors can dramatically reduce the effective dollar spreads (from 6.2 to 1.3 cents in their sample) by timing their option trades. The illiquidity premium may thus not be nearly as dominated by the spreads as the two last columns in Table 4 suggest.

Panels C and D of Table 4 repeat the robustness exercises for weekly returns. The base case from Table 3 is again shown in the first column. Note that the returns and alphas are again significant for calls but not for puts. We conclude that the equity call option return spreads are robustly positive when sorting firms on option illiquidity.

At-the-money options are of particular interest, because they provide investors with substantial exposure to volatility in the underlying stock. In Table 5 we therefore investigate the robustness of the daily ATM results in Table 3 when we narrow the width of the moneyness interval. Throughout we keep the moneyness interval centered on $\Delta = +0.5$ for calls and $\Delta = -0.5$ for puts. Table 5 shows that the illiquidity premium for calls is incredibly robust to changing the width of the moneyness interval from the original $\Delta \in (0.375; 0.625]$ in Table 3 to intervals ranging from $\Delta \in (0.4; 0.6]$ to $\Delta \in (0.49; 51]$. For puts, the ATM results in Table 5 are insignificant in all cases, confirming our findings in Table 3.

Finally, to investigate the robustness of the results over the sample period, Figure 6 shows the daily 5-1 spread returns and alphas computed year-by-year using relative effective spreads from LiveVol on the 2004-2012 sample. The positive spreads in returns and alphas are present throughout the sample for calls in the left-side panels. Note that the scale is different for OTM calls in the top-left panel, because the returns are very high throughout the period. For puts in the right-side panels, the average return and alpha are clearly not robustly different from zero.

iii. Double Sorting on Option and Stock Illiquidity

Even though our analysis uses delta-hedged returns, one may wonder if the strong results obtained when sorting on option illiquidity are in fact driven by illiquidity in the underlying stock market. To address this issue, we next investigate portfolio double-sorts on option and stock illiquidity.[18]

Table 6 reports double sorting results for delta-hedged call returns. We first sort firms into quintiles based on their lagged option illiquidity, then the firms in each option illiquidity quintile are sorted into quintiles based on lagged stock illiquidity. As in Section i, we skip one day between the computation of illiquidity measures and the computation of daily returns, both for stock and option illiquidity. For each of the 25 quintiles, we report the alpha (in percent) from the Carhart model. We only report results for daily call returns. The put returns are reported in the online appendix Table A.1. The weekly returns are similar and available upon request.

Consider first the ALL moneyness section at the bottom of Table 6. It shows that for each of the five levels of stock illiquidity, that is in each of the first five columns, the 5-1 alpha spread based on IL^O is positive and significant for call options. The level of the IL^O alpha spread ranges from 30 bps to 50 bps and is smallest for the most liquid stocks. Looking across moneyness categories in Table 6, we see that the IL^O alpha spread is always positive and largest for OTM options, again confirming the base case results.

Overall, in Table 6 the IL^O-based option alpha spread is statistically significant in all cases considered. The IL^S-based option alpha spread, on the other hand, is significant in only two cases in Table 6. Recall that we are analyzing delta-hedged option returns so that the expected effect from stock illiquidity on returns is not obvious.

Based on the double-sorts in Table 6, we conclude that the large and significant option illiquidity premia found previously for call options are not simply driven by the illiquidity of the underlying stock. For call options, only option illiquidity seems to drive alphas. The impact of IL^S and IL^O on cross-sectional option alphas could of course be partly due to other firm-specific explanatory variables. We investigate this important issue in Section 4 below. It is also possible that IL^S indirectly affects option returns

[18] Leland (1985), Boyle and Vorst (1992), and Constantinides and Perrakis (2007) analyze the effect of illiquidity in the underlying asset on option prices.

through its effect on IL^O. We investigate this in Section 5 below.

Given that we are focusing on large and liquid stocks, it is possible that the cross-sectional variation in IL^S is too small to generate an effect on option returns in our sample. As an alternative, we now investigate if the illiquidity premium for call options is related to stock volume instead of IL^S. We might expect high-volume stocks to have highly liquid options and thus earn lower option returns.

Table 7 addresses this issue by double sorting firms first on option illiquidity and then on stock volume. Table 7 shows that the call option illiquidity alphas are positive and significant in all cases. The option illiquidity premium thus appears to be present for all levels of stock volume. The second to last column of Table 7 shows that sorting on stock volume (for different categories of option illiquidity) typically produces significantly negative alphas for OTM call options and positive alphas for ATM call options. The stock volume effect is significant only for the most illiquid OTM call options and for the most liquid ATM call options. Table A.2 in the appendix contains the results for puts. The effect of stock volume on put option returns is mixed as well.

Our main conclusion from Tables 6 and 7 is that illiquidity alphas for call options are significant for different levels of stock illiquidity and stock volumes.

iv. Double Sorting on Option Illiquidity and O/S Volume

Several authors, including Roll, Schwartz, and Subrahmanyam (2010), have found that option volume divided by stock volume (O/S) carries significant cross-sectional information about trading costs, leverage (proxied by delta), institutional holdings, private information (proxied by analyst following), and investor disagreement (proxied by analyst forecast dispersion). As is standard in the literature, we construct O/S using delta-weighted option volumes.

Consider first the evolution of the cross-sectional distribution of average daily option volume over time. Figure 7 plots in the top row the mean and median for each year. The remaining panels show for each year the minimum and maximum as well as various percentiles from the cross-sectional distribution of average daily option volume. Notice that while the average daily call volumes (dashed lines) and put volumes (solid lines) are increasing dramatically over time for the firms with the largest option volumes (bottom three right panels), this is not the case for the firms with the lowest daily option volumes (bottom three left panels). Figure A.2 in the appendix shows the corresponding figure for ATM options only.

Figure 8 plots for each year the mean and various percentiles of the cross-sectional distribution of average daily O/S volume. Notice that the O/S volumes are relatively stable over time for all but the very largest O/S firms for which the O/S volume has declined through the sample. Notice also that option volumes are only comparable to stock volumes for stocks in the 99th percentile of O/S. Figure A.3 in the appendix shows the corresponding figure for ATM options only.

Table 8 provides option return alphas from first sorting stocks on IL^O and then on O/S. Table 8 shows that the alphas from sorting on IL^O are positive for all levels of O/S and significant in all but one case. We also see that sorting on O/S typically produces significantly negative alphas for OTM options, positive but insignificant alphas for ATM options, and positive alphas for ALL options. The O/S alphas thus vary by option category. Table A.3 in the appendix contains the results for puts.

Our main conclusion from Table 8 is that illiquidity alphas for call options are significant for different levels of O/S volume.

v. *Double Sorting on Option Illiquidity and Order Imbalances*

Inventory costs are one of the key components of illiquidity. Bollen and Whaley (2004) use order imbalances to capture net demand pressure, which in turn is one of the determinants of inventory costs. We therefore next investigate if the IL^O return spreads are simply driven by cross-sectional differences in order imbalances in the option market. Option order imbalances are computed according to equation (7) as the delta-weighted buy volume minus sell volume as a percentage of total volume. We only observe order imbalances starting in January 2005, and so we use the sample period from January 2005 to December 2012 for this analysis.

Table 9 provides call option return alphas from first sorting stocks on IL^O and then on imbalances. Table 9 shows that the alphas from sorting on IL^O are positive for all levels of imbalances and significant in all but one case. Sorting on imbalances mostly produces positive spreads in returns, but the effect is often not significant. Table A.4 in the appendix contains the results for puts.

We conclude from Table 9 that IL^O is not simply picking up effects from order imbalances.

4. *Multivariate Analysis*

So far we have relied on simple portfolio sorts to assess the relationship between option illiquidity and option returns. We used double sorts to verify that option illiquidity affects returns even after controlling for some determinants of returns and spreads. In this section we further investigate the robustness of the relation between option illiquidity and returns. We control for other firm-specific determinants of option returns as well as spreads using a Fama-MacBeth (1973) regression setup.

i. *Control Variables*

Our delta-hedged returns are adjusted for the first-order effect arising from the return on the underlying stock. In modern option-valuation models, volatility dynamics constitute a second important factor driving option returns. The benchmark model is Heston (1993), who develops a stochastic volatility model that allows for correlation between the shock to returns and the shock to volatility, as well as for a volatility risk premium to compensate sellers of options for volatility risk.[19] Broadie, Chernov, and Johannes (2009) and Duarte and Jones (2006) show that the expected option return in a Heston-type model is given by

$$\frac{1}{dt}\left(E\left[R^O\right]-r\right)=\left(E\left[R^S\right]-r\right)\frac{S}{O}\frac{\partial O}{\partial S}+\lambda\frac{\sigma}{O}\frac{\partial O}{\partial \sigma} \quad (8)$$

where the sensitivity of the option price to volatility (the option Vega), denoted by $\frac{\partial O}{\partial \sigma}$, is positive for all options. The price of volatility risk, λ, is typically found to be negative for equity index options but closer to zero on average for individual equity options (see Driessen, Maenhout and Vilkov, 2009). Equation (8) suggests that we should control for the time-varying volatility of the stock when regressing option returns on illiquidity.

The large-scale empirical study we undertake prohibits the estimation of a stochastic volatility model for each firm. We instead estimate dynamic volatility from the daily stock return

[19] Hull and White (1987), Wiggins (1987), and Scott (1987) developed some of the first option valuation models with stochastic volatility.

data on each firm using the simple symmetric $GARCH(1,1)$ model from Bollerslev (1986). For weekly results we average the daily GARCH volatility measure into a weekly one.

Index option prices display strong evidence of skewness dynamics–perhaps driven by jump risk–but for equity options these effects are much less pronounced (Bakshi, Kapadia and Madan, 2003). We therefore do not model and control for skewness dynamics.[20]

Duan and Wei (2009) argue that the proportion of systematic risk affects the prices of individual options, and therefore option returns. We thus include b_{t-1} as a firm-specific effect, which is the square root of the R-square from the regression of stock returns on the Fama-French and momentum factors. Following Duan and Wei (2009), we obtain daily estimates of b_{t-1} by using one-year rolling windows to run daily OLS regressions of the excess stock returns on the standard four equity factors (the market, size and book-to-market factors from Fama and French, 1993, and the momentum factor from Carhart, 1997). As in Duan and Wei (2009), we average the daily b_{t-1} estimate during the week to obtain a weekly estimate of the systematic risk proportion.

We also control for firm size and leverage, which have been shown to affect option prices, see for instance Dennis and Mayhew (2002) and Duan and Wei (2009). Following Duan and Wei (2009), we measure size using the natural logarithm of the firm's market capitalization. For weekly results, we use size observed on the last day of the previous week. We define leverage as the sum of long-term debt and the par value of the preferred stock, divided by the sum of long-term debt, the par value of the preferred stock, and the market value of equity. Data on long-term debt and the par value of preferred stock, which are used to compute firm leverage, are from Compustat. Because leverage is available at a quarterly frequency, we use leverage computed over the previous quarter both for daily and weekly results. To control for variations in moneyness within the moneyness categories, we include the average (across series) delta for firm i, and denote it $|\Delta_{i,t-1}|$.

In addition to these well-known determinants of option returns, we also include several variables that have been suggested as drivers of spreads in the microstructure literature, and that have been widely investigated in the empirical literature. These variables affect returns indirectly through their effect on illiquidity. However, several of these variables can also be thought of as direct determinants of prices and returns because they impact supply and demand in these markets.

In order to capture asymmetric information in the option market we include $\log(O/S)$ as defined above, and the probability of informed trading (PIN) measure from Easley, Hvidkjaer, and O'Hara (2002). Note that while O/S changes daily, PIN only exhibits quarterly variation. Hedging costs constitute an important part of inventory costs in option markets. Engle and Neri (2010) suggest using the interaction of the option Gamma and stock return volatility ($\Gamma * \sigma$). Following Leland (1985) and Boyle and Vorst (1992), we also use a commonly-used proxy for market makers' inventory rebalancing costs, the product of the option $Vega$ and the relative spread of the underlying stock ($Vega * IL^S$). Finally we include order imbalances as defined above in order to capture demand pressures.

ii. Return Regression Results

Table 10 contains the main result from the Fama-MacBeth regression analysis. Consistent

[20] The conditional skewness model in Jondeau and Rockinger (2003) could be used to control for dynamic skewness in the underlying equity return.

with implementation of the daily sorting results above, as well as the existing illiquidity literature, we skip one day between the illiquidity measures on the right-hand-side (measured at $t-1$) and the option returns on the left-hand-side (measured at $t+1$). Skipping one day has the additional advantage that it helps avoid endogeneity issues.[21]

We run the cross-sectional regression on every day (or week) using all firms available for a given moneyness category, and subsequently compute the time-series averages of the estimated coefficients.[22] These averages are reported in Table 10. To control for serial correlation, the Fama-MacBeth (1973) t-statistics are computed according to the Newey and West (1987) procedure, using eight lags.

Panel A of Table 10 contains the Fama-MacBeth regression results for call option returns. Notice first that the coefficient on option illiquidity is positive and significant for both moneyness categories, and of course, overall as well. The t-statistics are large and the coefficients range from 186 bps for ATM to 342 bps from OTM options, and 496 bps for ALL call options which include ITM options. Note that the positive coefficient on IL^O is consistent with the results from the cross-sectional sorts in Section 3 above.

The coefficient on stock illiquidity is significantly negative for ATM and OTM but not for ALL. This matches the result in Table 6 above from double-sorting on IL^O and IL^S.

In terms of control variables, volatility is significant for ATM calls, which are the most sensitive to volatility. Consistent with Duan and Wei (2009) the systematic risk proportion is positive and significant for ATM options. The log of firm size is significantly negative for OTM calls. The firm leverage variable is significantly positive, suggesting that more risky firms–from the perspective of leverage–have higher option returns. The coefficient on absolute moneyness is significantly negative for OTM and ATM but not overall. The asymmetric information variables $\log(O/S)$ and PIN are generally not significant. The $Vega * IL^S$ hedging variable is significantly positive for OTM and ATM but the results for $\Gamma * \sigma$ are mixed.

Finally, imbalances are significantly positive everywhere as in Muravyev (2014).[23] It is crucial to notice, however, that IL^O remains strongly significant after including imbalances in the regressions. The option illiquidity measure thus clearly captures more than just demand pressures. We will investigate the relation between imbalances and IL^O more in Section 5 below.

Panel B of Table 10 contains the results for daily put returns. Consistent with the sorting results, the option illiquidity measure is not significant.

In summary, the evidence in Table 10 indicates a significant impact of option illiquidity on expected call option returns. The adjusted R^2s in Table 10 are all small, which is not surprising given the large amount of noise in option returns, evident from Figure 1. The results are robust to controlling for a large number of variables that determine returns and spreads. This indicates not only that option illiquidity is an important determinant of returns, it also indicates that it is most straightforward to demonstrate this effect using an illiquidity measure such as IL^O. When including determinants of IL^O in the regression the effect of IL^O on returns remains, presumably because it is easier to measure the impact

[21] To this end Muravyev (2014) relies on an instrument variables approach.

