Illiquidity Premia in the Equity Options Market*

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Abstract

Illiquidity is well-known to be a significant determinant of stock and bond returns. We are the first to report on illiquidity premia in equity option markets using a large cross-section of firms. An increase in option illiquidity decreases the current option price and predicts higher expected delta-hedged option returns. This effect is statistically and economically significant, and it is consistent with existing evidence that market makers in the equity options market hold net long positions. The illiquidity premium is robust across puts and calls, moneyness levels, as well as across different empirical approaches. It is also robust when controlling for various firm-specific variables, including standard measures of illiquidity of the underlying stock.

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1 Introduction

The existing 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).[1] There is also a growing body of evidence on the existence of illiquidity premia in other markets, see for instance Deuskar, Gupta, and Subrahmanyam (2011) for evidence on interest rate derivatives, and Bongaerts, de Jong, and Driessen (2011) for evidence from the credit default swap market.

Vijh (1990) measures liquidity and market depth in the equity options market, and George and Longstaff (1993) measure bid-ask spreads in index options and explain the nature of cross-sectional differences in these spreads. More recently, Wei and Zheng (2010) study the relationship between trading activity and bid-ask spreads in equity options.

Until now, however, the literature has been mostly silent about the relationship between illiquidity and expected returns in equity option markets. This is surprising, because similar to stock and bond markets, market makers in option markets incur order processing and asymmetric information costs, and a substantial fraction of the bid-ask spread in option markets is attributed to premia compensating dealers for the risk of holding uncovered positions in illiquid options (see George and Longstaff, 1993). Moreover, equity option markets offer unique opportunities to learn about illiquidity because unlike stocks and bonds, they are in zero net supply. The impact of illiquidity on returns should therefore depend on whether liquidity providers are net long or net short equity options.

We study the effect of option and stock illiquidity on delta-hedged equity option returns. We document the statistical significance and economic magnitude of the impact of option illiquidity on option returns.

When sorting firms into quintiles based on the illiquidity of their options, 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. The returns and alphas on the spread portfolio for puts are positive across moneyness categories as well. Using daily returns, the average option return spread for calls is 21 basis points and for puts it is 15 basis points. The weekly results are consistent with the daily results.

[1] 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), and Acharya and Pedersen (2005). Bond market studies include Warga (1992), Boudoukh and Whitelaw (1993), Kamara (1994), Krishnamurthy (2002), Longstaff (2004), Goldreich, Hanke, and Nath (2005), Bao, Pan, and Wang (2011), and Beber, Brandt, and Kavajecz (2009).

We confirm 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, lagged option returns, and other firm characteristics, following Duan and Wei (2009). An increase in option illiquidity has a positive and significant impact on next period's option returns, suggesting the existence of illiquidity premiums in the options market. The effect of illiquidity on option returns is economically significant: for example, a two standard deviation positive shock to out-of-the money call option illiquidity on day $t-1$ would result in a 34 basis point increase in the day $t+1$ return on the call option. This is a significant magnitude for daily changes in prices.

Are these results consistent with theory? Seminal option pricing models ignore the role of financial intermediaries, and thus the impact of supply and demand on option prices. In his retrospection, Bates (2003) highlights the need to build models that incorporate demand effects. Garleanu, Pedersen, and Poteshman (2009) subsequently develop a demand-based option theory. In their model, market makers who incur higher unhedgeable risks will move the price up if the net demand is positive and down if it is negative. While this model does not consider illiquidity, it seems reasonable that illiquidity will amplify this effect. A negative net demand for equity options, as documented empirically by Lakonishok, Lee, Pearson, and Poteshman (2007) will therefore result in a negative relationship between illiquidity and option prices, consistent with the positive illiquidity premium we find in returns.[2] Intuitively, the equity options market is only nominally in zero net supply. Negative net demand by the end users in the equity options market is economically equivalent to the positive net supply in the equity market. Our empirical results are therefore consistent with those of Amihud (2002), who documents a positive effect of stock illiquidity on stock returns.

The theoretical literature also studies the impact of the illiquidity of underlying stocks on option prices. In a frictionless, complete-market model, the price of the option can be replicated by trading in the underlying asset and a risk free bond. If the underlying asset is illiquid, this should affect the return on options. Leland (1985) and Boyle and Vorst (1992) provide a theoretical analysis of this effect using a hedging argument. Because option market makers are net long in equity option markets, they need to create a synthetic short option using the underlying stock. If illiquidity increases, the price market makers receive from shorting the synthetic option decreases, therefore lowering the option price.

The theoretical impact on delta-hedged option returns is less clear, however. In our empirical work we do not find systematic evidence for an effect of stock illiquidity on delta-

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

hedged option returns. Bivariate sorts on option and stock illiquidity yield consistently large and positive option return premia for option illiquidity, but do not yield robust results for the effects of illiquidity in the underlying stock. Regression results indicate that the effects of stock illiquidity on option returns vary by moneyness and option style.

To the best of our knowledge, our results are new to the literature. The existing empirical evidence on equity option illiquidity is very limited. Using data from an interesting natural experiment, Brenner, Eldor, and Hauser (2001) compare central bank issued and exchange traded options and report a 21% illiquidity discount for non-tradable central bank issued options. Cao and Wei (2010) document commonality in the illiquidity on equity option markets, but do not investigate the impact of illiquidity on option returns. Muravyev, Pearson, and Broussard (2013) find that options markets do not facilitate stock price discovery which of course does not preclude an illiquidity premium in option returns.

The remainder of the paper is organized as follows. Section 2 introduces the data and defines delta-hedged options returns and illiquidity measures. Section 3 presents the univariate portfolio sorts on option illiquidity, as well as bivariate sorts on option and stock illiquidity. Section 4 contains cross-sectional multivariate regressions that control for various firm-specific variables including volatility, beta, market capitalization and leverage. It also investigates the role of temporary price pressures. Section 5 discusses the implications of our findings, and Section 6 concludes.

2 Option Returns and Illiquidity Measures

Motivated by the literature on illiquidity premia in the bond and equity markets, we investigate if illiquid options earn on average higher or lower expected returns in the cross-section, which would be evidence of an illiquidity premium. This requires us to define option returns and illiquidity measures. It is also critical to adjust option returns for the first-order effects from the underlying stock return. We now discuss these issues in detail.

2.1 Option Returns and Stock Returns

Mainstream option valuation theory assumes away illiquidity in option markets, as well as illiquidities in the market for the underlying security and bond markets.[3] These assumptions lead to option valuation expressions that are deterministic functions of the underlying asset price and the interest rate, as well as other variables such as volatility.

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

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

$$O = BS\left(S, K, r, T, \sigma\right) \tag{2.1}$$

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

$$E\left[R^{O}\right] = \left(r + \left(E\left[R^{S}\right] - r\right)\frac{S}{O}\frac{\partial O}{\partial S}\right)dt \tag{2.2}$$

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 (2.1). 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 (2.2) shows that it is critical to properly control for the return on the underlying stock when regressing option returns on illiquidity measures. We implement this control by using delta-hedged returns.

2.2 Computing Option Returns

We use daily delta-hedged returns, computed as

$$\tilde{R}^{O}_{t+1,n} = R^{O}_{t+1,n} - R^{S}_{t+1}S_t\frac{\Delta_{t,n}}{O_{t,n}} \tag{2.3}$$

where $R^{O}_{t+1,n}$ is the daily raw rate of return on option n and where $\Delta_{t,n} = \frac{\partial O_{t,n}}{\partial S_t}$ is computed from the Cox, Ross, and Rubinstein (1979) binomial tree model allowing for early exercise. We obtain daily stock returns, prices, and the number of outstanding shares from 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. We compute equally-weighted average daily returns on a firm-by-firm basis for different moneyness categories by averaging option returns for all available contracts. For each option category and for each firm, the delta-hedged return is then computed from (2.3) as

$$\tilde{R}^O_{t+1} = \frac{1}{N}\sum_{n=1}^{N}\frac{O_{t+1}(K_n, T_n - 1) - O_t(K_n, T_n)}{O_t(K_n, T_n)} - R^S_{t+1} S_t \frac{1}{N}\sum_{n=1}^{N}\frac{\Delta_t\,(K_n, T_n)}{O_t(K_n, T_n)} \tag{2.4}$$

where N is the number of available contracts in the particular category at time t with legitimate quotes at time $t+1$. $O_t(K_n, T_n)$ is the mid-point quote, (ask+bid)/2, for an option with strike price K_n and maturity T_n.[4]

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

$$\tilde{R}^O_{t:t+5} = R^O_{t:t+5} - \sum_{j=1}^{5}\frac{R^S_{t+j} S_{t+j-1}\Delta_{t+j-1}}{O_t}. \tag{2.5}$$

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. Although potentially interesting, we do not consider holding-periods longer than a week due to option data limitations.

Our benchmark sample period is January 2004-December 2012 for which we have intraday option prices and quotes from LiveVol as described below.

In the robustness section we will also consider the longer sample from January 2000 through December 2012 using daily option data from OptionMetrics. Although OptionMetrics contain data from January 1996 we do not use data prior to 1999 when major cross-listing reforms were enacted. Our extended sample consists of all S&P500 firms which enter and remain in the index between January 2000 and December 2012. We control for the index composition on the monthly basis and the last month of a firm in the index corresponds to the last month of a 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 in-the-money (ITM), 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

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

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. ATM options correspond to $0.375 < \Delta \leq 0.625$ for calls and $-0.625 < \Delta \leq -0.375$ for puts, and the ITM category is defined by $0.625 < \Delta \leq 0.875$ for calls and $-0.875 < \Delta \leq -0.625$ for puts.

Following Goyal and Saretto (2009) and Cao and Wei (2010), we apply filters to the option data, eliminating the following contracts: (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 prices lower than \$3 and bid-ask spread below \$0.05, or prices equal 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. We have also repeated the empirical tests without imposing any filters, and the results are robust.