[22] In all our tests, we require at least 30 firm-observations with all data available for each time t (day or week) to run a cross-sectional regression. We use exactly the same sample in the sorting exercise above.

[23] Interestingly, Hu (2014) finds that option imbalances have predictive power for the underlying stock return as well.

of illiquidity using spreads than by using the theoretical determinants of spreads, some of which are hard to quantify.

iii. Robustness Checks on Regression Results

In this section we investigate if the impact of IL^O on option returns documented in the cross-sectional regressions in Table 10 is robust to various permutations of the empirical setup.

In Table 11 we report Fama-MacBeth coefficients on the IL^O variable from multivariate regressions using daily option returns. We also report the corresponding t-statistics and regression R^2s. The first column reports the base case results from Table 10 for reference. Panel A contains daily call option regressions, and Panel B contains daily put option regressions. The results for weekly returns are qualitatively similar and are available upon request.

The six robustness tests we report on in Table 11 are as follows:

In the second column, we remove firms with SIC codes between 6200 and 6299 as well as between 6700 and 6799, corresponding to financials, insurance and real estate companies.

In the third column, we trim the largest 1% and smallest 1% option returns from the sample to assess if our results are driven by outliers.

In the fourth column, we add the contemporaneous stock return, $R^S_{i,t+1}$, to pick up any error in the delta-hedging procedure.

In the fifth column, we instead add the current stock price, S_{t+1} and option price, O_{t+1}, to pick up any biases from omitted regressors.

In the sixth column, we instead add the lagged option return, R^O_{t-1} and the lagged absolute stock return $\left|R^S_{t-1}\right|$ to pick up biases from omitted regressors.

In the seventh column, we add all the variables from columns four to six.

The results for call options in Panel A of Table 11 are quite striking. For the 18 additional regressions reported in Panel A of Table 11, the coefficient on IL^O is positive and highly significant in all cases. The robustness regressions in Table 11 indeed often yield even stronger results than the base case regressions in Table 10.

Notice in particular that when trimming the most extreme 1% of option returns from the sample, the IL^O coefficients are highly significant and virtually identical for OTM and ATM calls: Outliers tend to inflate the premium for OTM calls and deflate the premium on ATM calls.

In Panel B of Table 11, the coefficient on IL^O is almost always insignificant for OTM and ATM puts. For ALL puts the illiquidity premium is often significantly positive, driven mainly by ITM puts which are included in the ALL category. It appears that the added controls and filters in Table 11 lower the standard errors and thus increase the significance of the put return premia for ITM options.

Ignoring option illiquidity is tantamount to overestimating option prices, and this effect is significant. For example, for OTM call options, the average coefficient on IL^O in Panel A of Table 11 is 0.04. Table 2 shows that the standard deviation for OTM call option illiquidity is 0.0759. Therefore, a one standard deviation positive shock to OTM call option illiquidity on day $t-1$ would result in a 30 basis point increase in the day $t+1$ return on the call option. This is a large magnitude for daily changes in prices. For ATM call options the effect would be $0.025 * 0.0402 = 10$ bps per day which, while smaller, is still a substantial magnitude for daily changes in prices.

5. *What Determines Option Illiquidity?*

So far we have determined that IL^O is a robust determinant of option returns. This clearly begs the question: What determines IL^O? There is an extensive theoretical and empirical literature on the determinants of spreads in securities markets, and this work has inspired a growing empirical literature on the determinants of spreads in option markets.

The literature considers three major components of bid-ask spreads. Option market makers face fixed order processing costs set by the exchange, asymmetric information costs (Copeland and Galai, 1983, Glosten and Milgrom, 1985, and Easley and O'Hara, 1987), as well as inventory costs (Amihud and Mendelson, 1980, Ho and Stoll, 1983). Several studies discuss the importance of hedging costs. Cetin et al (2006) and Figlewski (1989) argue that delta hedging invokes model misspecification risks in option markets. Jameson and Wilhelm (1992), George and Longstaff (1993), and de Fontnouvelle, Fishe, and Harris (2003) find that inability to continuously rebalance the hedge increases options spreads. Battalio and Schultz (2011) document that option spreads increased dramatically during the September 2008 short-sale ban due to the inability of market makers to hedge their position in options on short-sale restricted stocks.[24] These hedging costs can be thought of as inventory costs; alternatively Engle and Neri (2010) argue that hedging costs can be viewed as a fourth class of costs that affects bid-ask spreads. Engle and Neri (2010) document that market makers in equity options face hedging costs which constitute a large part of the overall spread.

The different theories on the determinants of spreads in security markets all suggest variables that ought to affect bid-ask spreads in option markets, which may, in turn, impact option returns. Alternatively these potential risk factors may affect returns directly as we have investigated above. Information asymmetry theories (Copeland and Galai, 1983) suggest that spreads should decrease with market activity. In option markets evidence of informed trading has been presented by Easley, O'Hara, and Srinivas (1998) and Pan and Poteshman (2006).

Inventory models predict a negative relation between spreads and the price of the security (Ho and Stoll, 1983) and a positive relation between spreads and the security's volatility (Biais, 1993). These models also predict that spreads change with market maker risk aversion, which of course is difficult to measure. In option markets, Bollen and Whaley (2004) and Muravyev (2014) use order imbalances as a proxy for inventory, and we follow this approach.

We proceed by conducting a Fama-MacBeth regression analysis with IL^O on the left-hand-side and contemporaneous regressors that have been documented to capture liquidity in the literature. We also include standard control variables, including lags of IL^O to capture persistence.

Table 12 contains the IL^O regression results. We are most interested in call option illiquidity because the illiquidity premium is by far the strongest for calls. The most important results in Table 12 are:

- The coefficient on IL^S is significantly positive. While IL^S is not a significant driver of option returns, it is a significant driver of IL^O. Option returns are thus impacted by IL^S through IL^O.
- The PIN measure is a significant driver of

[24] See also Evans, Geczy, Musto, and Reed (2009) who show that stock specialness increases option bid-ask spreads.

IL^O. High PIN indicates high asymmetric information which in turn increases IL^O.

- The hedging variable, $\Gamma * \sigma$, is significantly positive as expected. Higher hedging risks increase IL^O. The effect from $Vega * IL^S$ is mixed. It is positive (but not significant) for ATM calls as expected. Its negative effect on OTM calls is difficult to interpret as vega is close to zero for those series.

- Size (in logs) has a significantly negative relationship and leverage has a significantly positive relationship with IL^O, as expected. Smaller and more highly leveraged firms are more risky and more expensive to hedge.

- The absolute imbalance variable significantly increases IL^O. The further imbalances are from zero the larger is the spread required by the market maker. Following Chordia, Roll, and Subrahmanyam (2002) we use absolute imbalances in the spread regressions.

- The effect of option volume on IL^O is negative which is not surprising. High volume leads to lower order processing costs.

We also include a number of control variables. The effect from systematic equity risk (the R^2 from the Carhart 4-factor model) and GARCH volatility are both negative which is perhaps surprising. But recall that GARCH volatility increases the option price which is in the denominator of IL^O. Systematic equity risk may increase the price of the option through the market variance risk premium as well. Stock volume effects are mixed as stock illiquidity is likely captured better by IL^S. The absolute value of delta is included, as before in the return regressions, to control for moneyness differences inside each category.

It is also crucial to note from Table 12 that the R^2s in the regressions are around 50%. About half of the variation in IL^O is explained by known factors while about half remains unexplained. IL^O drives option returns because it not only embodies information on well-known drivers of option illiquidity, it also contains a substantial amount of additional information about the costs and risks of market making in option markets that is otherwise hard to measure or quantify. This information is useful for explaining option returns.

Overall we conclude that the regressions in Table 12 confirm our hypotheses: Stock illiquidity, asymmetric information, and hedging costs increase IL^O, which confirms $H_0(2A)$, $H_0(2B)$, and $H_0(2C)$. Consistent with inventory theories and $H_0(2D)$, absolute order imbalances increase IL^O because market makers face buying or selling pressures in the equity options market.

6. *Conclusion*

We present evidence on illiquidity premia in equity option markets. Using portfolio sorts and cross-sectional regressions, we find a significant positive impact of option illiquidity on expected call option returns. We find strong evidence of positive option illiquidity premia in simple univariate portfolio sorts and in bivariate sorts on call option and stock illiquidity. We also find significantly positive coefficients on option illiquidity in multivariate regressions, even when controlling for volatility of the underlying equity, market capitalization, leverage, and other firm-specific variables. These results are not altered in a variety of robustness checks, and they are robust across different moneyness categories.

The economic mechanism underlying these findings is the market makers' compensation for absorbing supply and demand pressures in zero net supply markets. Illiquid options have lower current prices and higher expected option returns, thus compensating investors with long positions for holding illiquid series. Lakonishok et al. (2007) and Garleanu et al. (2009) document that end-users hold net short positions in the equity options market, requiring market makers to hold net long positions. Market makers respond by adjusting spreads and requiring higher expected returns, which leads to a positive relation between illiquidity and expected returns. Regression results confirm that option illiquidity increases with stock illiquidity, asymmetric information, and hedging costs.

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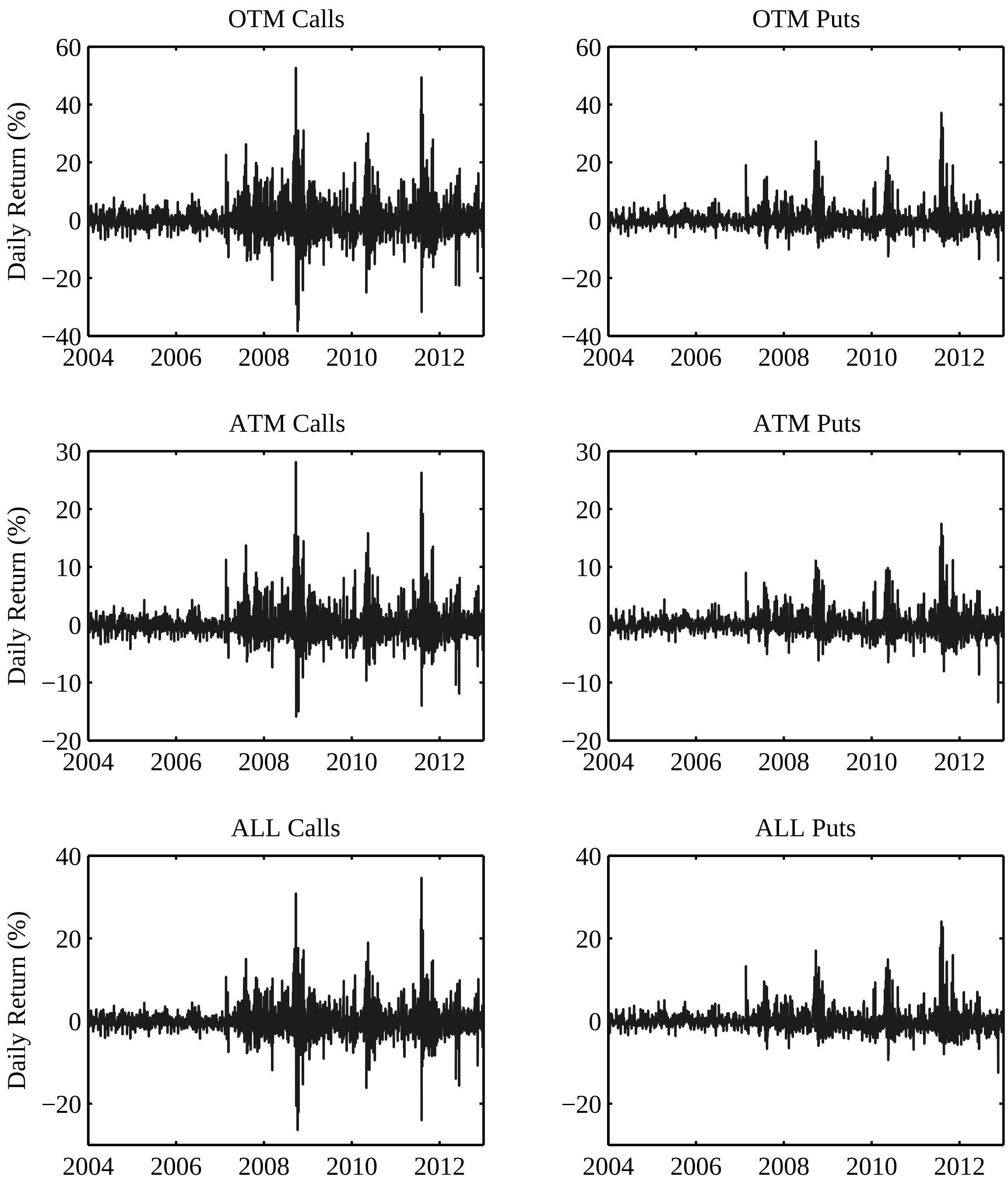
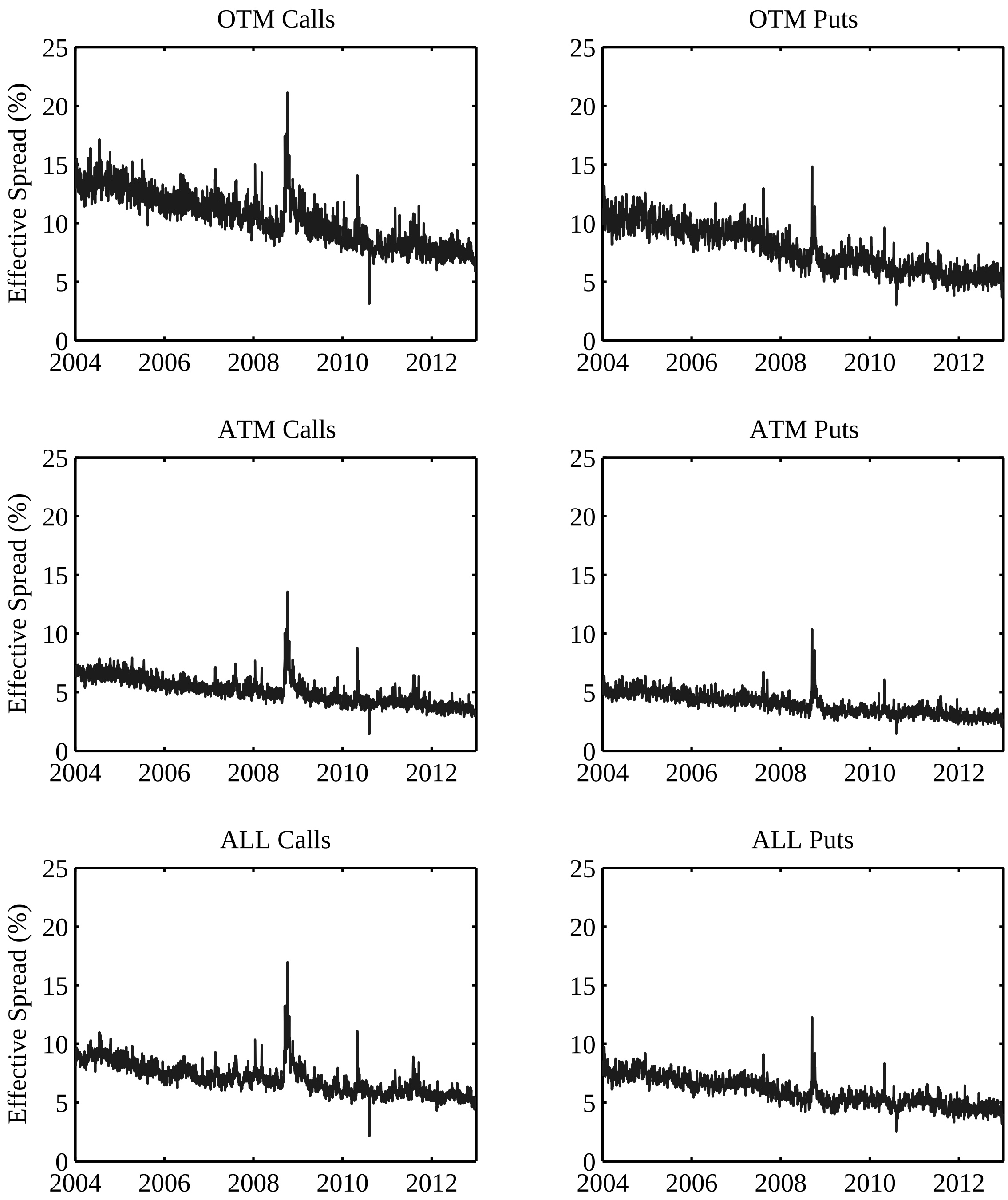
Figure 1. Average Daily Delta-Hedged Option Returns. 2004-2012.