In the cross-sectional analysis below we merge four datasets: CRSP daily data, OptionMetrics daily data, and intraday TAQ and LiveVol data. 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. This yields on average 420 firms for the daily data, and 437 firms in the weekly data for call contracts, and 367 and 387 firms for daily and weekly data respectively for puts.

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.

Table 1 reports summary statistics. We first compute the respective statistics for each firm and report the average across firms. The delta-hedged return averages are all close to zero and show no particular patterns across moneyness, and calls versus puts. 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 and exhibit higher skewness than do ATM and ITM options. The option returns display mixed evidence of serial dependence judging from the first-order autocorrelation, $\rho(1)$. The absolute return autocorrelation, $\rho^{abs}(1)$, is positive for all categories and nontrivial for the daily returns in Panel A and B, confirming the volatility clustering, apparent in Figure 1. The average number of observations refers to the number of option contracts per day (or week) in each moneyness category in our sample.

2.3 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. As discussed in the introduction, there is an extensive literature on stock market illiquidity. We follow the convention in this 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

$$IL_k^S = \frac{2|S_k^P - S_k^M|}{S_k^M}, \tag{2.6}$$

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 of the 500 stocks we investigate.

Motivated by the literature on illiquidity premia in the bond and equity markets, we investigate if illiquid options on average earn higher or lower expected returns in the cross-section, which would be evidence of an illiquidity premium. This requires us to define an option illiquidity measure.

Intraday options trading data are reported by all equity options exchanges via the Options Price Reporting Authority (OPRA). OPRA data therefore contain all information about trading in each option class for each day starting January 2004. LiveVol, a commercial data vendor, use the raw OPRA data to creates files for each company on each day with information about each option trade during the day including the national best bid and offer (NBBO) quotes prevailing at the time of the trade, execution price, trading volume, and options delta of each trade. LiveVol data begins in at the beginning of 2004 and our sample goes through the end of 2012.

Our sample contains all trades and NBBO matched quotes for all option contracts of 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. We compute IL^O for any option traded on any of the 500 firms on any day during our sample. The IL^O measure is then averaged using equal weights across contracts within the same moneyness category for each firm. 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 for calls on average is higher at 9.8% (ALL), compared with puts at 8.22%. OTM options have the highest effective spreads for both calls and puts, followed by ATM and then ITM options.

Panel A of Table 2 also contains information on option trading volume and 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. The difference is especially large for ATM and ITM options. While ATM call trading volume averages 875 contracts per day, ATM put volume is only 510 contracts per day. This difference in trading volume is also reflected in the frequency of trading. Panel A reports number of trades in each option category. The number of trades in ATM and ITM calls is around twice that in put options. The lower trading volume and lower frequency of trading in ATM and ITM puts implies that we should interpret results for these option categories with some caution.

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 during the 2008-2009 credit crisis, and during European debt crisis in 2010-2011. All series are trending down through our sample as the options markets get more efficient overall.

Panels B (for calls) and C (for puts) in Table 2 report firm-average correlations between IL^O for different moneyness categories as well as IL^S. The correlation of different option illiquidity categories with stock illiquidity ranges between 13% and 27%. The correlation across moneyness categories for each option class is also positive everywhere. For example the correlation between OTM and ATM call illiquidity is 48%. The correlation of IL^Oacross the ATM, ITM and OTM categories ranges between 33% and 48% for calls and puts.

3 The Cross-Section of Option Returns

We now investigate the cross-sectional relationship between option illiquidity and expected option returns. Our main hypothesis is that hedging costs and unhedged risk of option market makers positions which are reflected in wider options spreads, i.e. higher illiquidity, should contribute to higher illiquidity premium in option returns. We investigate this hypothesis in more detail in Section 5.1. Moreover, the illiquidity premium should be higher for contracts with higher hedging costs or higher unhedged risks which can be related to dealers' inventories. The contracts with higher volume potentially imply a higher participation rate of options market makers and higher inventories. We therefore expect OTM options to have a higher illiquidity premium than other moneyness categories, and we also expect call options to carry a higher illiquidity premium than put options.

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 and stock illiquidity respectively. Our treatment of illiquidity as an explanatory variable in the cross-section follows Amihud's (2002) investigation of expected stock returns.

3.1 Sorting on Option Illiquidity

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

Following Amihud (2002) and French, Schwert, and Stambaugh (1987), we use ex-post realized 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 (2.4) for the daily horizon and (2.5) 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.[5]

Table 3 reports some of our key 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 availability of LiveVol data. We sort firms into quintiles based on their lagged option illiquidity. For each quintile, we report the percentage average return

[5]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.

as well as the corresponding alpha from the Carhart model. 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. Put option returns are in Panel B. We report average returns and alphas for ALL call or put options and for the three moneyness categories. Panel A shows that 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 varies from 6 bps for ITM calls to 48 bps for OTM calls.

Panel B of Table 3 reports the results for daily delta-hedged returns on put. Overall (see the ALL category) the spread returns are positive and significant. The individual moneyness categories show that the put results are driven by OTM contracts. The daily alpha spread for puts is 13 bps overall and 28 bps for OTM contracts. Interestingly, Bollen and Whaley (2004) find relatively weak evidence for the effect of ATM put options order imbalances on options implied volatility for the cross-section of individual stock options, whereas they find strong results for ATM calls. The partial explanation for their findings is the level of market activity which is attributed to substantially lower trading volume in ATM puts compared to similar calls. This is also true for our sample as we saw in Table 2 above.

Panels C and D of Table 3 report the results for weekly delta-hedged returns on call and put options. In general, weekly results are stronger in both statistical and economic magnitudes. Here, the 5-1 return spreads are large, positive, and highly statistically significant in all moneyness categories for calls and puts. The alpha spreads are between 31 and 241 bps per week. While some of the alphas in Table 3 may appear to be unrealistically large, it is important to remember from Table 2 that option bid-ask spreads are very large. Therefore, the alphas computed from mid-point returns are not readily earned by investors who must pay the spread.

For call options in Panel C, where the trading volume is on average higher, the magnitudes of 5-1 spreads are consistent with our hypotheses about higher illiquidity premium for OTM options followed by ATM options and then ITM options. Further, for call options, across all moneyness categories, the portfolio returns and alphas are monotonically increasing with illiquidity which signals a systematic relationship between option illiquidity and expected returns.

Figure 4 gives a visual impression of Table 3 by plotting the average return across quantiles for daily calls (top left), weekly calls (top right), daily puts (bottom left), and weekly puts (bottom right). Figure 4 highlights that the effect from IL^O is strongest for OTM options (circle markers) as compared to ATM options (diamonds markers) and ITM options (star markers).

Finally, note that for the ALL moneyness category in each of Panels A, B, C and D in Table 3, the average portfolio returns and alphas are monotonically increasing with illiquidity for both calls and puts. If market makers are net long equity options, as the empirical evidence in Lakonishok et al. (2007) and Garleanu et al. (2009) suggests, then our results are consistent with the liquidity effects found in positive net-supply (stock and bond) markets. We will discuss this further in Section 5.2 below.

3.2 Robustness Checks on Option Illiquidity Sorts

Before proceeding to the double-sorting results below, it is natural to ask if the single-sort results in Table 3 are robust to various permutations in the empirical design. The results from this robustness exercise are presented in Table 4. Panel A contains results for calls and Panel B for puts. To save space we only report the results for the 5-1 quintile spread returns, and only for the daily frequency. The complete sorting tables corresponding to each column in Table 4 are reported in the online appendix. The results for weekly returns are available upon request.

The first column in Table 4 contains the base case sorting results from Table 3. It is repeated here just for convenience.

The second column in Table 4 contains the results when option returns are weighted by their open-interest rather than by equal weights as is done 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 significant overall and for OTM (as in Table 3) and now also for ITM options

The third column in Table 4 computes option returns from ask-price to ask-price rather than from mid-point to mid-point as is done in the base case. Notice that the Ask-to-Ask results are very close to the base case results in the first column of Table 4.

Option spreads can be very large as we saw in Table 2. The fourth column of Table 4 therefore omit observations with an effective relative spread larger than 50%. Removing options with extremely large spreads lowers the mean 5-1 spread return for OTM calls but significance remains everywhere in Panel A. For puts in Panel B the 5-1 returns are again significant overall as are the 5-1 returns for OTM and ITM puts. The put return spreads are thus similar to the base case as well.

One may also wonder if the results in Table 3 are driven by options with very low price levels and thus potentially extreme returns. In column 5 we therefore omit options with price below $0.50. Not surprisingly, this filter affects OTM options the most. Nevertheless, the 5-1 return spreads are still significant for all call option categories, for put options overall as well as for OTM puts. Thus the conclusion from Table 3 remains.

In the final robustness check, we extend the sample back to 2000 and rely on relative quoted spreads[6] from OptionMetrics because the option TAQ data from LiveVol only starts in 2004.[7] For each option contract, we compute the daily relative quoted spread as

$$ILQ_{t,n}^{O} = \frac{OA_t(K_n, T_n) - OB_t(K_n, T_n)}{O_t(K_n, T_n)} \tag{3.1}$$

where the prices $O_t(K_n, T_n)$, $OA_t(K_n, T_n)$, and $OB_t(K_n, T_n)$ are, respectively, the end of day closing mid-point, ask, and bid quotes reported in OptionMetrics, for an option with strike price K_n and maturity T_n. Note $O_t(K_n, T_n) = (OA_t(K_n, T_n) + OB_t(K_n, T_n))/2$.

From $ILQ_{t,n}^{O}$ we compute equally-weighted average relative spreads

$$ILQ_t^O = \frac{1}{N} \sum_{n=1}^{N} ILQ_{t,n}^{O} \tag{3.2}$$

where N is the number of available contracts that are within the particular option category for a given firm.

The average cross-sectional correlation between our relative effective spreads, IL^O from LiveVol, and the relative quoted spreads, ILQ^O from OptionMetrics is 51%. A detailed correlation table can be found in the online appendix.