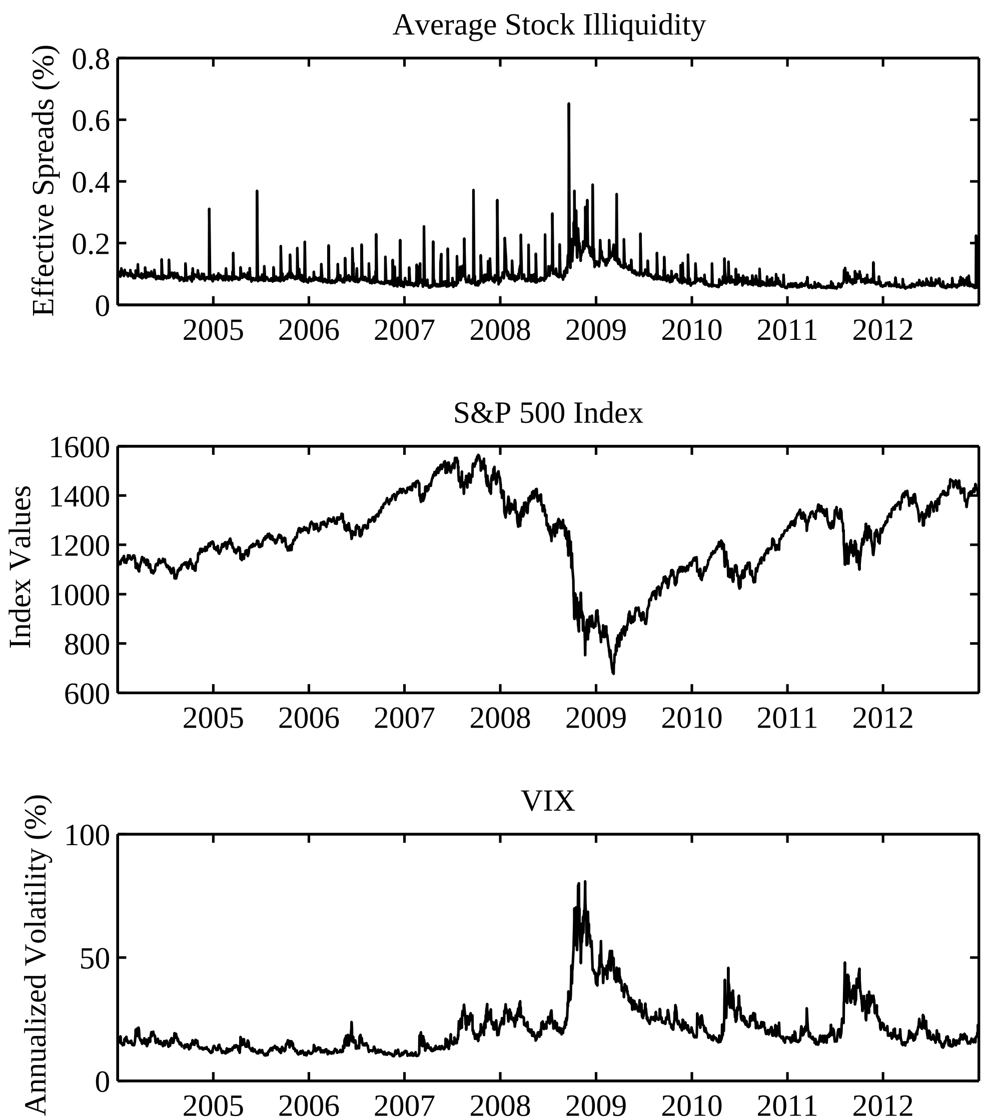
Notes to figure: We plot the daily delta-hedged returns on equally-weighted portfolios of call and put options. Option returns are computed from closing bid-ask price midpoints. OTM refers to out-of-the-money, ATM refers to at-the-money, and ALL includes all strikes. The sample starts January 2004 and ends December 2012.

Figure 2. Average Option Illiquidity Measured Using Effective Relative Spreads. 2004-2012.



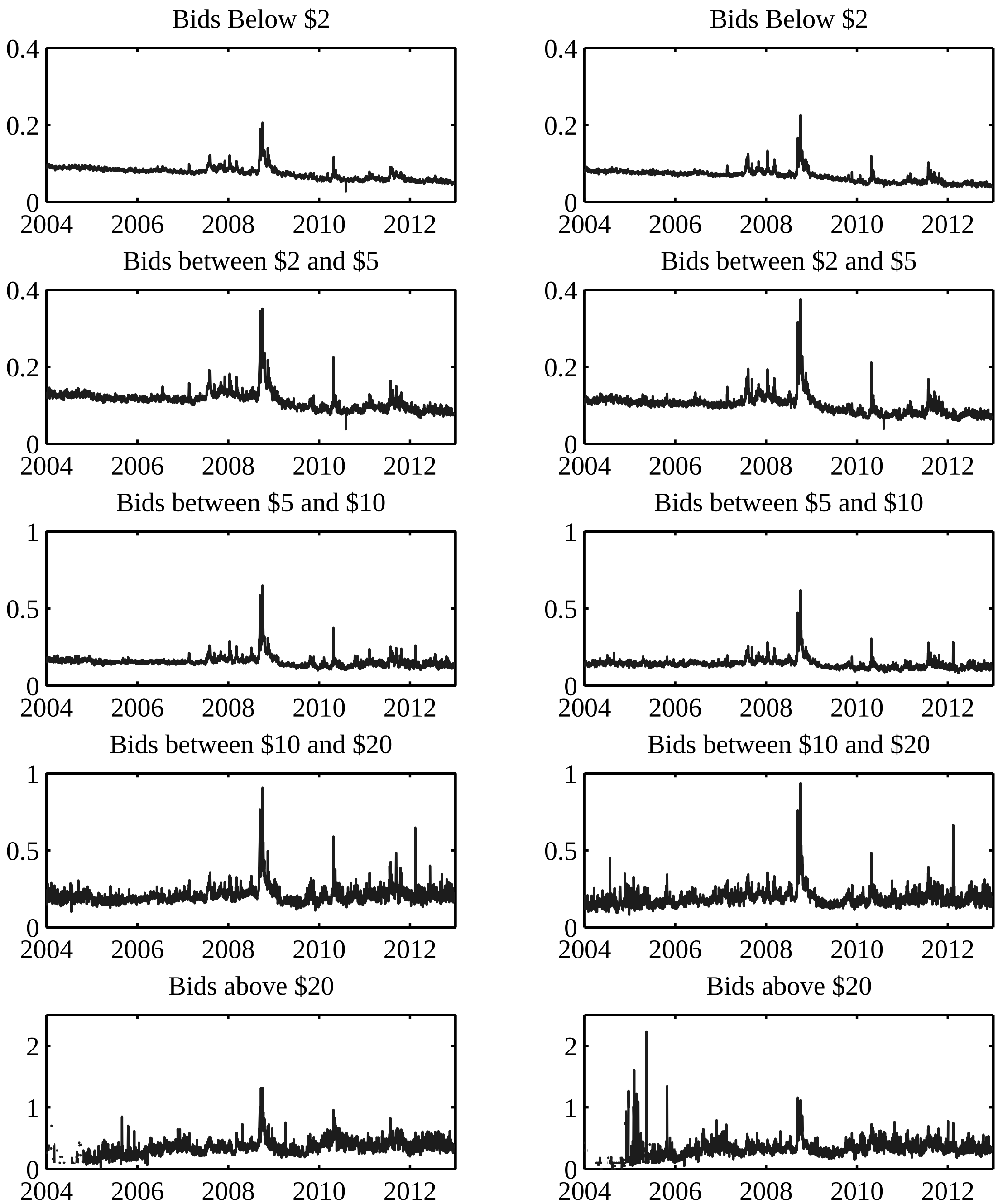
Notes to figure: Daily option illiquidity is computed as the volume-weighted relative effective spread equal-weighted average across firms. The underlying trade and quote data are from LiveVol and include the S&P 500 constituents for which options trade during our sample. The sample period is January 2004 to December 2012.

Figure 3. Daily Average Stock Illiquidity, S&P500 Index, and the VIX



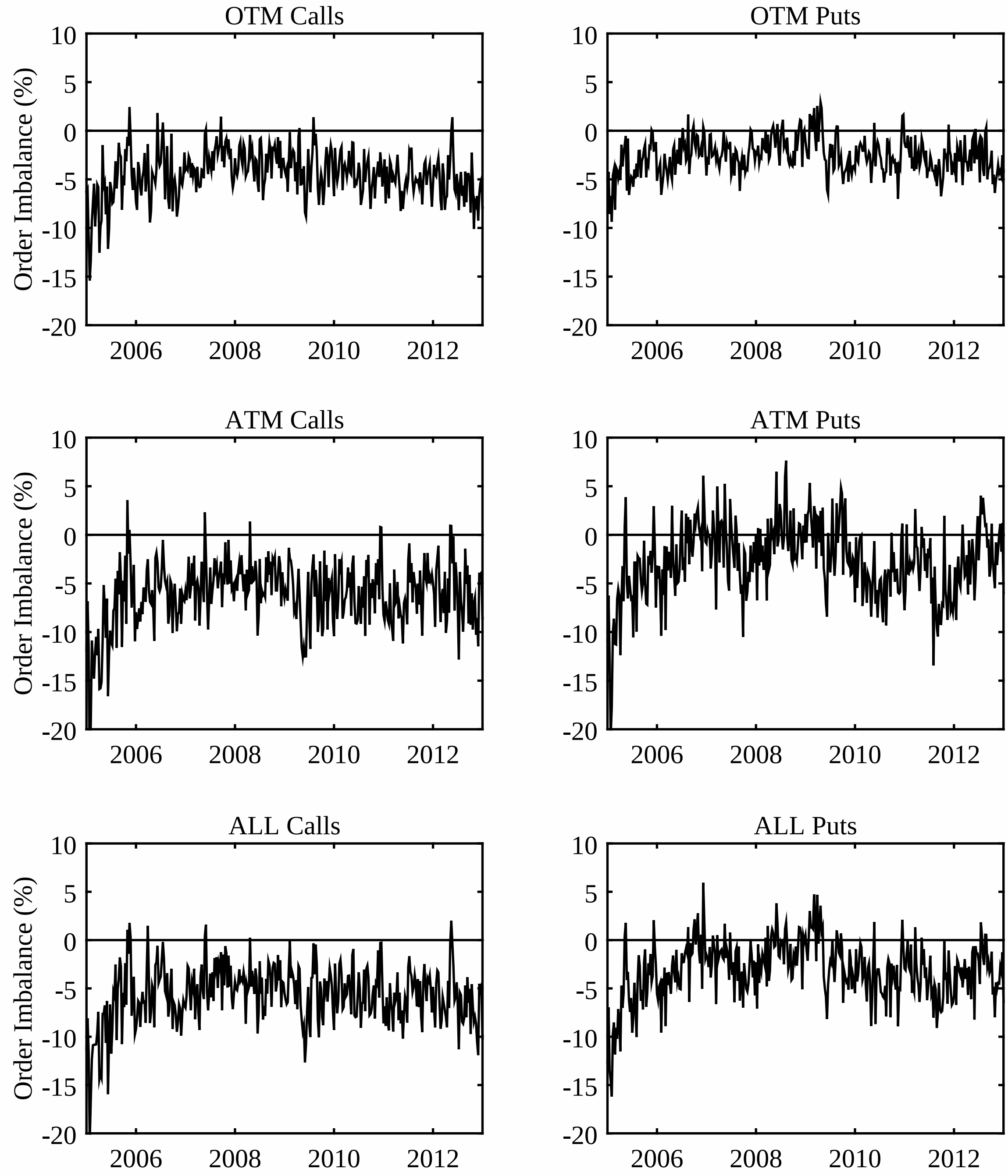
Notes to Figure: We plot the daily average stock illiquidity, the daily level of the S&P 500 index, and the daily VIX. Stock illiquidity is estimated from TAQ (Trade and Quote) intra-day data as the dollar-volume-weighted average of effective relative spreads for each day. The sample period is January 2004 to December 2012.