The last column in Table 4 shows that the 5-1 spread returns for the longer sample using relative quoted spreads are positive and significant in all moneyness categories for both call and put contracts. The daily alpha spread varies from 13 bps for ATM puts to 79 bps for OTM call options.

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

Figure 5 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 evident throughout the sample for both calls and puts. The spread return and alpha are both positive for calls and puts in every year in the sample. The alpha is only significantly negative for puts in 2010.

[6] Dollar quoted bid-ask spreads are not a good alternative as liquidity indicators, because they are mainly driven by the maturity and moneyness of the option contract. See Cao and Wei (2010) for a discussion.

[7] For studies on stock market illiquidity that use relative bid-ask spreads, see for instance Hasbrouck and Seppi (2001), Huberman and Halka (2001), Chordia, Roll, and Subrahmanyam (2000, 2001), and Chordia, Sarkar, and Subrahmanyam (2005).

3.3 Double Sorting on Option and Stock Illiquidity

One may wonder if the strong results obtained when sorting on option illiquidity are in fact driven by illiquidity in the underlying stock. To address this issue, we next investigate portfolio double-sorts on option and stock illiquidity.

Table 5 reports double sorting results for delta-hedged call and put 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 3.1, 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. Panel A of Table 5 reports the results for call options and Panel B shows results for put options. We only report results for daily returns. The weekly returns are available upon request.

Consider first the ALL moneyness section at the bottom of Panel A. It shows that for each of the five levels of stock illiquidity, that is in each of the first five columns, the 5-1 return spread based on IL^O is positive and significant. The level of IL^O return spread ranges from 19 bps to 31 bps and interestingly tends to be larger for relatively liquid stocks. Looking across the individual moneyness categories in Panel A, we see that the IL^O spread return is always positive and largest for OTM options as noted above as well.

Note that the IL^O-based option return spread is significant in fifteen of twenty cases in Panel A. The The IL^S-based option return spread, on the other hand, is significant in only two of twenty cases in Panel A.

Panel B of Table 5 reports double sorting results for put options. Consider first the bottom part of Panel B which contains ALL moneyness levels together. For the five different levels of stock illiquidity, the option illiquidity spread returns are positive in all cases and significant in three cases. Consider next the OTM moneyness category at the top of Panel B. Again, the option illiquidity spread returns are positive for all five levels of stock illiquidity and now significant in four cases. For the ATM and ITM puts, the results are mixed.

For puts, the The IL^S-based option return spread is positive in all cases and it is significant in nine of twenty cases in Panel B. Puts and calls are thus quite different in this regard: The underlying stock illiquidity appears to matter more for put options than for call options.

Based on the double-sorts in Table 5, we conclude that the large and significant option illiquidity premia found in Tables 3 and 4 is not simply driven by the illiquidity of the underlying stock. Put option returns do seem to be partly explained by stock illiquidity but option illiquidity matters as well. For call options, only option illiquidity seems to drive returns. The effects on cross-sectional option returns from IL^S and IL^O could of course be driven by other firm-specific explanatory variables. We investigate this important issue next.

4 Option Returns Controlling for Firm-Specific Effects

So far we have relied on simple portfolio sorts to assess the relationship between option illiquidity and option returns. Now we control for other firm-specific determinants of option returns, using a cross-sectional regression analysis following Fama and MacBeth (1973). We first describe the firm-specific control variables, and then discuss the regression results.

4.1 Firm-Specific Volatility Dynamics

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. Heston (1993) 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.[8] Broadie, Chernov, and Johannes (2009) and Duarte and Jones (2007) show that the expected option return in a Heston-type model is given by

$$\frac{1}{dt}\left(E\left[R^O\right]-r\right)=\left(E\left[R^S\right]-r\right)\frac{S}{O}\frac{\partial O}{\partial S}+\lambda\frac{\sigma}{O}\frac{\partial O}{\partial \sigma} \tag{4.1}$$

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 (4.1) 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 data on each firm using a simple $GARCH(1,1)$ model defined by

$$R_{i,t}^S = \mu_i+\sigma_{i,t-1}z_{i,t}, \text{ where} \tag{4.2}$$

$$\sigma_{i,t}^2 = \alpha_{0,i}+\alpha_{1,i}\sigma_{i,t-1}^2+\alpha_{2,i}\sigma_{i,t-1}^2 z_{i,t-1}^2 \tag{4.3}$$

and where $R_{i,t}^S$ is the stock return on firm i, μ_i is the conditional mean, $\sigma_{i,t}^2$ is the conditional variance, and $z_{i,t}$ is a standard normal i.i.d. innovation. For weekly results we add the daily

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

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.[9]

4.2 Other Firm-Specific Variables

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 daily b_{t-1} over 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 the 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 the one computed over the previous quarter both for daily and weekly results.

4.3 Regression Results

The most general daily regression we consider is given by

$$\tilde{R}^O_{i,t+1} = \beta_{0,t}+\beta_{1,t}IL^O_{i,t-1}+\beta_{2,t}IL^S_{i,t-1}+\beta_{3,t}\sigma_{i,t-1}+\beta_{4,t}b_{i,t-1}+\beta_{5,t}\ln(size_{i,t-1})+\beta_{6,t}lev_{i,t-1}+\varepsilon_{i,t+1} \tag{4.4}$$

We run a similar regression on a weekly basis, where the regressors are based on information from the previous week. Note that the regressors are dated $t-1$. This ensures consistency with the daily sorting results above and in the illiquidity literature, which skip one day

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

between the illiquidity measures and option returns. The results are even stronger for IL^O when we use regressors at date t.

We run this 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.[10] These averages are reported in Table 6. To control for serial correlation, the Fama-MacBeth (1973) t-statistics are corrected according to the Newey and West (1987) procedure using eight lags for daily data and three lags for weekly data.

Panel A of Table 6 contains the Fama-McBeth regressions for daily call option returns. Notice first that the coefficient on option illiquidity is positive and significant for all three moneyness categories, and of course, overall as well. The t-statistics are large and the coefficients range from 69 bps for ITM to 171 bps from OTM options. Note that the positive coefficient on IL^O is consistent with the results from the cross-sectional sorts in Section 3 above.

Stock illiquidity is negative and significant overall. It is negative for each moneyness category but not significant anywhere for call options. The negative sign for IL^S is inconsistent with the hedging argument. Perhaps more illiquid underlying suggests more liquid options which was suggested by Mayhew et al (1999). We further explore this in Section 5.1 below.

In terms of control variables, log of firm size has a robustly negative coefficient, suggesting that smaller firms have higher option returns matching the finding in stock returns. The firm leverage variable is significantly positive, suggesting that more risky firms–from the perspective of leverage–have higher option returns. Consistent with Duan and Wei (2009) the systematic risk proportion is positive and significant overall and for ATM options. The idiosyncratic risk from GARCH do not seem to be robustly priced in the cross-section of call option returns.

In unreported results we also run univariate regressions for $IL^O_{i,t-1}$ only, and we find that the $IL^O_{i,t-1}$ coefficient is often not much affected when including the control variables. This suggests that option illiquidity is an independent determinant of option returns, and that this effect is not captured by other well-known determinants of option returns. Moreover the coefficient of $IL^O_{i,t-1}$ is the highest for OTM options and then slowly decreases for other moneyness categories which is consistent with portfolio sorting results.

Panel B of Table 6 contains the results for weekly call option returns. Not again that our option illiquidity measure has a positive and significant coefficient in all three moneyness categories. The coefficient is largest for OTM calls which was also the case for daily returns in Panel A. The coefficient on stock illiquidity is again negative and significant overall but

[10] 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. For consistency the sample used in the sorting exercise is identical.

not significant for ITM options. The coefficients on the control variables are similar to those for daily returns.

Panel C of Table 6 contains results for daily put option returns. We see that the IL^O coefficient is again positive and significant overall. The effect is strongest for OTM options and significant also for ITM options.

The IL^S coefficient is not significant anywhere. Recall the double-sort results in Table 5.B above. They suggested a positive relationship between IL^S and put option returns. Table 6 shows that this result is not robust when controlling for other variables. The positive relationship between IL^O and option returns on the other hand is still positive and significant when controlling for other variables. In terms of control variables, the coefficient on GARCH volatility is now significant which was not the case for call options. The coefficients on the other control variables are generally not significant in Panel C.

Finally, in Panel D of Table 6 we investigate weekly put option returns. Once again, the coefficient on IL^O is positive and significant for all categories. The coefficient on IL^S is insignificant as was the case for daily put returns in Panel C. The GARCH volatility is again significant but the other controls are not.

Although not reported, we have also run the regressions in Table 6 on raw (i.e. not delta-hedged) option returns controlling for the underlying stock return in the regression instead. The coefficient on IL^O is robustly positive and significant in this case as well.

In summary, the evidence in Table 6 documents a statistically and economically significant impact of option illiquidity on expected option returns. These results are robust to controlling for the systematic risk and stock volatility, as well as stock illiquidity and other firm-specific characteristics. The adjusted R^2 in Table 6 are all small, which is not surprising given the large amount of noise in option returns, evident from Figure 1.

The positive predictive effect of option illiquidity on expected option returns is consistent with existing findings on the effect of stock illiquidity on stock returns (Amihud, 2002). The positive contemporaneous illiquidity shock decreases current prices and thus increases the expected return over the next period. However, the similarity between these findings in the equity and equity option markets is far from obvious, because unlike stocks, equity options are in zero net supply. We discuss these issues in more detail in Section 5.2.

4.4 Controlling for Temporary Price Pressures

In this section we attempt to assess if the strong effects on option returns from IL^O arise from temporary price pressures (Bollen and Whaley (2004), Muravyev (2014)) which dealers can potentially alleviate by adjusting bid-ask spreads (Madhavan and Smidt (1993)), or from more permanent effects associated with hedging costs and unhedged risks in dealer positions.

To analyze this issue we follow Bollen and Whaley (2004) who construct a measure of order imbalance to capture temporary price pressures. If IL^O is important only because it captures temporary price pressures then a Fama-McBeth regression including order imbalances should render the coefficient on IL^O insignificant.

To be specific, we define option order imbalances as

$$IMB^O = \frac{\sum_k Vol_k^B \Delta_k - \sum_k Vol_k^S \Delta_k}{\sum_k Vol_k}$$

where Vol_k^B and Vol_k^S are buy and sell volume (measured in number of contracts) respectively and where Δ_k is the delta of k^{th} trade. If an execution price is above the quoted mid-point then the order is identified as buyer-initiated, and if the execution price is below the quoted mid-point then the order is classified as seller-initiated. We compute IMB^O across all trades on all stocks each day in our 2004-2012 sample.

Order imbalances are on average negative and higher in absolute value for calls at -3%, than for puts, at -1% (not reported in the tables). This suggests that on average sell pressure exceeds buy pressure in our sample. Although we observe aggregate market imbalance and cannot separate market makers and non-market makers orders, this is consistent with the results in the literature that end-users are on average short of individual option contracts (Garleanu et al (2009), Lakonishok et al (2007)).

Table 7 contains the Fama-McBeth regressions in (4.4) but now including lagged IMB^O on the right-hand-side. Note again that we skip a day between the right- and left-hand-side variables. Panel A reports on daily call option returns and Panel B on daily put option returns. The results from weekly returns are similar and available upon request.

First, note that the coefficient on IMB^O is positive and significant overall for calls and puts. The effect of order imbalances is positive everywhere and significant for OTM and ATM calls and puts. We thus find support for Bollen and Whaley (2004) on a more recent sample, and confirm the results in Muravyev (2014).

Second, note that the coefficients on IL^O for call options in Panel A of Table 7 are very similar to those in Panel A of Table 6. As well, the coefficients on IL^O for put options in Panel B are very similar to those in Panel C of Table 6. This shows that options effective spreads and options inventory pressures capture different features of options returns. Order imbalances are associated with temporary inventory price pressures (Bollen and Whaley (2004)) while effective spreads are related to hedging costs, and the risks of unhedged positions.

Ignoring option illiquidity is tantamount to overestimating option prices, and this effect is economically significant. For example, for OTM call options, the coefficient on IL^O is 0.0165 (Panel A of Table 7). Table 2 shows that the standard deviation for OTM call option illiquidity is 0.104. Therefore, a two standard deviation positive shock to OTM call option illiquidity on the day $t-1$ would result in a 34 basis point increase in the day $t+1$ return on the call option. This is a significant magnitude for daily changes in prices. By comparison, the coefficient on IMB^O is 0.0051 in Panel A of Table 7, its standard deviation is 0.18 (not reported in the tables). Therefore, a two standard deviation shock to OTM call option order imbalances would result in a 18 basis points increase in returns in two days. Therefore, in economic magnitudes, the effect of option illiquidity on option returns twice exceeds that of order imbalances. This succinctly quantifies the difference between temporary price impacts and hedging and unhedged/unhedgable costs/risks captured by option illiquidity.

4.5 Robustness Checks

In this section we investigate if the impact of IL^O on option returns found in the cross-sectional regressions in Tables 6 and 7 is robust to various permutations of the empirical setup.

In Table 8 we report the Fama-MacBeth coefficient on the IL^O variable from multivariate regressions on daily option returns. We also report the corresponding T-stat and regression R^2. The full regression output is reported in the online appendix. Columns 1-3 report on three different variations on the regressions in Table 6. Columns 4-6 report on the same three variations but now using the regressions in Table 7, which include order imbalances, as the base case. Panel A contains daily call option regressions, and Panel B contains daily put option regressions.

The three robustness tests we run for Table 6 and Table 7 and report in Table 8 are as follows:

First, we trim the largest 1% and smallest 1% option returns from the sample. This is done to assess if our results are driven by a few outliers.

Second, we add the stock return, $R^S_{i,t+1}$ matching the option return date to the regression in (4.4) in order to pick up any error in the delta-hedging procedure.

Third, we add a number of control variables. In addition to the day $t+1$ stock return, we include the day $t+1$ stock price, the day $t+1$ value-weighted option price, the day $t-1$ absolute stock return, and the day $t-1$ return on the option delta hedge. These variables are added to reduce any potential omitted variables bias in the IL^O coefficient.

The results in Table 8 are striking. Of the 48 regressions reported in Table 8, the coefficient on IL^O is positive and highly significant in all cases. The robustness regressions in Table 8 indeed often yield even stronger results than the base case regressions in Tables 6 and 7.

In summary, the average coefficient on IL^O using ALL options is 127 bps for calls and 125 bps for puts across the regressions in Table 8. We conclude that option illiquidity is a statistically significant and economically meaningful driver of the cross-section of equity option returns.

5 Exploring the Results

In this section we first investigate the potential determinants of option spreads and then outline some broader implications of our results.

5.1 Determinants of Option Spreads

In this section we attempt to shed some light on the economic channels for our results by investigating the determinants of options spreads. Above, we have used option effective spreads as a proxy for the costs and risks faced by option market makers. Similar to market makers in the stock market, option dealers are facing inventory costs (Amihud and Mendelson (1980), Ho and Stoll (1983)) and asymmetric information costs (Copeland and Galai (1983), Glosten and Milgrom (1985), and Easley and O'Hara (1987)). However, unlike market makers in the stock market, option market makers can (imperfectly) hedge their option inventory positions using the underlying stock.

The previous literature argues that delta hedging invokes model misspecification risks (Cetin et al (2006), Figlewski (1989)), and inability to continuously rebalance the hedge increases options spreads (Jameson and Wilhelm (1992), George and Longstaff (1993), de Fontnouvelle, Fishe, and Harris (2003)). Regarding the latter, more recently Battalio and Schultz (2011) have reported that options spreads increased dramatically during the September 2008 short-sale ban due to the inability of market makers to hedge their position in the options of short-sale restricted stocks. Overall, our hypothesis is that due to systematic demand pressures in individual stock options (Lakonishok et al (2007), Garleanu et al (2009)), the inability to continuously rebalance and unhedged inventory positions should affect options spreads which in turn impact option returns.

Following Leland (1985) and Boyle and Vorst (1992) we apply a commonly-used proxy for market makers' inventory rebalancing costs, namely the product of the option vega and the relative spread of the underlying stock ($Vega * IL^S$). This term is intended to capture variations in the hedging costs of the market makers' existing inventories. This term should also capture the risks of unhedged positions. Either way, these costs should positively affect spreads in the options market.

As a control variable, we also use stock illiquidity (IL^S). Our intuition is as follows. If options market makers are hedging in the underlying stock then a higher IL^S should cause larger variation in options prices (Leland (1985) and Boyle and Vorst (1992)), as well as wider options bid-ask spreads (Huh et al (2013)). However, if the hedge is imperfect, or if there are unhedged positions then the effect of IL^S is unclear. In this case, our main control variable, $Vega * IL^S$, should be picking up the residual unhedged risks.

Among other variables relevant to our analysis of option spreads are the volatility of underlying assets, stock return, options volume and options order imbalances which were all defined above.

Order imbalances should not affect the magnitudes of bid ask spreads. Depending on whether there is buying or selling pressure dealers should be able to adjust quotes either up or down to mitigate their inventory pressures (Madhavan and Smidt (1993)). However, given hedging (Huh et al (2013)) spreads may well widen to incorporate the higher hedging costs associated with disproportionate order flow.

The inventory theory models (Amihud and Mendelson (1980), Ho and Stoll (1983)) predict that bid-ask spreads decrease with trading volume. Information asymmetry theories (Copeland and Galai (1983)) also suggest that spreads should decrease with market activity.

Asymmetric information theory argues that bid-ask spreads are positive function of return volatility (Copeland and Galai (1983)). However, for options spreads higher volatility and uncertainty in the stock market might attract a higher proportion of liquidity traders to the options market and thus decrease their spreads.

Stock return control for general market activity of underlying.

Our left-hand side variables are average percentage volume-weighted quoted or effective spreads where the quoted spreads are NBBO of each option trade weighted by transaction volume for each day. As before these data are estimated from intraday transactions using LiveVol data. Since market makers can hedge in other options across moneyness, we run our estimations for the ALL moneyness call and put categories.

Table 9 presents the results for call effective (Panel A) and call quoted (Panel B) spreads, and for put effective (Panel C) and put quoted (Panel D) spreads. Here, among other variables we also control for 1/(Option Price) since spreads are often affected by the magnitude of the price with lower-priced assets having wider spreads. We also control for the lagged dependent variable to control for the past information already incorporated in the options spreads. Note that all variables enter the regressions contemporaneously in Table 9.

Table 9 shows that for both, call and put options, and regardless of the regression specification, $Vega * IL^S$ is always positive and highly significant. In contrast to our expectations, IL^S is always negative and significant.[11] The negative sign is not consistent with the hedging argument. It is also not consistent with common perception that options spreads are largely following spreads of underlying. However, it is consistent with the idea that if the stock is illiquid then it is easier and safer to trade in the options of this underlying rather than in underlying itself. As such higher stock illiquidity is associated with higher trading activity in the options and lower spreads. This idea is consistent with the previous findings of Mayhew et al. (1999).

The unexpected sign of IL^S also is evidence of imperfect hedges. In this case $Vega * IL^S$ should also be picking up the risk of unhedged or imperfectly hedged positions.

Option imbalances have a positive impact on call and put options spreads suggesting that options market makers partially subsume the temporary price impacts by widening the spreads. This result is also informative about the microstructure of the options market. Garleanu et al. (2009) argue that demand pressures impose on market makers higher unhedgable risks and cause them to move prices up if the net demand is positive or down if the net demand is negative. Garleanu et al. (2009) and Lakonishok et al. (2007) show that net demand in individual equity options by end-users is negative. Consistent with these observations we find a positive effect of order imbalances on expected options returns in Table 7. The results in Table 9 suggest that given demand pressures, option market makers not only decrease current option prices they also widen the bid-ask spreads.