Figure 4. Average Option Dollar Spreads by Option Bid Level. Calls in Left Column and Puts in Right Column



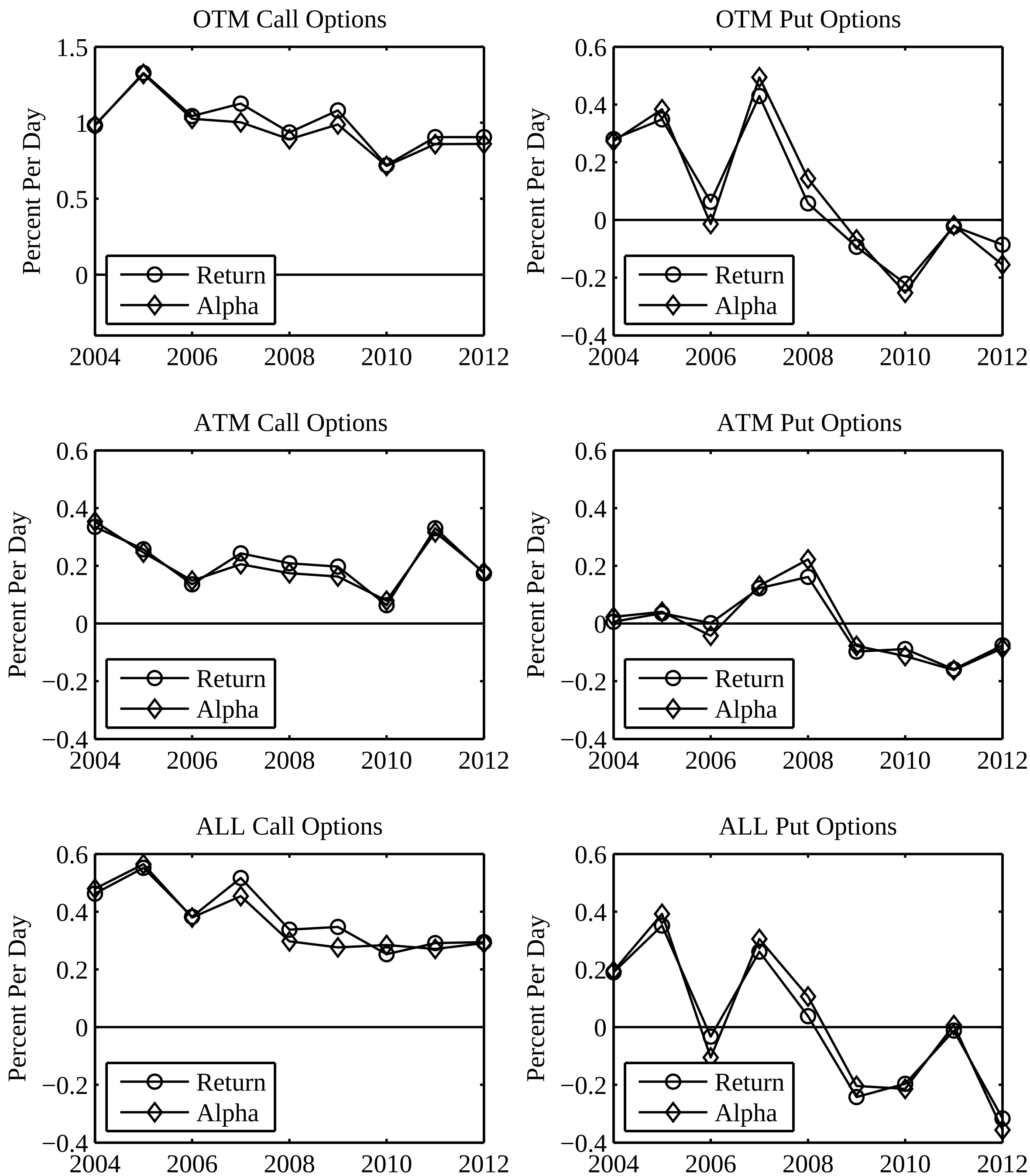
Notes to Figure: We plot the average dollar effective spreads across firms and across option series with bid prices as indicated in the titles to each panel. The sample period is January 2004 to December 2012.

Figure 5. Order Imbalances



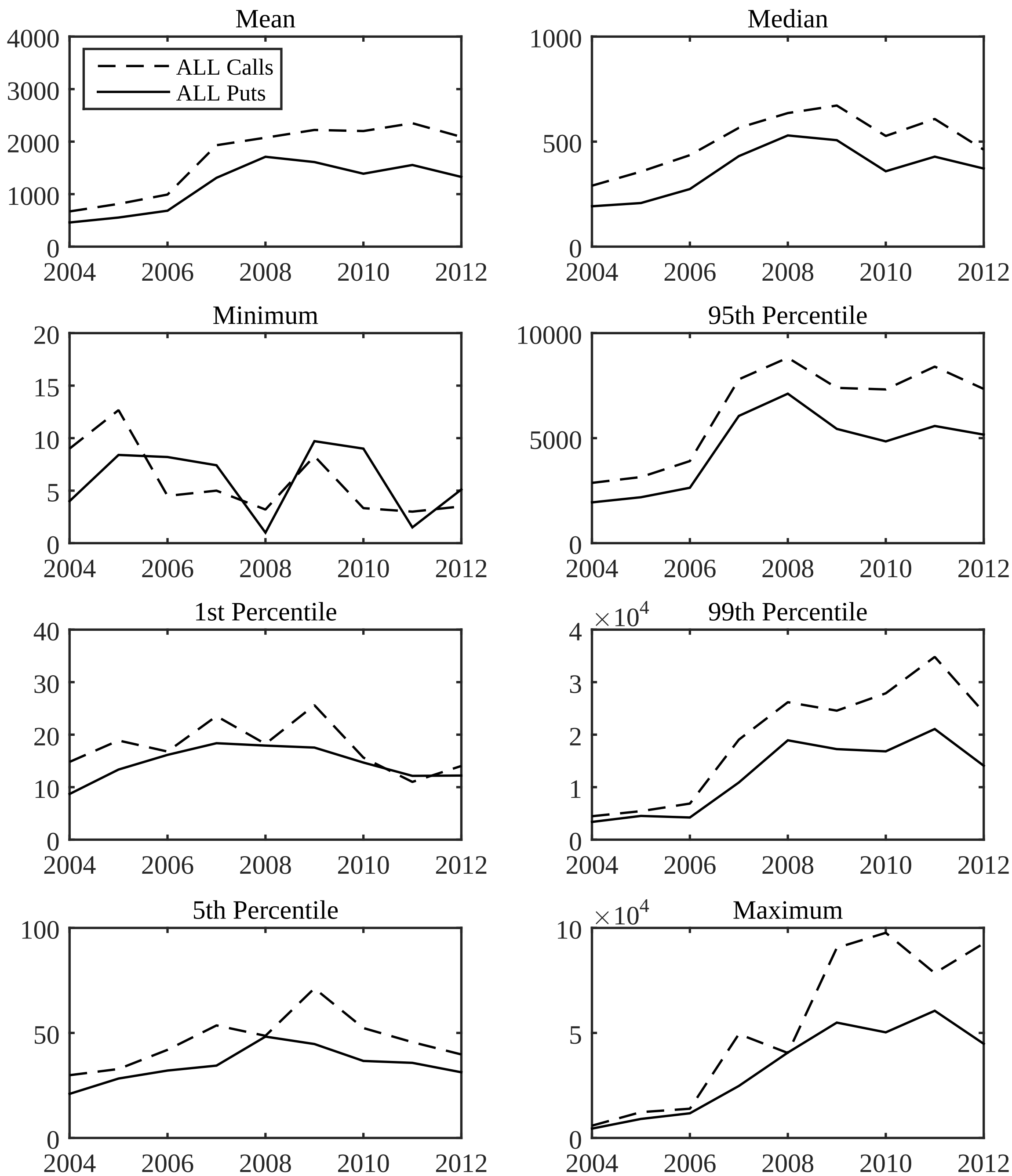
Notes to figure: Weekly order imbalances are computed as the delta-weighted buy volume less sell volume in percent of total volume. The underlying option data include the S&P 500 constituents for which options trade during our sample. The sample period is January 2005 to December 2012.

Figure 6. Long-Short Option Illiquidity Return and Alpha Spreads by Year.



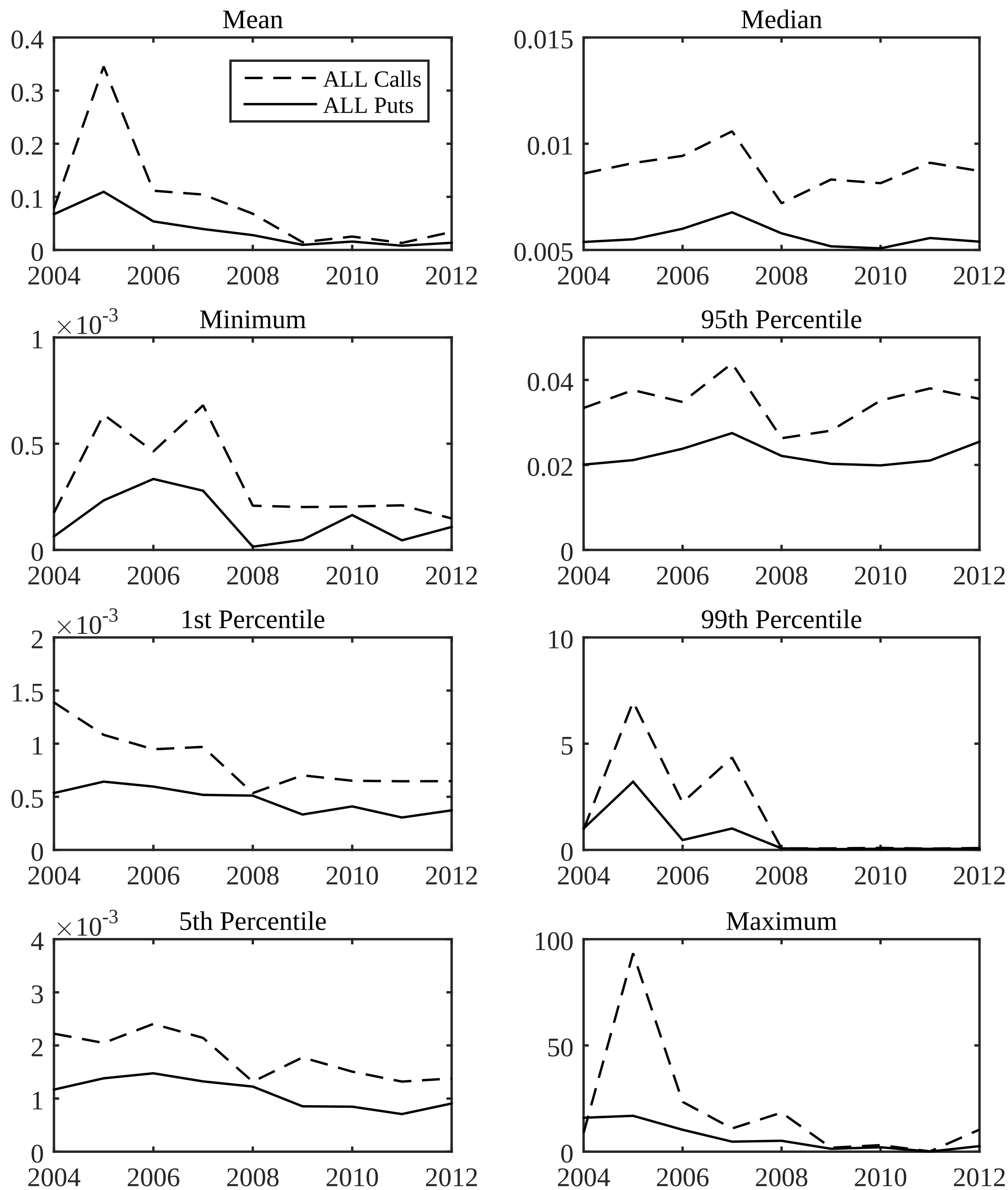
Notes to Figure: We sort firms into quintiles based on their lagged illiquidity measured by effective relative spreads. Year by year we plot the average option return and alpha for the 5-1 option illiquidity quintiles. The sample includes the S&P 500 constituents with valid options data during 2004-2012. Note that OTM calls are plotted on a different scale.

Figure 7. The Cross Sectional Distribution of Average Daily Option Volume. ALL Options.



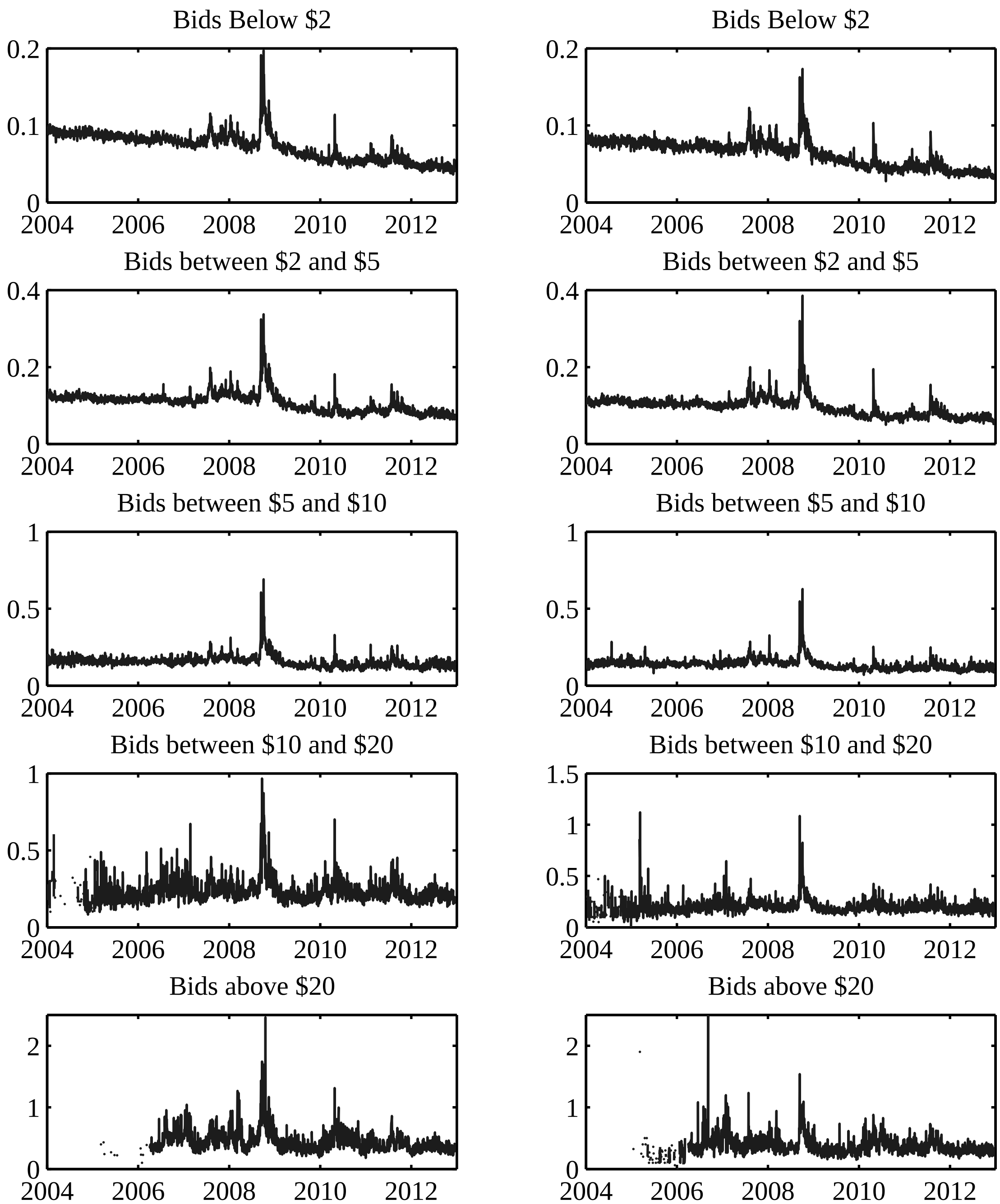
Notes to figure: Each year we compute the mean and various percentiles from the distribution of average daily option trading volume across firms. Options across all moneyness levels are used here.