Among other variables, stock volatility has a negative impact on options spreads. Higher volatility in the stock market perhaps causes more trading in the options market and therefore decreases options spreads. Consistent with the latter option trading volume has negative impact on options spreads for both calls and puts.

An increase in stock returns has a positive impact on put options spreads (Panels C and D) and this effect is insignificant for call options (Panels A and B).

Overall, the results are largely consistent across calls and puts for $Vega * IL^S$ suggesting that effective or quoted spreads in the option markets also absorb either the costs of dynamic inventory hedging and/or the risks of unhedged positions. This is consistent with earlier findings in George and Longstaf (1993) who also argue that wider options spreads compensate options market makers for the risk of unhedged positions.

Finally, note that when we add the $Vega * IL^S$ variable to the Fama-MacBeth regressions for option returns, its coefficient is insignificant, and the effect of IL^O on returns is virtually unchanged.

[11] The correlation between $Vega * IL^S$ and ILS is 0.26 in our sample. Therefore our results are not likely driven by multicollinearity.

5.2 Further Implications of Results

Our key finding of a positive and significant option illiquidity premium is consistent with the results reported for the stock market by Amihud (2002), and Pastor and Stambaugh (2003). However, option markets and stock markets are fundamentally different, and therefore our finding of a positive liquidity premium is not necessarily expected. While it is natural to expect a positive liquidity premium in a positive net supply market such as bond or stock markets, the sign of the premium could be positive, negative, or zero in a zero net supply market such as the equity option market. For example, Bongaerts, De Jong, and Driessen (2011) find a negative illiquidity premium in the CDS market, and Deuskar, Gupta, and Subrahmanyam (2011) similarly find a negative illiquidity premium in the interest-rate options market.

Is our finding consistent with option valuation theory? The option valuation literature is voluminous, but most models, including the seminal contributions by Black and Scholes (1973), Heston (1993), and Bates (1996) do not allow for transactions costs nor liquidity risk.

Using proprietary data, Lakonishok et al. (2007) and Garleanu et al. (2009) find that in the equity option market, end-users hold short positions. This negative net demand for equity options implies a negative relationship between illiquidity and option prices, consistent with the positive illiquidity premium we find. If net demand from end-users is negative, then dealers are required to absorb it. The marginal investor in equity option markets are thus dealers who hold long positions and require higher compensation in more illiquid contracts, consistent with lower current prices and higher expected returns.

Using data from the short-sell ban in 2008, Battalio and Schultz (2011) provide empirical evidence that equity option market makers indeed lower their bid prices on options when the hedging in underlying stocks becomes costlier and they therefore discourage further writing of options by investors. Engle and Neri (2010) decompose equity option spreads and find that in addition to the traditional order-processing costs, cost of inventory, and cost of trading against informed investors, market makers in equity options face additional hedging costs which constitute a large part of the overall spread. Note further that the fact that market makers are net long both puts and calls implies that they cannot readily use put-call parity to hedge their positions.

We examine the impact of illiquidity in the underlying stocks on option returns, which is the subject of a substantial theoretical literature.[12] Using delta-hedged option returns, we

[12] See Leland (1985), Boyle and Vorst (1992), Toft (1996), Cho and Engle (1999), and Cetin, Jarrow and Protter (2004). In related work, Constantinides and Perrakis (2002, 2007), Oancea and Perrakis (2007), and Constantinides, Jackwerth, and Perrakis (2009) rely on a stochastic dominance approach to characterize

find that the effect of stock illiquidity on options returns varies greatly across moneyness, option styles, and empirical setup. The stock illiquidity effect is sometimes positive and significant, sometimes negative and significant, but most often insignificant.

Our results have additional important implications for the option valuation literature. Bakshi, Kapadia and Madan (2003) and others find that S&P500 index options are relatively more expensive than individual equity options, particularly in the case of OTM options: Index options display much larger risk-neutral kurtosis, (negative) skewness and volatility than equity options. This is regarded as somewhat of a puzzle because an index is a portfolio of equities and so one would expect index options to display less evidence of nonnormality than individual equity options. Our results suggest that this valuation difference could be partly driven by differences in liquidity. Index options are well-known to be much more liquid than individual equity options. Thus individual equity option prices are relatively more depressed by illiquidity than are index options. This is particularly true for short-term OTM options where the difference in pricing between index and equity options is the greatest.

6 Conclusion

We present evidence on illiquidity premia in equity option markets. Using portfolio sorts and cross-sectional regressions, we find an economically and statistically significant positive impact of option illiquidity on expected option returns. We find strong evidence of positive option illiquidity premia in simple univariate portfolio sorts and in bivariate sorts on option and stock illiquidity. We also find significantly positive coefficients on option illiquidity in multivariate regressions controlling for volatility of the underlying equity, market capitalization, leverage and other firm-specific variables. The results are robust across different moneyness categories.

The intuition for these empirical findings is easily understood by referring to the stylized facts in equity markets, where Amihud (2002) reports a positive effect of stock illiquidity on stock returns. A shock to option illiquidity decreases the current price and increases expected option returns, thus compensating investors with long positions for holding illiquid contracts. This finding is consistent with end-users in equity option markets being net short, requiring market makers to hold net long positions, which leads to higher expected returns. Lakonishok et al. (2007) and Garleanu, et al. (2009) document that end-users indeed hold net short positions in the equity options market, which effectively makes the illiquidity premia in the zero net supply equity options market comparable to those in equity markets.

bounds on option prices.

Several potentially interesting topics are left for future research.

First, we have incorporated dynamic volatility into our analysis of liquidity effects, but allowing for return jumps may be interesting as well. Note, however, that the illiquidity premia we find are robust across moneyness categories which makes it unlikely that they are driven by jump risk.

Second, we have focused on delta-hedged returns and controlled for volatility separately. Directly using vega-hedged returns would be a potential alternative. However, the choice of option valuation model becomes more contentious in that case. Standard option valuation models ignore the role of option illiquidity and so using those models to control for volatility and jump risk is not obvious.

Third, analyzing the relatively exogenous liquidity shock arising from the penny pilot may reveal additional information about option illiquidity premia.

Fourth, while we do not have access to the proprietary position data used in Lakonishok et al. (2007) and Garleanu et al. (2009), such data would clearly be helpful in mapping out the relationship between option net-demand by end-users and the option illiquidity premia that we find. Alternatively, it may be possible to construct proxies for net demand from intraday option trades and quotes.

Fifth, developing a theoretical model that generates endogenous option illiquidity effects in option returns would be of great interest. Bongaerts, De Jong, and Driessen (2011) provide a theoretical model for credit derivatives, but their approach using background risk does not immediately translate to the equity options market we study.