Figure 8. The Cross Sectional Distribution of Average Daily O/S Volume. ALL Options



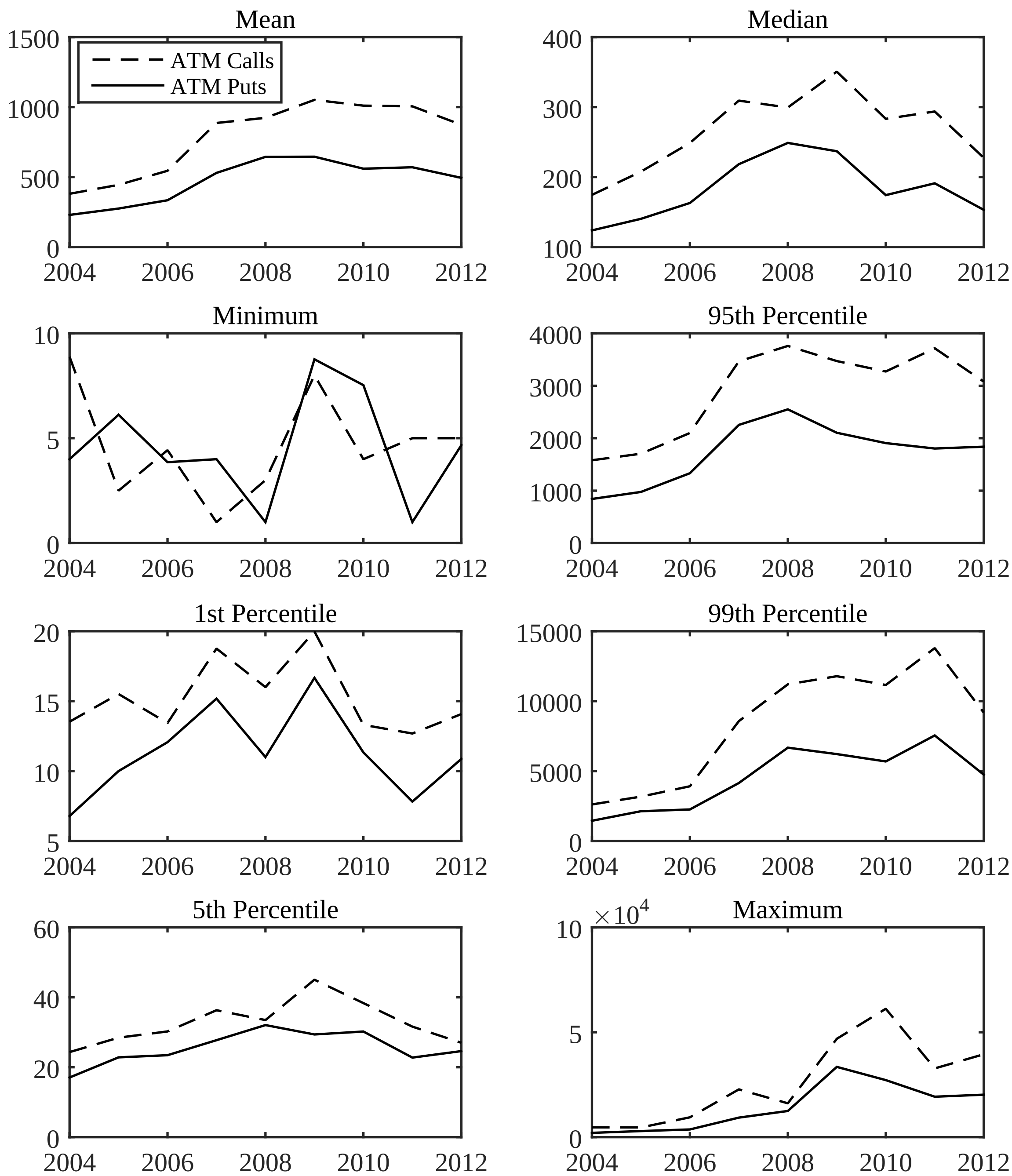
Notes to figure: Each year we compute the mean and various percentiles from the distribution of average daily O/S volume across firms. Option volume is delta-weighted and multiplied by 100 for comparison with stock volume. Options across all moneyness levels are used here.

Figure A.1. Average ATM Option Dollar Spreads by Option Bid Level. Calls in Left Column and Puts in Right Column



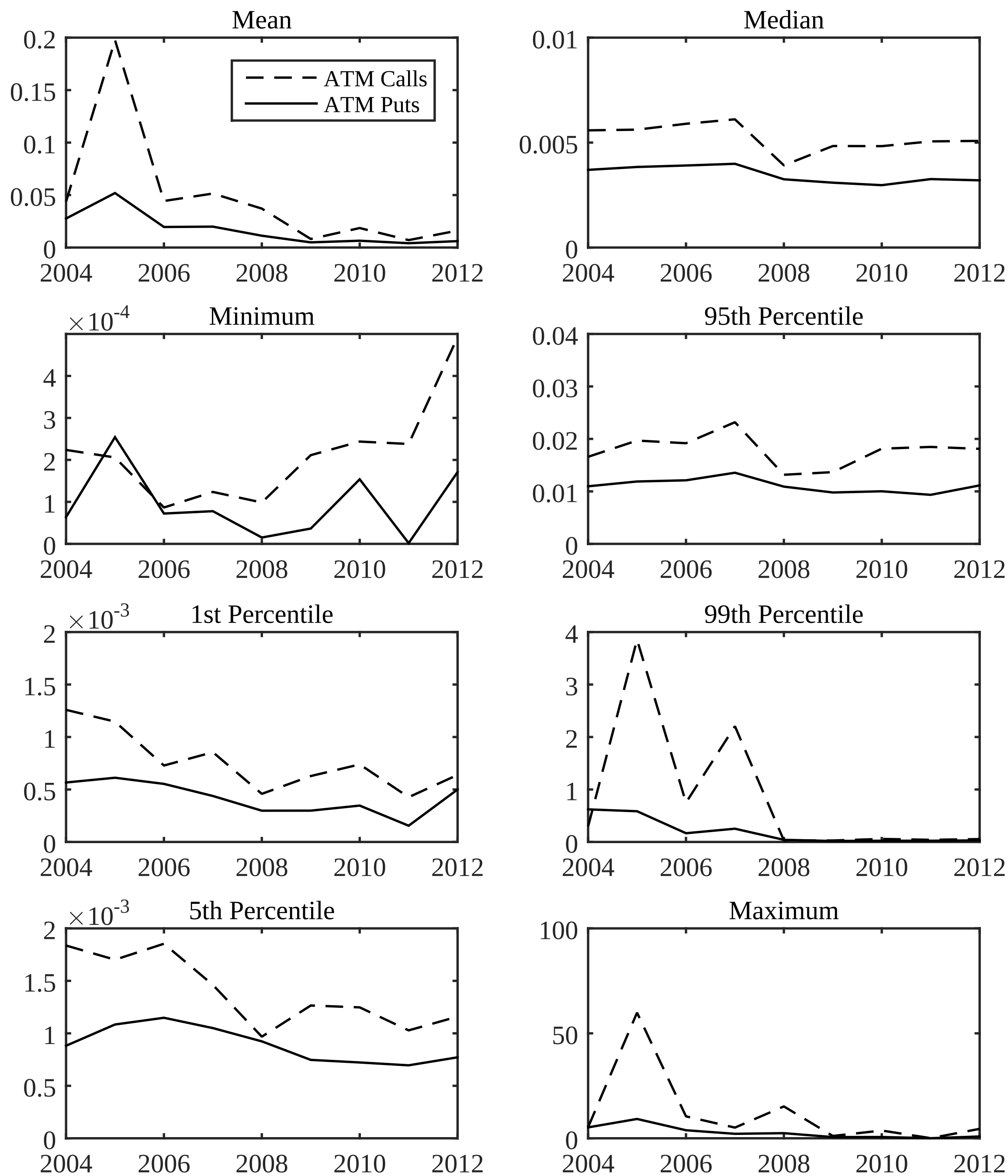
Notes to Figure: We plot the average dollar effective spreads across firms and across ATM option series with bid prices as indicated in the titles to each panel. The sample period is January 2004 to December 2012.

Figure A.2. The Cross Sectional Distribution of Average Daily Option Volume. ATM Options



Notes to figure: Each year we compute the mean and various percentiles from the distribution of average daily option trading volume across firms. Only at-the-money options are used here.

Figure A.3. The Cross Sectional Distribution of Average Daily O/S Volume. ATM Options



Notes to figure: Each year we compute the mean and various percentiles from the distribution of average daily O/S volume across firms. Option volume is delta-weighted and multiplied by 100 for comparison with stock volume. Only at-the-money options are used.

Table 1. Descriptive Statistics of Delta-Hedged Option Returns and Stock Returns

Panel A. Daily Delta-Hedged Call Returns	OTM	ATM	ALL
Average	0.40	0.01	0.00
Std.dev.	14.42	6.65	8.45
Skewness	3.43	2.52	3.59
Kurtosis	67.18	55.15	84.98
ρ(1)	-0.05	-0.06	-0.07
abs [ρ(1)]	0.11	0.14	0.14
Avg # obs	1205	1240	1445
Avg # firms	379	390	487

Panel B. Daily Delta-Hedged Put Returns	OTM	ATM	ALL
Average	0.25	0.08	0.05
Std.dev.	10.09	5.88	7.29
Skewness	3.51	2.54	3.75
Kurtosis	75.78	53.85	91.24
ρ(1)	0.00	-0.02	-0.12
abs [ρ(1)]	0.09	0.10	0.10
Avg # obs	1143	1080	1349
Avg # firms	359	339	423

Panel E: Daily Stock Returns	
Average	0.04
Std.dev.	2.40
Skewness	0.49
Kurtosis	19.60
ρ(1)	-0.04
abs [ρ(1)]	0.21
Avg # obs	1578
Avg # firms	498

Panel C. Weekly Delta-Hedged Call Returns	OTM	ATM	ALL
Average	1.18	0.10	0.06
Std.dev.	28.93	13.18	17.15
Skewness	2.10	1.44	2.32
Kurtosis	17.48	13.78	24.10
ρ(1)	-0.02	0.01	0.00
abs [ρ(1)]	0.02	0.04	0.04
Avg # obs	219	237	286
Avg # firms	335	363	440

Panel D. Weekly Delta-Hedged Put Returns	OTM	ATM	ALL
Average	0.57	-0.05	0.03
Std.dev.	21.30	11.29	15.16
Skewness	2.62	1.80	2.81
Kurtosis	22.39	16.97	28.26
ρ(1)	0.03	0.00	0.03
abs [ρ(1)]	0.02	0.01	0.03
Avg # obs	213	205	264
Avg # firms	327	316	407

Panel F: Weekly Stock Returns	
Average	0.29
Std.dev.	5.46
Skewness	0.49
Kurtosis	9.22
ρ(1)	0.10
abs [ρ(1)]	0.18
Avg # obs	329
Avg # firms	498

Notes to Table: We provide descriptive statistics for daily and weekly delta-hedged option returns as well as stock returns. First we compute the descriptive statistics for each firm and then we take the cross-sectional averages of these statistics. We report the mean (in percent), standard deviation (in percent), skewness, kurtosis, first-order autocorrelation of delta-hedged returns ρ(1), and first-order autocorrelation of the absolute value of delta-hedged returns, abs[ρ(1)]. The option returns are computed using closing bid-ask price midpoints. OTM (out-of-the-money) corresponds to $0.125<\Delta\leq 0.375$ for calls and $-0.375<\Delta\leq -0.125$ for puts, where Δ is the Black-Scholes delta. ATM (at-the-money) corresponds to $0.375<\Delta\leq 0.625$ for calls and $-0.625<\Delta\leq -0.375$ for puts. Options are aggregated across maturities between 30 and 180 days. The option data are from Ivy DB OptionMetrics. The sample includes the S&P 500 constituents with valid traded options data from January 2004 to December 2012.

Table 2. Descriptive Statistics on Iliquidity Measures

Panel A. Descriptive Statistics of Option and Stock Illiquidity

Calls	OTM	ATM	ALL	Puts	OTM	ATM	ALL		Stocks
Mean	12.58	6.41	8.03	Mean	9.77	5.25	7.01	Mean	0.09
Std	7.59	4.02	4.95	Std	6.54	3.62	4.76	Std	0.07
Min	0.34	0.20	0.46	Min	0.28	0.11	0.21	Min	0.03
Max	63.61	39.79	47.78	Max	56.57	34.46	45.31	Max	1.18
ρ(1)	0.27	0.33	0.34	ρ(1)	0.27	0.28	0.30	ρ(1)	0.28
Avg # Firms	379	390	487	Avg # Firms	359	339	423	Avg # Firms	498
Avg Volume	740	759	1595	Avg Volume	646	453	1098		
Avg # Trades	36	41	87	Avg # Trades	28	23	53		
Avg Imbalance	-20.72	-15.78	-15.61	Avg Imbalance	-13.63	-7.62	-10.72		
Avg Imbalance (Δ)	-6.15	-7.65	-6.55	Avg Imbalance Δ	-3.43	-3.97	-4.10		

Panel B. Correlations of Call Option and Stock Illiquidity

	OTM	ATM	ALL	Stocks
ATM	0.48	1.00		
ALL	0.88	0.70	1.00	
Stocks	0.17	0.18	0.17	1.00

Panel C. Correlations of Put Option and Stock Illiquidity

	OTM	ATM	ALL	Stocks
ATM	0.45	1.00		
ALL	0.89	0.68	1.00	
Stocks	0.15	0.12	0.14	1.00

Notes to Table: The table presents summary statistics for the illiquidity measures (in %) in Panel A and the correlations between the illiquidity measures for call and put options (in Panels B and C respectively). Option and stock illiquidity are estimated from intra-day data as the volume weighted average of the effective relative spread for each day. For each firm and on each day, we compute the average illiquidity of all the available options in a given category, and then we compute across time the mean, the minimum, the maximum, the standard deviation and the first-order autocorrelation, ρ(1). Finally, we report the cross-firms averages of these statistics in Panel A. Panel A also reports the average option volume (in number of contracts), average number of trades per firm per day, and the average order imbalance (buy minus sell orders in percent of total) equal and delta-weighted. We compute the cross-sectional correlations between the illiquidity measures on each day and report the time-series averages of these correlations in Panel B for call options and Panel C for put options. The sample includes the S&P500 constituents with valid traded options data from January 2004 to December 2012 except for imbalances which are available only from 2005.