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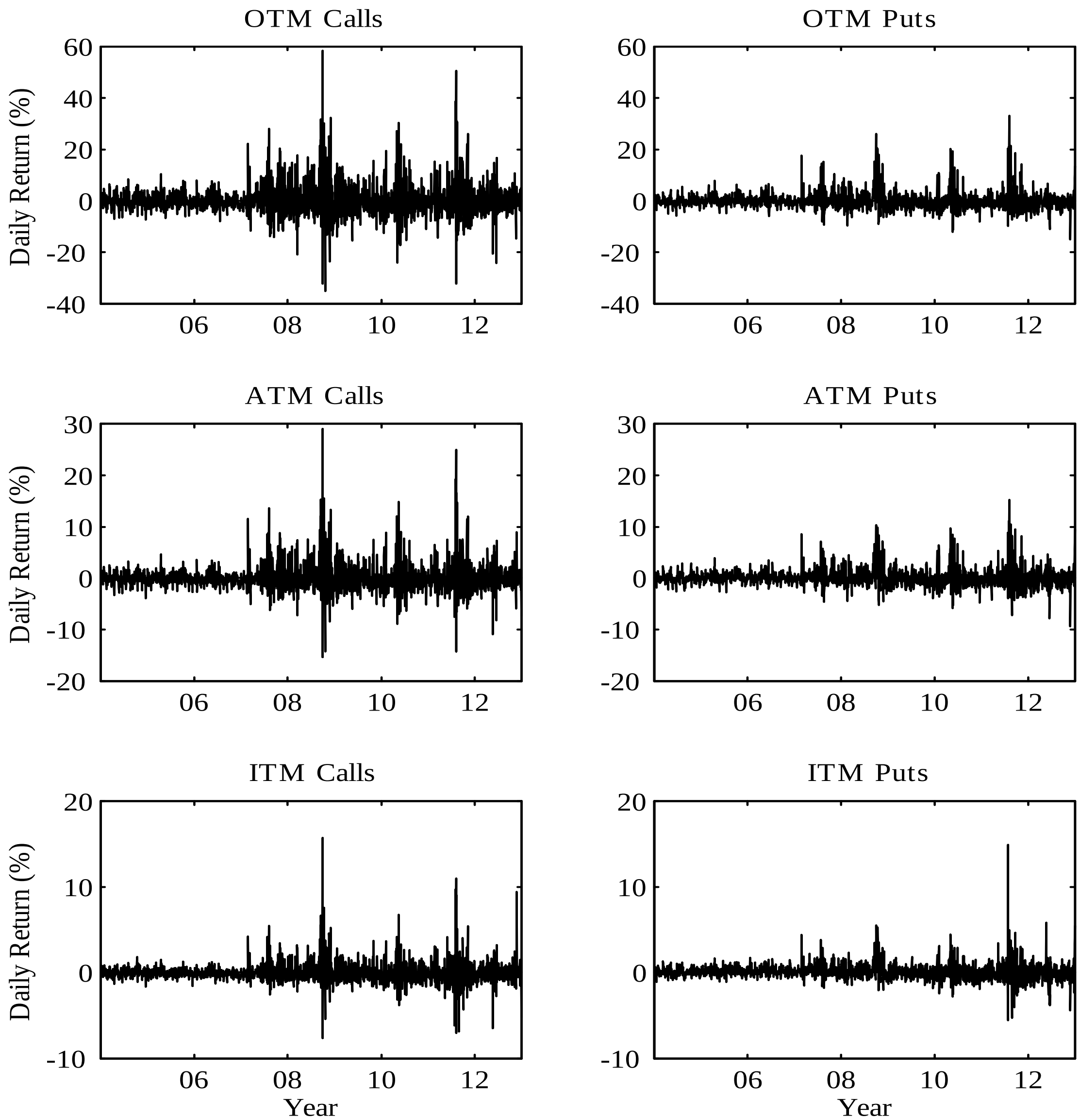
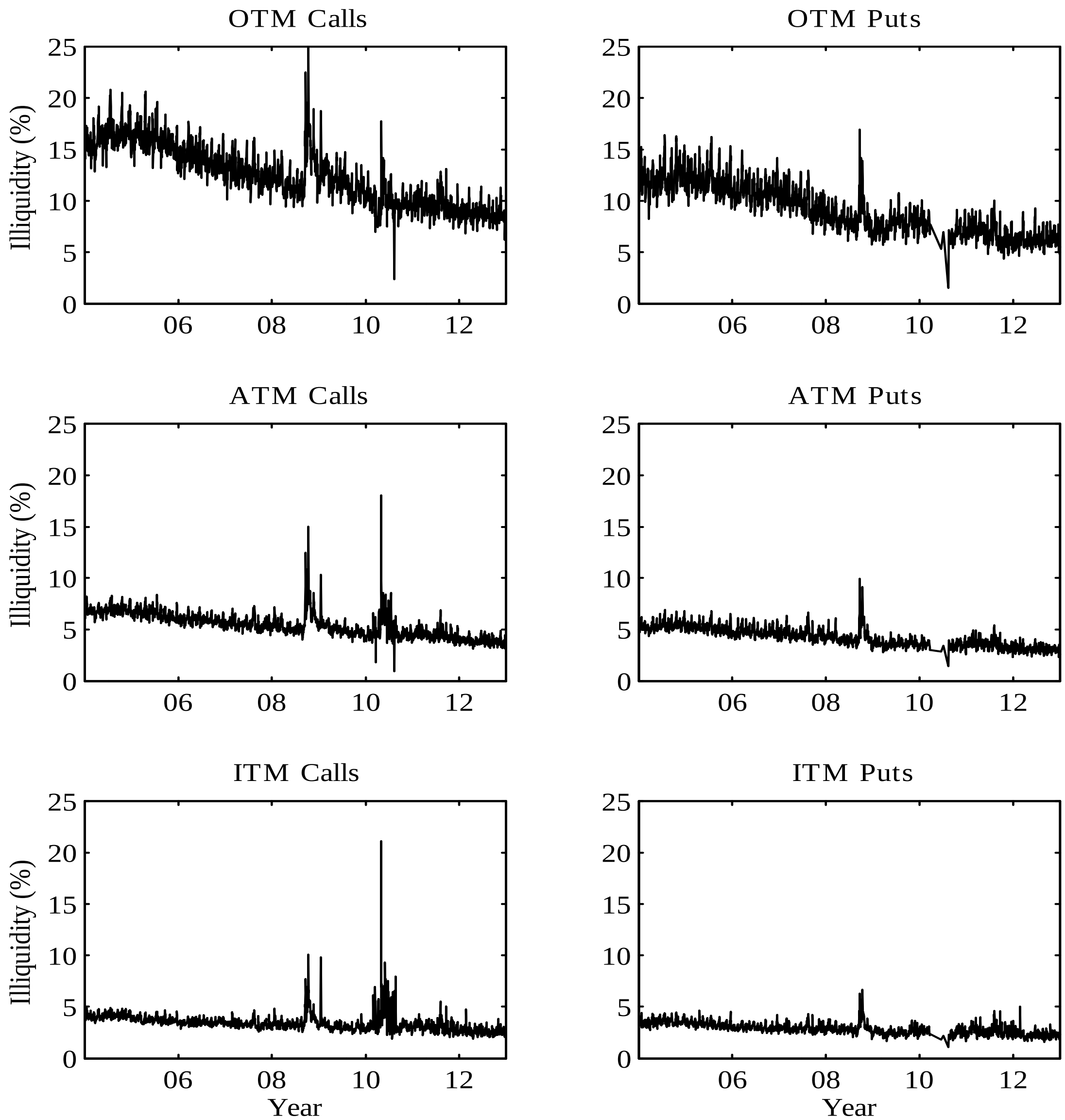
Figure 1. Average Daily Delta-Hedged Option Returns. 2004-2012.



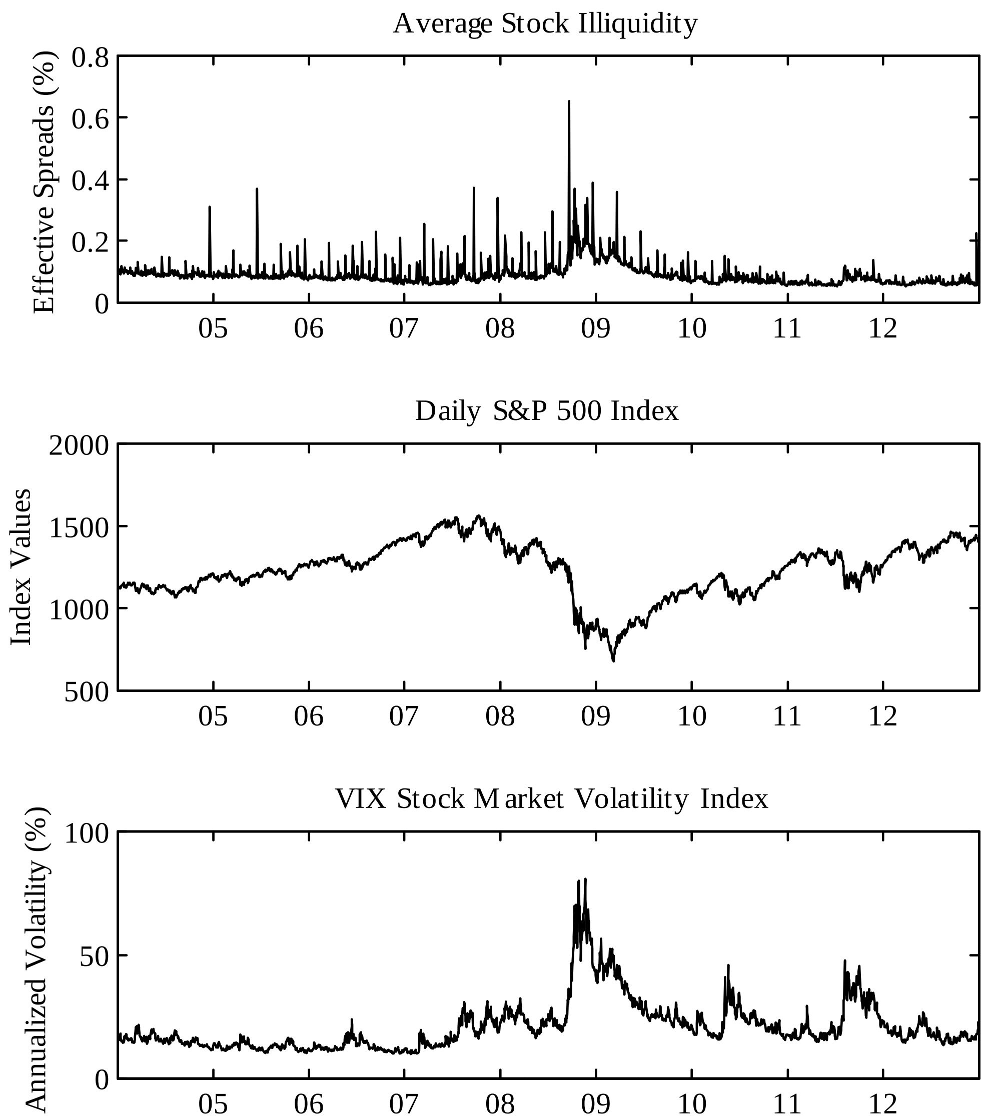
Notes to figure: We plot the daily delta-hedged returns on equally-weighted portfolios of call and put options. Option returns are computed from closing bid-ask price midpoints. OTM refers to out-of-the-money, ATM refers to at-the-money and ITM refers to in-the-money options.