Table 2. Descriptive Statistics on Iliquidity Measures (continued)

Panel D. Volume Weighted Effective Dollar Spreads by Bid Size

Bid Interval	Calls	OTM	ATM	ALL	Puts	OTM	ATM	ALL
(0; $2)	Mean	0.081	0.089	0.087	Mean	0.077	0.082	0.080
	Std	0.048	0.058	0.052	Std	0.049	0.056	0.052
	Min	0.002	0.004	0.003	Min	0.002	0.005	0.001
	Max	0.473	0.603	0.649	Max	0.498	0.477	0.569
	Avg # Firms	358	256	426	Avg # Firms	334	180	383
	Avg Volume	662.0	592.6	1058.5	Avg Volume	514.6	364.7	695.8
	Avg # Trades	28.2	28.5	45.4	Avg # Trades	20.0	16.9	27.1
($2; $5)	Mean	0.136	0.128	0.134	Mean	0.125	0.124	0.127
	Std	0.084	0.086	0.090	Std	0.088	0.090	0.092
	Min	0.036	0.009	0.005	Min	0.020	0.009	0.004
	Max	0.510	0.788	1.020	Max	0.597	0.835	0.968
	Avg # Firms	63	217	325	Avg # Firms	108	202	290
	Avg Volume	478.0	343.7	374.5	Avg Volume	373.0	244.8	320.2
	Avg # Trades	24.2	19.9	22.8	Avg # Trades	16.3	12.5	16.5
($5; $10)	Mean	0.251	0.200	0.200	Mean	0.218	0.198	0.200
	Std	0.135	0.130	0.158	Std	0.128	0.138	0.150
	Min	0.138	0.046	0.019	Min	0.086	0.041	0.027
	Max	0.565	0.859	1.513	Max	0.647	0.920	1.251
	Avg # Firms	10	56	160	Avg # Firms	20	70	136
	Avg Volume	998.1	291.4	161.7	Avg Volume	400.1	170.4	151.8
	Avg # Trades	44.6	18.5	13.7	Avg # Trades	20.0	10.3	10.1
($10; $20)	Mean	0.389	0.279	0.302	Mean	0.354	0.289	0.300
	Std	0.151	0.170	0.244	Std	0.200	0.191	0.234
	Min	0.272	0.119	0.071	Min	0.184	0.101	0.068
	Max	0.743	0.853	1.602	Max	0.796	1.046	1.272
	Avg # Firms	4	13	51	Avg # Firms	7	19	47
	Avg Volume	777.6	386.5	221.8	Avg Volume	385.4	164.1	126.0
	Avg # Trades	82.0	34.0	17.5	Avg # Trades	31.4	12.8	9.2
($20; ∞)	Mean	0.432	0.425	0.480	Mean	0.497	0.451	0.448
	Std	0.259	0.197	0.352	Std	0.229	0.299	0.387
	Min	0.147	0.226	0.174	Min	0.291	0.190	0.145
	Max	1.146	1.075	1.815	Max	1.036	1.400	2.039
	Avg # Firms	2	5	12	Avg # Firms	3	7	14
	Avg Volume	719.4	508.9	165.6	Avg Volume	1059.8	213.4	619.8
	Avg # Trades	114.6	98.1	29.1	Avg # Trades	110.1	27.6	13.3

Notes to Table: The table presents summary statistics for the illiquidity measures at different option bid levels. Option illiquidity is estimated from intra-day data as the volume weighted average of the effective dollar spread for each day. For each firm and on each day, we compute the average illiquidity of all the available options in a given category, and then we compute across time the mean, standard deviation, minimum, and maximum. Finally, we report the cross-firms averages of these statistics. We also report the average number of firms per day, the average option volume (in number of contracts) and average number of trades per firm per day. The sample includes the S&P500 constituents with valid traded options data from January 2004 to December 2012.

Table 3. Portfolio Returns and Alphas. Sorting on Option Illiquidity

		Panel A. Daily Call Option Returns						Panel B. Daily Put Option Returns					
		1	2	3	4	5	5-1	1	2	3	4	5	5-1
OTM	Mean	-0.200	-0.154	-0.020	0.143	0.888	1.088	-0.030	-0.071	-0.056	-0.080	0.051	0.081
	Alpha	-0.115	-0.071	0.062	0.225	0.976	1.091	-0.001	-0.044	-0.032	-0.060	0.064	0.065
	T-stat	-1.300	-0.780	0.700	2.500	9.800	17.830	-0.010	-0.500	-0.340	-0.630	0.600	1.300
ATM	Mean	-0.103	-0.039	-0.056	0.007	0.108	0.211	0.053	0.036	0.025	-0.008	0.023	-0.030
	Alpha	-0.069	-0.005	-0.023	0.043	0.151	0.220	0.073	0.055	0.043	0.007	0.032	-0.041
	T-stat	-1.480	-0.110	-0.480	0.890	2.850	7.140	1.850	1.350	0.920	0.140	0.580	-1.320
ALL	Mean	-0.159	-0.205	-0.182	-0.079	0.259	0.418	-0.033	-0.065	-0.098	-0.060	-0.025	0.008
	Alpha	-0.113	-0.158	-0.136	-0.029	0.318	0.431	-0.012	-0.045	-0.080	-0.045	-0.016	-0.005
	T-stat	-2.200	-3.020	-2.370	-0.520	4.980	11.060	-0.220	-0.760	-1.290	-0.670	-0.210	-0.110

		Panel C. Weekly Call Option Returns						Panel D. Weekly Put Option Returns					
		1	2	3	4	5	5-1	1	2	3	4	5	5-1
OTM	Mean	-0.600	-0.362	-0.148	0.152	2.471	3.071	-0.295	-0.479	-0.539	-0.700	-0.447	-0.152
	Alpha	-0.297	-0.072	0.135	0.432	2.753	3.050	-0.093	-0.292	-0.338	-0.500	-0.221	-0.128
	T-stat	-0.720	-0.160	0.310	0.980	5.150	8.650	-0.210	-0.700	-0.750	-1.060	-0.400	-0.530
ATM	Mean	-0.185	-0.159	-0.141	-0.076	0.244	0.429	0.076	-0.010	0.072	-0.064	-0.082	-0.158
	Alpha	-0.070	-0.035	-0.018	0.039	0.355	0.425	0.195	0.108	0.203	0.055	0.050	-0.145
	T-stat	-0.310	-0.150	-0.080	0.170	1.330	3.230	1.000	0.530	0.880	0.210	0.190	-1.040
ALL	Mean	-0.560	-0.594	-0.427	-0.238	0.871	1.431	-0.213	-0.230	-0.402	-0.361	-0.240	-0.028
	Alpha	-0.405	-0.436	-0.276	-0.089	1.040	1.444	-0.073	-0.086	-0.255	-0.206	-0.069	0.004
	T-stat	-1.630	-1.740	-1.080	-0.340	3.130	7.580	-0.260	-0.310	-0.790	-0.600	-0.170	0.020

Notes to Table: The table reports portfolio results for delta-hedged call and put returns and alphas. We sort firms into quintiles based on their lagged option illiquidity. Option illiquidity is obtained as volume-weighted effective spreads from intra-day LiveVol data. For each quintile, we report in percentage the mean, the alpha from the Carhart model and its t-statistic with Newey-West correction for serial correlation, using 8 lags for daily returns and 3 lags for weekly returns. The sample includes the S&P 500 constituents with valid traded options data from January 2004 to December 2012.

Table 4. Option Return Spreads. Various Robustness Checks

Panel A. Daily Call Option Return Spreads. Quintile 5-1

		Base Case from Table 3	OI-Weighted Returns	Ask-to-Ask Returns	Bid-to-Bid Returns	Only Nonfinancial Firms	Bid-to-Ask return	Ask-to-Bid returns
OTM	Mean	1.088	0.949	1.047	1.922	0.982	22.714	-12.753
	Alpha	1.091	0.955	1.042	1.936	0.983	22.701	-12.745
	T-stat	17.830	14.170	17.030	21.260	15.880	137.780	-111.190
ATM	Mean	0.211	0.190	0.235	0.369	0.204	11.122	-8.315
	Alpha	0.220	0.199	0.242	0.383	0.211	11.134	-8.307
	T-stat	7.140	6.470	7.670	8.900	6.760	96.820	-96.780
ALL	Mean	0.418	0.353	0.335	1.078	0.375	17.943	-11.608
	Alpha	0.431	0.369	0.342	1.097	0.387	17.937	-11.588
	T-stat	11.060	8.500	8.420	16.900	10.040	113.720	-105.990

Panel B. Daily Put Option Return Spreads. Quintile 5-1

		Base Case from Table 3	OI-Weighted Returns	Ask-to-Ask Returns	Bid-to-Bid Returns	Only Nonfinancial Firms	Bid-to-Ask return	Ask-to-Bid returns
OTM	Mean	0.081	0.014	0.170	0.394	0.070	16.867	-11.539
	Alpha	0.065	-0.001	0.156	0.375	0.054	16.872	-11.567
	T-stat	1.300	-0.020	3.190	5.540	1.070	130.970	-133.170
ATM	Mean	-0.030	-0.071	-0.032	0.114	-0.004	7.970	-6.501
	Alpha	-0.041	-0.082	-0.040	0.100	-0.015	7.964	-6.515
	T-stat	-1.320	-2.520	-1.300	2.360	-0.450	77.640	-96.760
ALL	Mean	0.008	-0.028	-0.024	0.445	0.013	14.182	-10.164
	Alpha	-0.005	-0.038	-0.033	0.429	0.001	14.191	-10.189
	T-stat	-0.110	-0.920	-0.780	6.630	0.030	101.710	-104.060

Notes to Table: We report daily return spreads and alphas for delta-hedged call and puts. Firms are sorted into quintiles based on their lagged option illiquidity. For the 5-1 quintiles, we report (in percent) the mean, the alpha from the Carhart model and its t-statistic with Newey-West correction for serial correlation using 8 lags. The sample includes the S&P 500 constituents with valid traded options data from January 2004 to December 2012. Each column corresponds to a different robustness check described in the text.

Table 4 (Continued). Option Return Spreads. Various Robustness Checks

Panel C. Weekly Call Option Return Spreads. Quintile 5-1

		Base Case from Table 3	OI-Weighted Returns	Ask-to-Ask Returns	Bid-to-Bid Returns	Only Nonfinancial Firms	Bid-to-Ask return	Ask-to-Bid returns
OTM	Mean	3.071	1.584	2.810	4.163	2.816	23.233	-9.826
	Alpha	3.050	1.592	2.768	4.178	2.808	23.158	-9.823
	T-stat	8.650	4.080	8.600	9.400	7.100	39.200	-32.060
ATM	Mean	0.429	0.366	0.426	0.686	0.325	9.614	-6.791
	Alpha	0.425	0.365	0.413	0.690	0.311	9.604	-6.793
	T-stat	3.230	2.500	3.250	4.170	1.960	42.650	-42.200
ALL	Mean	1.431	0.727	1.321	2.195	1.364	16.856	-9.088
	Alpha	1.444	0.768	1.319	2.229	1.379	16.809	-9.045
	T-stat	7.580	3.560	7.590	8.950	6.840	46.230	-45.930

Panel D. Weekly Put Option Return Spreads. Quintile 5-1

		Base Case from Table 3	OI-Weighted Returns	Ask-to-Ask Returns	Bid-to-Bid Returns	Only Nonfinancial Firms	Bid-to-Ask return	Ask-to-Bid returns
OTM	Mean	-0.152	-0.345	-0.116	0.163	-0.207	12.922	-9.464
	Alpha	-0.128	-0.317	-0.097	0.204	-0.184	13.048	-9.493
	T-stat	-0.530	-1.260	-0.430	0.690	-0.680	30.840	-45.640
ATM	Mean	-0.158	-0.595	-0.148	-0.044	-0.200	6.039	-5.268
	Alpha	-0.145	-0.590	-0.130	-0.039	-0.186	6.078	-5.277
	T-stat	-1.040	-3.900	-0.960	-0.250	-1.340	27.560	-37.890
ALL	Mean	-0.028	-0.492	0.092	0.547	-0.055	10.911	-7.743
	Alpha	0.004	-0.449	0.133	0.598	-0.021	11.048	-7.755
	T-stat	0.020	-2.260	0.670	2.290	-0.100	28.890	-42.700

Notes to Table: We report weekly return spreads and alphas for delta-hedged call and puts. Firms are sorted into quintiles based on their lagged option illiquidity. For the 5-1 quintiles, we report (in percent) the mean, the alpha from the Carhart model and its t-statistic with Newey-West correction for serial correlation using 3 lags. The sample includes the S&P 500 constituents with valid traded options data from January 2004 to December 2012. Each column corresponds to a different robustness check described in the text.

Table 5. ATM Portfolio Returns and Alphas using Various Moneyness Intervals. Sorting on Option Illiquidity

	Panel A. Daily ATM Call Option Returns							Panel B. Daily ATM Put Option Returns						
	Delta Interval	1	2	3	4	5	5-1	Delta Interval	1	2	3	4	5	5-1
Mean		-0.089	-0.064	-0.030	0.015	0.111	0.200		0.056	0.022	0.024	0.027	0.045	-0.011
Alpha	(0.4; 0.6]	-0.055	-0.030	0.003	0.050	0.153	0.208	(-0.6 ; -0.4]	0.076	0.041	0.042	0.043	0.055	-0.020
T-stat		-1.190	-0.660	0.050	1.030	2.910	7.250		1.950	1.040	0.920	0.870	1.050	-0.690
Mean	(0.425; 0.575]	-0.074	-0.056	-0.024	0.019	0.120	0.194	(-0.575 ; -0.425]	0.063	0.036	0.046	0.016	0.045	-0.017
Alpha		-0.040	-0.023	0.008	0.053	0.161	0.201		0.082	0.056	0.064	0.032	0.056	-0.026
T-stat		-0.860	-0.490	0.180	1.110	3.010	6.280		2.120	1.390	1.350	0.650	1.030	-0.750
Mean	(0.45; 0.55]	-0.055	-0.063	-0.016	0.026	0.131	0.186	(-0.55; -0.45]	0.085	0.055	0.040	0.037	0.068	-0.017
Alpha		-0.022	-0.030	0.017	0.059	0.170	0.192		0.104	0.075	0.059	0.053	0.080	-0.025
T-stat		-0.470	-0.630	0.360	1.260	3.210	5.610		2.770	1.910	1.240	1.170	1.410	-0.710
Mean	(0.475; 0.525]	-0.040	-0.046	-0.049	0.014	0.156	0.196	(-0.525; -0.475]	0.092	0.067	0.041	0.066	0.104	0.012
Alpha		-0.007	-0.013	-0.017	0.048	0.194	0.201		0.112	0.086	0.060	0.084	0.117	0.005
T-stat		-0.150	-0.270	-0.340	0.910	3.450	5.310		2.890	2.140	1.350	1.500	1.900	0.120
Mean	(0.49; 0.51]	-0.076	-0.048	-0.022	0.086	0.139	0.215	(-0.51; -0.49]	0.099	0.071	0.097	0.098	0.113	0.014
Alpha		-0.043	-0.015	0.013	0.119	0.177	0.220		0.118	0.092	0.116	0.118	0.126	0.008
T-stat		-0.780	-0.290	0.220	2.060	2.650	3.660		2.670	2.060	2.330	2.170	1.850	0.140

Notes to Table: The table reports portfolio results for delta-hedged ATM call and put returns and alphas. We sort firms into quintiles based on their lagged option illiquidity. For each quintile, we report in percentage the mean, the alpha from the Carhart model and its t-statistic with Newey-West correction for serial correlation, using 8 lags for daily returns and 3 lags for weekly returns. The sample includes the S&P 500 constituents with valid traded options data from January 2004 to December 2012.

Table 6. Daily Call Option Portfolio Alphas. Double Sorting on Option and Stock Illiquidity

		$1.IL^S$	2	3	4	$5.IL^S$	5-1	t-stat
OTM	$1.IL^O$	-0.180	-0.179	-0.057	-0.097	-0.062	0.118	1.590
	2	-0.125	-0.120	-0.007	-0.069	-0.030	0.094	1.140
	3	-0.058	0.233	-0.002	0.091	0.053	0.112	1.190
	4	0.194	0.221	0.302	0.191	0.232	0.039	0.370
	$5.IL^O$	0.794	0.863	0.980	1.048	1.166	0.373	2.360
	5-1	0.974	1.042	1.037	1.145	1.228		
	t-stat	9.390	10.130	7.750	10.540	9.050		
ATM	$1.IL^O$	-0.108	-0.029	-0.083	-0.090	-0.034	0.074	1.490
	2	-0.016	-0.042	0.043	0.014	-0.023	-0.006	-0.150
	3	-0.036	-0.029	0.004	-0.044	-0.011	0.025	0.560
	4	0.031	0.056	0.087	0.029	-0.001	-0.033	-0.660
	$5.IL^O$	0.079	0.175	0.216	0.122	0.150	0.071	0.960
	5-1	0.187	0.204	0.300	0.212	0.184		
	t-stat	2.680	3.260	5.880	3.270	3.660		
ALL	$1.IL^O$	-0.111	-0.147	-0.080	-0.130	-0.090	0.021	0.500
	2	-0.173	-0.145	-0.151	-0.176	-0.147	0.026	0.590
	3	-0.123	-0.170	-0.109	-0.159	-0.113	0.009	0.190
	4	-0.099	0.029	0.009	-0.059	-0.041	0.058	1.030
	$5.IL^O$	0.186	0.277	0.399	0.366	0.355	0.169	1.990
	5-1	0.297	0.424	0.479	0.496	0.445		
	t-stat	4.410	5.720	6.760	6.410	6.730		

Notes to Table: We provide portfolio alphas for daily delta-hedged call options. We first sort firms into quintiles based on their lagged option illiquidity, then firms in each option illiquidity quintile are sorted into quintiles based on their lagged stock illiquidity. Option illiquidity is obtained as volume-weighted effective spreads from intra-day LiveVol data. Stock illiquidity is computed as dollar volume-weighted effective spreads from TAQ data. For each of the 25 quintiles, we report in percentage the alpha from the Carhart model. The t-statistics are corrected for serial correlation (Newey-West correction with 8 lags). The sample includes the S&P 500 constituents with valid traded options data from January 2004 to December 2012.

Table 7. Daily Call Option Portfolio Alphas.
Double Sorting on Option Illiquidity and Stock Volume

		1.Volume	2	3	4	5.Volume	5-1	t-stat
OTM	1.IL^O	-0.097	-0.019	-0.158	-0.072	-0.213	-0.116	-1.320
	2	0.010	-0.093	-0.052	-0.079	-0.154	-0.164	-1.880
	3	0.225	0.151	0.052	-0.035	0.021	-0.204	-1.650
	4	0.441	0.085	0.268	0.249	0.078	-0.363	-3.000
	5.IL^O	1.105	1.025	0.866	0.889	0.558	-0.547	-3.180
	5-1	1.203	1.044	1.024	0.962	0.771		
	t-stat	7.610	9.950	11.280	7.740	8.570		
ATM	1.IL^O	-0.150	-0.055	-0.035	-0.086	-0.035	0.115	2.410
	2	-0.012	-0.028	-0.024	0.001	-0.012	0.000	0.010
	3	-0.039	-0.004	-0.051	-0.010	0.020	0.060	1.300
	4	0.036	0.072	0.045	0.074	0.035	0.000	-0.010
	5.IL^O	0.108	0.129	0.202	0.209	0.119	0.011	0.160
	5-1	0.257	0.184	0.237	0.295	0.154		
	t-stat	3.990	3.430	5.390	4.350	3.000		
ALL	1.IL^O	-0.123	-0.098	-0.093	-0.120	-0.133	-0.010	-0.240
	2	-0.173	-0.122	-0.168	-0.151	-0.100	0.073	1.890
	3	-0.126	-0.158	-0.156	-0.111	-0.127	-0.001	-0.010
	4	-0.017	-0.012	-0.039	-0.003	-0.035	-0.017	-0.340
	5.IL^O	0.368	0.328	0.200	0.340	0.163	-0.205	-2.130
	5-1	0.491	0.426	0.293	0.460	0.296		
	t-stat	5.950	5.940	5.240	7.010	5.770		

Notes to Table: We provide portfolio alphas for daily delta-hedged call options. We first sort firms into quintiles based on their lagged option illiquidity, then firms in each option illiquidity quintile are sorted into quintiles based on their lagged stock volume. Option illiquidity is obtained as volume-weighted effective spreads from intra-day LiveVol data. For each of the 25 quintiles, we report in percentage the alpha from the Carhart model. The t-statistics are corrected for serial correlation (Newey-West correction with 8 lags). The sample includes the S&P 500 constituents with valid traded options data from January 2004 to December 2012.

Table 8. Daily Call Option Portfolio Alphas.
Double Sorting on Option Illiquidity and Option over Stock (O/S) Volume

		1.OS	2	3	4	5.OS	5-1	t-stat
OTM	$1.IL^O$	0.087	0.029	-0.052	-0.266	-0.352	-0.439	-5.120
	2	0.190	-0.070	-0.103	-0.151	-0.228	-0.418	-4.980
	3	0.294	0.077	0.102	-0.097	0.036	-0.258	-2.450
	4	0.371	0.213	0.268	0.161	0.083	-0.296	-3.170
	$5.IL^O$	1.345	0.731	0.824	0.707	0.747	-0.585	-3.260
	5-1	1.232	0.680	0.884	0.989	1.101		
	t-stat	7.550	6.220	9.470	11.000	9.230		
ATM	$1.IL^O$	-0.116	-0.055	-0.048	-0.054	-0.083	0.033	0.630
	2	-0.046	0.001	-0.017	0.011	-0.028	0.016	0.490
	3	-0.048	-0.014	0.009	-0.061	0.028	0.076	1.530
	4	0.001	0.073	0.054	0.104	0.031	0.027	0.590
	$5.IL^O$	0.119	0.065	0.161	0.197	0.211	0.099	1.440
	5-1	0.223	0.113	0.236	0.261	0.297		
	t-stat	3.440	1.350	3.930	5.130	4.860		
ALL	$1.IL^O$	-0.142	-0.134	-0.088	-0.102	-0.100	0.043	0.980
	2	-0.222	-0.138	-0.186	-0.102	-0.071	0.151	3.650
	3	-0.209	-0.190	-0.197	-0.050	-0.033	0.176	2.210
	4	-0.142	-0.067	0.013	0.017	0.070	0.212	4.190
	$5.IL^O$	0.285	0.204	0.298	0.278	0.346	0.062	0.730
	5-1	0.428	0.338	0.389	0.378	0.448		
	t-stat	5.870	4.450	5.080	7.130	6.890		

Notes to Table: We provide portfolio alphas for daily delta-hedged call options. We first sort firms into quintiles based on their lagged option illiquidity, then firms in each option illiquidity quintile are sorted into quintiles based on their lagged option over stock (O/S) volume. Option illiquidity is obtained as volume-weighted effective spreads from intra-day LiveVol data. For each of the 25 quintiles, we report in percentage the alpha from the Carhart model. The t-statistics are corrected for serial correlation (Newey-West correction with 8 lags). The sample includes the S&P 500 constituents with valid traded options data from January 2004 to December 2012.

Table 9. Daily Call Option Portfolio Alphas.
Double Sorting on Option Illiquidity and Option Order Imbalances

		1.Imbal	2	3	4	5.Imbal	5-1	t-stat
OTM	1.IL^O	-0.191	-0.141	-0.205	-0.136	-0.054	0.137	1.870
	2	-0.208	-0.150	-0.104	-0.086	-0.035	0.173	2.170
	3	-0.260	-0.100	-0.007	-0.090	0.161	0.422	3.960
	4	-0.153	0.222	0.154	0.317	0.101	0.254	2.320
	5.IL^O	0.205	0.566	0.846	0.803	0.737	0.532	3.150
	5-1	0.396	0.707	1.052	0.939	0.791		
	t-stat	4.080	6.510	8.440	5.840	4.950		
ATM	1.IL^O	-0.052	-0.080	-0.024	0.005	-0.075	-0.027	-0.730
	2	-0.026	-0.027	0.003	-0.012	0.029	0.055	1.300
	3	-0.060	0.003	0.037	0.015	0.033	0.092	2.230
	4	0.006	0.000	0.116	0.055	0.053	0.053	0.810
	5.IL^O	-0.005	0.258	0.267	0.224	0.168	0.205	3.080
	5-1	0.043	0.340	0.259	0.221	0.276		
	t-stat	0.820	4.270	3.960	3.520	4.700		
ALL	1.IL^O	-0.254	-0.250	-0.314	-0.363	-0.201	0.053	1.150
	2	-0.276	-0.272	-0.259	-0.277	-0.256	0.020	0.400
	3	-0.189	-0.154	-0.150	-0.046	-0.087	0.103	1.700
	4	-0.075	0.019	0.137	0.273	0.053	0.127	2.130
	5.IL^O	0.302	0.386	0.527	0.650	0.606	0.304	2.250
	5-1	0.555	0.636	0.841	1.013	0.807		
	t-stat	8.900	8.530	10.990	11.120	6.030		

Notes to Table: We provide portfolio alphas for daily delta-hedged call options. We first sort firms into quintiles based on their lagged option illiquidity, then firms in each option illiquidity quintile are sorted into quintiles based on their lagged option order imbalances. Option illiquidity is obtained as volume-weighted effective spreads from intra-day LiveVol data. For each of the 25 quintiles, we report in percentage the alpha from the Carhart model. The t-statistics are corrected for serial correlation (Newey-West correction with 8 lags). The sample includes the S&P 500 constituents with valid traded options data from January 2005 to December 2012.

Table 10. Fama-MacBeth Regressions for Delta-Hedged Option Returns

Panel A. Daily Call Option Returns

	OTM		ATM		ALL	
	coeff	t-stat	coeff	t-stat	coeff	t-stat
IL^O	0.0342	6.51	0.0186	4.90	0.0496	11.69
IL^S	-2.8449	-3.02	-0.9446	-2.57	-0.6985	-1.63
σ	-0.0036	-1.37	0.0039	3.56	0.0034	2.59
b	0.0019	0.80	0.0032	2.81	0.0021	1.64
log(Size)	-0.0018	-7.06	0.0000	-0.07	-0.0004	-3.10
Leverage	0.0065	4.35	0.0025	3.69	0.0024	3.16
|Delta|	-0.0918	-15.26	-0.0231	-11.24	0.0080	3.79
log(O/S)	-0.0001	-1.01	0.0000	-0.25	0.0003	3.82
PIN	0.0002	0.02	-0.0007	-0.23	0.0015	0.35
Vega*ILS	0.2608	3.91	0.0619	2.75	0.0371	1.40
Gamma*σ	0.0533	2.38	-0.0159	-2.09	-0.0247	-2.69
Imbalances	0.0023	2.32	0.0006	2.53	0.0013	2.70
Adjusted R^2	0.056		0.056		0.056	
# CS regressions	2011		2011		2011	
# Obs in CS (avg)	279		298		366	

Panel B. Daily Put Option Returns

	OTM		ATM		ALL	
	coeff	t-stat	coeff	t-stat	coeff	t-stat
IL^O	0.0026	0.27	0.0008	0.13	0.0190	1.83
IL^S	-1.5833	-2.35	-0.7205	-2.14	-0.5892	-1.63
σ	0.0043	2.28	0.0029	2.96	0.0047	3.58
b	0.0023	1.07	0.0031	2.89	0.0038	2.66
log(Size)	-0.0003	-1.57	-0.0003	-3.29	-0.0004	-2.33
Leverage	0.0015	1.14	0.0005	0.78	-0.0003	-0.38
|Delta|	0.0091	1.40	0.0126	4.76	0.0191	5.96
log(O/S)	-0.0001	-0.73	-0.0001	-1.73	0.0001	1.23
PIN	-0.0063	-1.07	-0.0050	-1.16	-0.0069	-1.33
Vega*ILS	0.2358	4.55	0.0763	3.71	0.0856	2.44
Gamma*σ	0.0235	1.36	0.0045	0.65	-0.0080	-1.02
Imbalances	0.0051	5.94	0.0010	4.27	0.0017	5.42
Adjusted R^2	0.056		0.059		0.061	
# CS regressions	2011		2011		2011	
# Obs in CS (avg)	239		223		303	

Notes to Table: We report the results of cross-sectional Fama-Macbeth regressions for daily delta-hedged call option (Panel A) and put option (Panel B) returns. The regressors are described in the text. Reported are coefficients and Fama-Macbeth t-statistics with Newey-West correction for serial correlation using 8 lags. The sample starts in January 2005 and ends in December 2012 following the availability of the imbalance variable.

Table 11. Option Illiquidity Coefficients from Fama-Macbeth Regressions. Various Robustness Checks

Panel A. Daily Call Option Return Regressions. IL^O Coefficients and Statistics

		Base case from Table 10	Nonfinancial Firms Only	Trim 1% of Returns	Add $R^S(t+1)$	Add S(t+1), O(t+1)	Add $R^O(t-1)$, $\lvert R^S(t-1)\rvert$	Add All Variables
OTM	Coeff	0.0342	0.0307	0.0247	0.0443	0.0430	0.0420	0.0645
	T-stat	6.5100	5.3000	8.6600	10.0800	9.7600	8.2200	15.0800
	Adj R^2	0.0558	0.0503	0.0585	0.1479	0.0967	0.0833	0.1976
ATM	Coeff	0.0186	0.0158	0.0239	0.0263	0.0213	0.0293	0.0400
	T-stat	4.9000	3.8200	9.9000	7.1300	5.6200	8.2700	11.5100
	Adj R^2	0.0560	0.0519	0.0552	0.1434	0.0785	0.0862	0.1823
ALL	Coeff	0.0496	0.0480	0.0374	0.0536	0.0446	0.0590	0.0609
	T-stat	11.6900	9.9500	16.9100	14.9700	11.4900	14.6600	17.0900
	Adj R^2	0.0560	0.0524	0.0590	0.1353	0.0728	0.0866	0.1715

Panel B. Daily Put Option Return Regressions. IL^O Coefficients and Statistics

		Base case from Table 10	Nonfinancial Firms Only	Trim 1% of Returns	Add $R^S(t+1)$	Add S(t+1), O(t+1)	Add $R^O(t-1)$, $\lvert R^S(t-1)\rvert$	Add All Variables
OTM	Coeff	0.0026	0.0023	-0.0010	0.0182	-0.0022	0.0056	0.0193
	T-stat	0.2700	0.2200	-0.3100	1.9000	-0.4300	0.5800	3.8300
	Adj R^2	0.0560	0.0544	0.0596	0.1889	0.0808	0.0795	0.2226
ATM	Coeff	0.0008	-0.0002	0.0029	0.0104	0.0040	0.0071	0.0203
	T-stat	0.1300	-0.0300	0.8900	1.8000	0.6900	1.1100	3.2700
	Adj R^2	0.0590	0.0564	0.0620	0.1585	0.0735	0.0873	0.1931
ALL	Coeff	0.0190	0.0192	0.0090	0.0265	0.0089	0.0275	0.0255
	T-stat	1.8300	1.7400	3.4900	2.5600	1.9800	2.6300	5.5100
	Adj R^2	0.0610	0.0599	0.0653	0.1653	0.0722	0.0869	0.1944

Notes to Table: We report the coefficients on option illiquidity from Fama-Macbeth regressions on daily option returns for different option categories (OTM, ATM, and ALL). The regressors in Table 10 are always included in the regressions but not reported here. T-statistics are computed with Newey-West correction for serial correlation using 8 lags. Adjusted R^2 are reported as well. The sample includes the S&P 500 constituents with valid traded options data from January 2005 to December 2012. Each column corresponds to a different robustness check described in the text. "All Variables" refers to the current stock price, the current stock return, the current value-weighted option price, the lagged absolute stock return and the lagged return on the option delta hedge.