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



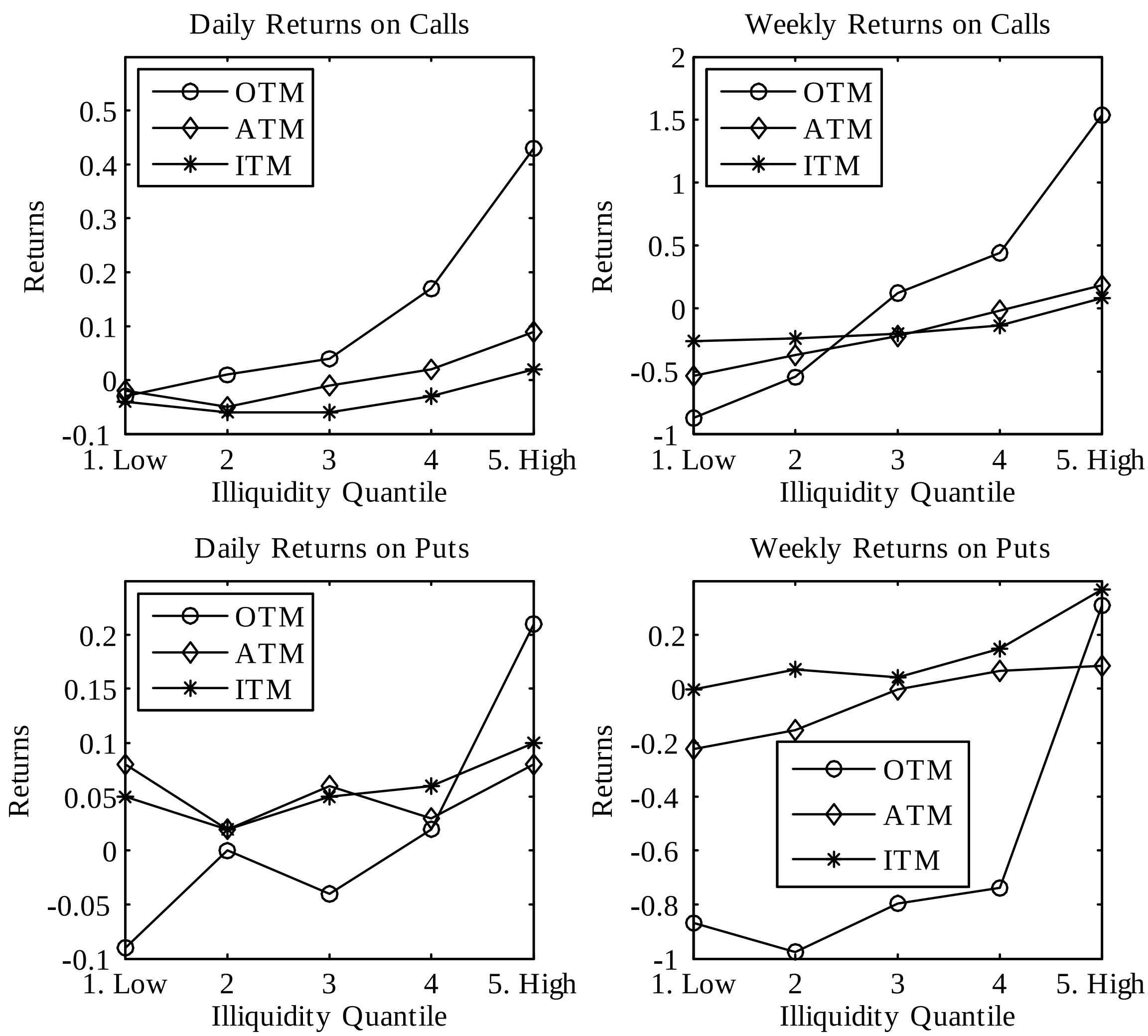
Notes to figure: Option illiquidity is computed as the relative volume-weighted effective spread for each day. We plot the equal-weighted average across firms for each option category. The underlying trade and quote data are from LiveVol and include the S&P 500 constituents for which options trade during our sample.

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



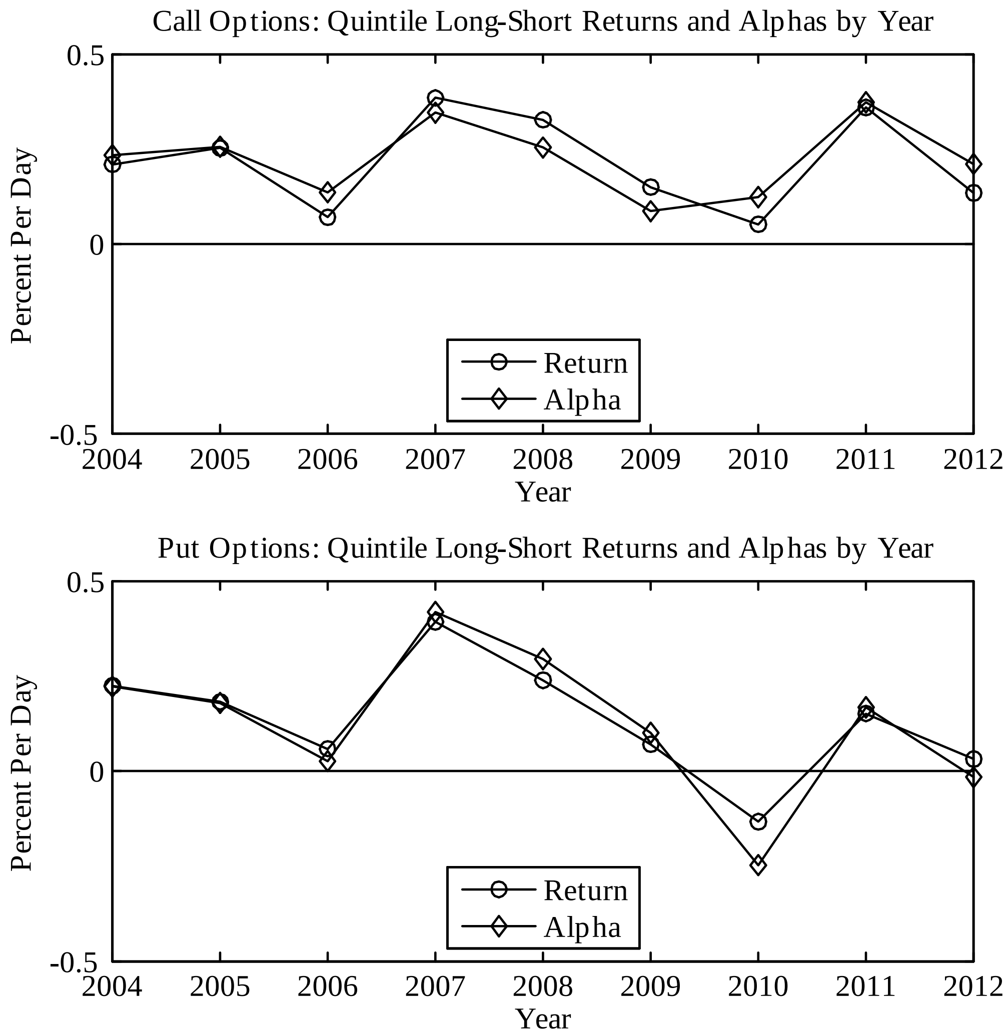
Notes to Figure: We plot the average stock illiquidity, the level of the S&P 500 index, and the VIX. Stock illiquidity is estimated from TAQ (Trade and Quote) intra-day data as the dollar-volume-weighted average of effective relative spreads for each day. The sample period is from January 2004 through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

Figure 4. Portfolios Sorted by Illiquidity Level



Notes to Figure: We sort firms into quintiles based on their lagged illiquidity measured by effective relative spreads. We plot the average delta-hedged daily (left column) and weekly (right column) returns for calls (top row) and puts (bottom row) in percent. The sample includes the S&P 500 constituents with valid options data from January 2004 to December 2012.

Figure 5. 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 firms in the highest option illiquidity quintile less the aveage option return for the firms in the lowest option illiquidity quintile. The top panel shows call option returns and the bottom panel shows put option returns. The sample includes the S&P 500 constituents with valid options data from January 2004 to December 2012.

Table 1. Descriptive Statistics of Delta-Hedged Option Returns

	Panel A. Daily Delta-Hedged Call Returns				Panel B. Daily Delta-Hedged Put Returns			
	OTM	ATM	ITM	ALL	OTM	ATM	ITM	ALL
Average	0.26	0.05	0.09	0.05	0.30	0.13	0.25	0.12
Std.dev.	14.29	6.39	3.44	7.49	9.81	5.28	3.43	6.18
Skewness	3.11	2.72	2.80	3.58	3.77	3.04	2.90	4.42
Kurtosis	57.97	55.48	64.74	87.73	74.28	57.89	53.00	99.75
ρ(1)	-0.07	-0.07	-0.10	-0.10	-0.01	-0.02	-0.05	-0.03
abs [ρ(1)]	0.14	0.15	0.17	0.20	0.12	0.11	0.11	0.14
Av. # obs	993	1072	918	1345	941	902	654	1216
Av. # firms	313	339	290	425	296	285	205	384

	Panel C. Weekly Delta-Hedged Call Returns				Panel D. Weekly Delta-Hedged Put Returns			
	OTM	ATM	ITM	ALL	OTM	ATM	ITM	ALL
Average	0.34	-0.09	-0.01	-0.02	0.15	0.09	0.27	-0.04
Std.dev.	26.52	11.45	5.18	13.33	19.83	9.68	5.35	11.36
Skewness	2.16	1.88	1.96	2.32	2.59	1.83	1.62	2.57
Kurtosis	19.11	17.83	19.70	23.67	24.18	17.07	14.82	25.84
ρ(1)	0.00	0.02	0.00	0.01	0.06	0.03	-0.01	0.04
abs [ρ(1)]	0.06	0.08	0.07	0.11	0.06	0.06	0.04	0.07
Av. # obs	231	241	215	297	216	210	164	272
Av. # firms	346	361	322	446	321	311	240	407

Notes to Table: We provide descriptive statistics for daily and weekly delta-hedged 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. ITM (in-the-money) corresponds to $0.625<\Delta\leq 0.875$ for calls and $-0.875<\Delta\leq -0.625$ 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 on Option and Stock Illiquidity

Calls	OTM	ATM	ITM	ALL	Puts	OTM	ATM	ITM	ALL		Stocks
mean	14.81	6.74	4.41	9.80	mean	11.51	5.58	4.02	8.22	mean	0.22
std	10.40	4.84	3.71	7.48	std	8.84	4.20	3.48	6.75	std	0.16
min	0.23	0.13	0.07	0.33	min	0.17	0.11	0.05	0.17	min	0.05
max	95.97	57.52	47.52	76.40	max	81.64	44.27	38.87	69.70	max	2.60
ρ(1)	0.30	0.30	0.21	0.28	ρ(1)	0.29	0.27	0.18	0.26	ρ(1)	0.44
# firms	419	403	338	472	# firms	386	361	284	441	# firms	500
Avr Volume	879	875	366	1967	Avr Volume	725	510	180	1290		
Avr # Trades	41	46	18	99	Avr # Trades	30	25	9	59		

Panel B. Correlations of Call Option and Stock Illiquidity

	OTM	ATM	ITM	ALL	Stocks
OTM	1.00				
ATM	0.48	1.00			
ITM	0.37	0.40	1.00		
ALL	0.78	0.60	0.43	1.00	
Stocks	0.26	0.27	0.19	0.26	1.00

Panel C. Correlations of Put Option and Stock Illiquidity

	OTM	ATM	ITM	ALL	Stocks
OTM	1.00				
ATM	0.45	1.00			
ITM	0.33	0.35	1.00		
ALL	0.79	0.57	0.41	1.00	
Stocks	0.22	0.20	0.13	0.21	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 dollar-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 take the mean, the minimum, the maximum, the standard deviation and the first-order autocorrelation, ρ(1), of these averages. We report the cross-sectional averages of these statistics in Panel A. Panel A also reports the average option volume (in number of contracts) and average number of trades per firm per day. 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.