Table 12. Option Illiquidity (ILO) Regressions

Panel A. Daily Call Option Returns

	OTM		ATM		ALL	
	coeff	t-stat	coeff	t-stat	coeff	t-stat
ILO(t-1)	0.2852	77.18	0.2962	81.94	0.3256	102.20
ILO(t-2)	0.2026	56.12	0.2311	63.04	0.2390	74.72
IL^S	4.8450	7.87	2.0351	7.85	4.4393	13.89
σ	-0.1171	-28.68	-0.0480	-26.64	-0.0515	-33.45
b	-0.0033	-3.39	-0.0023	-4.53	-0.0038	-7.54
log(Size)	-0.0075	-33.80	-0.0031	-28.09	-0.0034	-28.49
Leverage	0.0111	18.96	0.0050	17.17	0.0063	18.34
|Delta|	-0.2974	-50.92	-0.0805	-63.73	-0.1044	-71.01
Log(OptionVolume)	-0.0031	-34.41	-0.0012	-24.24	-0.0025	-41.92
Log(StockVolume)	0.0002	0.93	-0.0003	-2.76	0.0017	16.62
PIN	0.0344	11.16	0.0200	12.62	0.0192	10.23
Vega*ILS	-0.5494	-7.96	0.0243	1.65	-0.3624	-8.61
Gamma*σ	0.9057	24.06	0.3133	23.20	0.2669	30.28
|Imbalances|	0.0234	20.37	0.0085	23.26	0.0075	18.96
Adjusted R^2	0.490		0.52372		0.558	
# CS regressions	2009		2009		2009	
# Obs in CS (avg)	311		327		398	

Panel B. Daily Put Option Returns

	OTM		ATM		ALL	
	coeff	t-stat	coeff	t-stat	coeff	t-stat
ILO(t-1)	0.3087	73.07	0.2921	71.99	0.3379	102.06
ILO(t-2)	0.2325	53.58	0.2329	63.59	0.2525	72.03
IL^S	2.6786	5.54	0.8618	3.80	2.7863	10.08
σ	-0.0893	-26.20	-0.0420	-27.78	-0.0517	-32.25
b	-0.0060	-8.27	-0.0031	-8.16	-0.0053	-11.20
log(Size)	-0.0055	-29.39	-0.0027	-27.12	-0.0037	-30.88
Leverage	0.0066	15.54	0.0041	17.23	0.0056	19.33
|Delta|	-0.2201	-42.19	-0.0591	-45.04	-0.0807	-58.33
Log(OptionVolume)	-0.0012	-16.51	-0.0005	-13.95	-0.0014	-26.65
Log(StockVolume)	0.0001	0.59	-0.0001	-0.47	0.0017	15.03
PIN	0.0275	11.03	0.0214	13.62	0.0216	12.03
Vega*ILS	-0.3361	-6.79	0.0144	1.09	-0.3169	-8.55
Gamma*σ	0.7564	20.54	0.2201	21.15	0.2166	26.03
|Imbalances|	0.0201	23.57	0.0072	23.76	0.0068	18.03
Adjusted R^2	0.480		0.469		0.513	
# CS regressions	2009		2009		2009	
# Obs in CS (avg)	283		263		353	

Notes to Table: We report the results of cross-sectional Fama-Macbeth regressions for daily call option ILO (Panel A) and put option (Panel B) ILO. The regressors are described in the text. Reported are coefficients and Fama-Macbeth t-statistics with Newey-West correction for serial correlation using 8 lags. The sample starts in January 2005 and ends in December 2012 following the availability of the imbalance variable.

Table A.1. Daily Put Option Portfolio Alphas. Double Sorting on Option and Stock Illiquidity

		$1.IL^S$	2	3	4	$5.IL^S$	5-1	t-stat
OTM	$1.IL^O$	-0.096	-0.020	0.027	0.036	0.046	0.142	2.580
	2	-0.167	-0.102	0.041	-0.016	0.028	0.195	3.330
	3	-0.096	0.049	-0.049	-0.012	-0.048	0.048	0.590
	4	-0.214	-0.053	-0.067	0.003	0.023	0.237	3.160
	$5.IL^O$	-0.169	-0.092	0.023	0.188	0.363	0.532	5.080
	5-1	-0.073	-0.072	-0.004	0.153	0.317		
	t-stat	-0.790	-0.900	-0.050	2.050	4.120		
ATM	$1.IL^O$	0.016	0.097	0.069	0.067	0.112	0.096	2.690
	2	0.015	0.040	0.087	0.082	0.051	0.036	0.940
	3	-0.016	0.026	0.035	0.096	0.065	0.081	1.780
	4	-0.014	-0.021	0.037	0.086	-0.053	-0.039	-0.610
	$5.IL^O$	-0.085	0.108	0.025	0.069	0.062	0.147	3.050
	5-1	-0.101	0.011	-0.044	0.002	-0.050		
	t-stat	-2.040	0.140	-0.790	0.040	-1.120		
ALL	$1.IL^O$	-0.061	-0.019	-0.002	-0.003	0.024	0.085	2.390
	2	-0.139	0.008	-0.026	-0.025	-0.033	0.106	2.730
	3	-0.157	-0.044	-0.045	-0.063	-0.044	0.113	2.310
	4	-0.163	-0.018	-0.067	0.041	-0.061	0.102	1.910
	$5.IL^O$	-0.176	-0.147	-0.029	0.091	0.180	0.357	5.130
	5-1	-0.116	-0.128	-0.027	0.094	0.156		
	t-stat	-1.710	-1.810	-0.390	1.740	3.270		

Notes to Table: We provide portfolio alphas for daily delta-hedged put options. We first sort firms into quintiles based on their lagged option illiquidity, then firms in each option illiquidity quintile are sorted into quintiles based on their lagged stock illiquidity. Option illiquidity is obtained as volume-weighted effective spreads from intra-day LiveVol data. Stock illiquidity is computed as dollar volume-weighted effective spreads from TAQ data. For each of the 25 quintiles, we report in percentage the alpha from the Carhart model. The t-statistics are corrected for serial correlation (Newey-West correction with 8 lags). The sample includes the S&P 500 constituents with valid traded options data from January 2004 to December 2012.

Table A.2. Daily Put Option Portfolio Alphas.
Double Sorting on Option Illiquidity and Stock Volume

		1.Volume	2	3	4	5.Volume	5-1	t-stat
OTM	1.IL^O	-0.033	-0.036	0.031	0.012	0.095	0.128	1.720
	2	-0.052	-0.035	-0.046	-0.015	-0.059	-0.006	-0.110
	3	-0.003	-0.011	0.027	0.006	-0.121	-0.118	-1.610
	4	0.085	-0.027	-0.079	-0.048	-0.135	-0.220	-2.370
	5.IL^O	0.185	0.071	0.035	0.077	0.038	-0.147	-1.390
	5-1	0.218	0.107	0.004	0.065	-0.057		
	t-stat	2.090	1.430	0.050	0.910	-0.730		
ATM	1.IL^O	0.086	0.069	0.091	0.075	0.045	-0.041	-1.100
	2	0.091	0.073	0.064	0.046	0.001	-0.090	-2.740
	3	0.103	0.042	0.007	0.032	0.021	-0.083	-1.770
	4	0.068	-0.017	0.015	0.002	-0.001	-0.070	-1.250
	5.IL^O	0.149	0.029	0.072	0.009	0.034	-0.115	-1.200
	5-1	0.063	-0.040	-0.019	-0.066	-0.011		
	t-stat	0.690	-0.740	-0.380	-1.490	-0.220		
ALL	1.IL^O	-0.055	-0.007	-0.005	0.017	0.042	0.098	2.580
	2	-0.013	-0.070	-0.034	-0.004	-0.044	-0.031	-0.720
	3	-0.083	-0.022	-0.085	-0.084	-0.123	-0.039	-0.920
	4	-0.037	0.035	-0.093	0.008	-0.081	-0.044	-0.750
	5.IL^O	0.035	-0.047	-0.091	-0.013	0.062	0.027	0.360
	5-1	0.090	-0.040	-0.086	-0.030	0.020		
	t-stat	0.990	-0.560	-1.490	-0.620	0.360		

Notes to Table: We provide portfolio alphas for daily delta-hedged put options. We first sort firms into quintiles based on their lagged option illiquidity, then firms in each option illiquidity quintile are sorted into quintiles based on their lagged stock volume. Option illiquidity is obtained as volume-weighted effective spreads from intra-day LiveVol data. For each of the 25 quintiles, we report in percentage the alpha from the Carhart model. The t-statistics are corrected for serial correlation (Newey-West correction with 8 lags). The sample includes the S&P 500 constituents with valid traded options data from January 2004 to December 2012.

Table A.3. Daily Put Option Portfolio Alphas.
Double Sorting on Option Illiquidity and Option over Stock (OS) Volume

		1.OS	2	3	4	5.OS	5-1	t-stat
OTM	1.IL^O	0.005	-0.013	0.041	0.073	-0.044	-0.044	-0.700
	2	0.064	-0.098	-0.055	0.011	-0.131	-0.192	-2.350
	3	0.137	-0.042	-0.141	-0.039	-0.031	-0.170	-1.650
	4	0.077	-0.082	-0.053	0.001	-0.185	-0.251	-2.960
	5.IL^O	0.156	0.291	-0.070	-0.047	0.030	-0.292	-3.160
	5-1	0.205	0.210	-0.070	-0.028	-0.107		
	t-stat	2.860	1.470	-0.780	-0.340	-1.100		
ATM	1.IL^O	0.109	0.055	0.108	0.076	0.025	-0.079	-1.560
	2	0.119	0.027	0.051	0.062	0.018	-0.105	-2.520
	3	0.094	0.067	0.105	0.002	-0.054	-0.145	-2.540
	4	0.088	0.030	0.038	-0.007	-0.057	-0.125	-1.520
	5.IL^O	0.206	-0.013	-0.013	0.140	0.030	-0.102	-1.870
	5-1	-0.015	-0.071	-0.138	0.099	0.017		
	t-stat	-0.280	-1.330	-2.450	1.160	0.340		
ALL	1.IL^O	-0.057	0.006	0.033	0.039	-0.032	0.025	0.680
	2	-0.033	0.004	0.013	-0.023	-0.129	-0.097	-1.770
	3	-0.098	-0.104	-0.055	-0.003	-0.138	-0.040	-0.620
	4	0.001	0.011	-0.078	-0.099	-0.002	-0.001	-0.010
	5.IL^O	0.099	0.094	-0.079	-0.014	-0.063	-0.131	-2.070
	5-1	0.096	0.094	-0.140	-0.022	-0.048		
	t-stat	1.750	0.630	-1.890	-0.360	-0.810		

Notes to Table: We provide portfolio alphas for daily delta-hedged put options. We first sort firms into quintiles based on their lagged option illiquidity, then firms in each option illiquidity quintile are sorted into quintiles based on their lagged option over stock (O/S) volume. Option illiquidity is obtained as volume-weighted effective spreads from intra-day LiveVol data. For each of the 25 quintiles, we report in percentage the alpha from the Carhart model. The t-statistics are corrected for serial correlation (Newey-West correction with 8 lags). The sample includes the S&P 500 constituents with valid traded options data from January 2004 to December 2012.

Table A.4. Daily Put Option Portfolio Alphas.
Double Sorting on Option Illiquidity and Option Order Imbalances

		1.Imbal	2	3	4	5.Imbal	5-1	t-stat
OTM	1.IL^O	-0.015	-0.089	0.037	0.066	0.222	0.237	2.970
	2	-0.215	-0.111	-0.005	0.009	0.064	0.278	3.540
	3	-0.230	-0.107	-0.067	0.291	0.015	0.245	3.490
	4	-0.025	-0.261	-0.161	0.100	0.084	0.109	1.100
	5.IL^O	-0.090	-0.114	-0.090	-0.011	0.051	0.140	1.550
	5-1	-0.074	-0.025	-0.127	-0.077	-0.171		
	t-stat	-0.930	-0.260	-1.130	-0.440	-1.950		
ATM	1.IL^O	0.043	0.034	0.094	0.093	0.116	0.073	1.870
	2	0.017	-0.002	0.095	0.068	0.156	0.139	3.910
	3	-0.007	-0.038	0.057	0.091	0.111	0.118	2.740
	4	0.036	-0.043	0.014	0.014	0.112	0.076	1.030
	5.IL^O	0.059	-0.104	0.068	0.079	0.030	-0.029	-0.400
	5-1	0.016	-0.137	-0.025	-0.014	-0.086		
	t-stat	0.240	-2.210	-0.250	-0.230	-1.550		
ALL	1.IL^O	-0.130	-0.132	-0.138	0.014	-0.013	0.118	3.200
	2	-0.090	-0.141	-0.203	-0.027	0.002	0.092	2.010
	3	-0.134	-0.126	-0.137	-0.077	-0.019	0.115	1.570
	4	-0.096	-0.142	-0.177	0.041	-0.022	0.074	1.310
	5.IL^O	0.097	-0.155	0.313	0.382	0.341	0.244	0.850
	5-1	0.227	-0.024	0.450	0.368	0.354		
	t-stat	3.260	-0.360	4.750	2.210	1.250		

Notes to Table: We provide portfolio alphas for daily delta-hedged put options. We first sort firms into quintiles based on their lagged option illiquidity, then firms in each option illiquidity quintile are sorted into quintiles based on their lagged option order imbalances. Option illiquidity is obtained as volume-weighted effective spreads from intra-day LiveVol data. For each of the 25 quintiles, we report in percentage the alpha from the Carhart model. The t-statistics are corrected for serial correlation (Newey-West correction with 8 lags). The sample includes the S&P 500 constituents with valid traded options data from January 2004 to December 2012.