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	-0.025	0.007	0.043	0.169	0.435	0.460	-0.087	0.000	-0.044	0.023	0.212	0.299
	Alpha	0.047	0.080	0.117	0.249	0.526	0.479	-0.066	0.018	-0.028	0.032	0.211	0.277
	T-stat	0.517	0.882	1.236	2.721	5.074	7.210	-0.771	0.199	-0.291	0.320	1.962	5.423
ATM	Mean	-0.022	-0.045	-0.014	0.020	0.089	0.110	0.078	0.017	0.057	0.028	0.080	0.002
	Alpha	0.007	-0.018	0.014	0.050	0.128	0.121	0.093	0.033	0.072	0.039	0.082	-0.011
	T-stat	0.143	-0.394	0.291	1.033	2.459	3.920	2.226	0.748	1.554	0.847	1.597	-0.367
ITM	Mean	-0.042	-0.060	-0.062	-0.026	0.021	0.063	0.051	0.023	0.048	0.058	0.103	0.052
	Alpha	-0.031	-0.048	-0.050	-0.012	0.038	0.069	0.058	0.029	0.055	0.063	0.103	0.045
	T-stat	-1.506	-2.355	-2.320	-0.514	1.558	3.831	2.273	1.328	1.814	2.666	3.771	1.755
ALL	Mean	-0.071	-0.065	-0.027	-0.011	0.140	0.211	-0.036	-0.026	-0.012	0.027	0.112	0.149
	Alpha	-0.040	-0.031	0.011	0.031	0.193	0.233	-0.024	-0.014	-0.002	0.033	0.108	0.132
	T-stat	-0.920	-0.659	0.221	0.574	3.369	6.455	-0.541	-0.280	-0.032	0.568	1.598	3.509

		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	-0.871	-0.548	0.120	0.439	1.535	2.406	-0.868	-0.975	-0.795	-0.739	0.309	1.178
	Alpha	-0.547	-0.213	0.438	0.770	1.889	2.435	-0.628	-0.738	-0.552	-0.482	0.578	1.206
	T-stat	-1.370	-0.503	0.999	1.618	3.688	8.041	-1.607	-1.657	-1.135	-0.915	0.906	3.431
ATM	Mean	-0.540	-0.371	-0.221	-0.019	0.182	0.722	-0.223	-0.154	-0.003	0.067	0.086	0.309
	Alpha	-0.411	-0.239	-0.094	0.121	0.321	0.732	-0.088	-0.022	0.140	0.217	0.225	0.313
	T-stat	-2.096	-1.137	-0.440	0.514	1.249	5.743	-0.525	-0.122	0.658	0.885	0.917	2.609
ITM	Mean	-0.259	-0.240	-0.199	-0.138	0.082	0.341	-0.003	0.073	0.043	0.149	0.368	0.371
	Alpha	-0.217	-0.195	-0.156	-0.091	0.134	0.350	0.057	0.135	0.103	0.215	0.443	0.386
	T-stat	-2.517	-2.249	-1.685	-0.827	1.154	4.825	0.784	1.654	1.138	2.355	3.967	5.816
ALL	Mean	-0.462	-0.376	-0.353	0.063	0.444	0.906	-0.488	-0.465	-0.397	-0.277	0.270	0.758
	Alpha	-0.329	-0.224	-0.192	0.236	0.631	0.961	-0.361	-0.326	-0.247	-0.131	0.429	0.789
	T-stat	-1.710	-1.022	-0.824	0.885	2.197	5.522	-2.017	-1.471	-0.887	-0.464	1.193	3.200

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. Quintile 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**	**Large Spreads Omitted**	**Low Prices Omitted**	**Quoted Spreads, 2000-2012**
OTM	Mean	0.460	0.328	0.458	0.206	0.160	0.744
	Alpha	0.479	0.348	0.466	0.207	0.165	0.790
	T-stat	7.210	8.136	7.568	3.983	2.990	12.417
ATM	Mean	0.110	0.079	0.118	0.090	0.102	0.202
	Alpha	0.121	0.086	0.126	0.098	0.111	0.227
	T-stat	3.920	4.428	4.340	3.684	3.938	7.300
ITM	Mean	0.063	0.054	0.046	0.054	0.062	0.146
	Alpha	0.069	0.058	0.050	0.060	0.068	0.161
	T-stat	3.831	5.824	2.705	3.458	3.729	8.920
ALL	Mean	0.211	0.093	0.245	0.099	0.107	0.307
	Alpha	0.233	0.101	0.260	0.109	0.121	0.355
	T-stat	6.455	7.125	8.028	3.791	4.219	9.403

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

		Base Case from Table 3	OI-Weighted Returns	Ask-to-Ask Returns	Large Spreads Omitted	Low Prices Omitted	Quoted Spreads, 2000-2012
OTM	Mean	0.299	0.196	0.272	0.216	0.188	0.534
	Alpha	0.277	0.190	0.253	0.199	0.168	0.502
	T-stat	5.423	5.634	5.323	4.577	3.901	7.361
ATM	Mean	0.002	0.024	-0.008	-0.012	-0.018	0.149
	Alpha	-0.011	0.019	-0.018	-0.023	-0.030	0.132
	T-stat	-0.367	1.044	-0.580	-0.833	-1.034	4.065
ITM	Mean	0.052	0.049	-0.006	0.060	0.045	0.202
	Alpha	0.045	0.047	-0.011	0.053	0.038	0.191
	T-stat	1.755	3.116	-0.392	2.381	1.630	6.741
ALL	Mean	0.149	0.060	0.173	0.113	0.123	0.301
	Alpha	0.132	0.056	0.161	0.100	0.109	0.277
	T-stat	3.509	4.552	4.352	3.294	3.188	6.433

Notes to Table: We reports returns and alphas for delta-hedged call and puts. Firms are sorted into quintiles based on their lagged option illiquidity. For each quintile, 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. The rightmost column uses end-of-day relative quoted spreads from January 2000 through December 2012.

Table 5.A. 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	$1.IL^O$	0.059	0.039	-0.029	0.073	0.085	0.026	0.299
	2	-0.101	0.065	0.170	0.130	0.123	0.224	1.703
	3	-0.031	0.093	0.084	0.128	0.308	0.338	1.742
	4	0.158	0.191	0.222	0.385	0.249	0.091	0.838
	$5.IL^O$	0.585	0.543	0.390	0.606	0.558	-0.027	-0.175
	5-1	0.526	0.504	0.419	0.533	0.473		
	t-stat	4.144	2.950	4.102	4.608	4.036		
ATM	$1.IL^O$	-0.004	0.027	-0.042	0.006	0.043	0.048	1.180
	2	-0.038	-0.056	-0.001	-0.028	0.034	0.071	1.661
	3	-0.019	-0.047	0.015	0.062	0.055	0.074	1.571
	4	0.083	0.068	0.080	0.025	0.013	-0.070	-1.201
	$5.IL^O$	0.080	0.180	0.071	0.192	0.135	0.055	0.768
	5-1	0.084	0.154	0.113	0.186	0.092		
	t-stat	1.391	2.559	2.343	2.904	1.696		
ITM	$1.IL^O$	-0.005	-0.033	-0.036	-0.083	0.000	0.005	0.182
	2	-0.033	-0.067	-0.051	-0.025	-0.048	-0.015	-0.563
	3	-0.056	-0.039	-0.075	-0.037	-0.033	0.024	0.854
	4	-0.052	-0.005	0.002	-0.016	0.011	0.063	1.529
	$5.IL^O$	0.062	0.041	0.020	0.046	0.031	-0.031	-0.750
	5-1	0.067	0.074	0.056	0.129	0.031		
	t-stat	1.873	1.597	2.221	3.173	0.889		
ALL	$1.IL^O$	-0.059	-0.014	-0.064	-0.045	-0.007	0.052	1.305
	2	-0.095	-0.060	0.036	-0.065	0.023	0.118	2.724
	3	-0.049	0.015	0.020	0.016	0.051	0.100	1.714
	4	-0.035	0.002	0.025	0.027	0.145	0.180	2.040
	$5.IL^O$	0.247	0.229	0.176	0.130	0.184	-0.062	-0.766
	5-1	0.306	0.242	0.240	0.175	0.191		
	t-stat	4.573	3.963	4.170	3.241	3.002		

Notes: 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 5.B. 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	$1.IL^O$	-0.106	-0.065	-0.084	-0.117	-0.010	0.097	1.541
	2	-0.021	-0.017	0.046	0.038	0.014	0.035	0.437
	3	-0.169	-0.024	-0.100	0.123	-0.014	0.155	2.038
	4	-0.184	-0.046	0.051	0.213	0.057	0.241	2.819
	$5.IL^O$	0.134	0.042	0.175	0.256	0.383	0.249	2.615
	5-1	0.241	0.106	0.260	0.373	0.393		
	t-stat	2.916	1.361	2.189	4.042	4.901		
ATM	$1.IL^O$	0.043	0.123	0.105	0.098	0.077	0.034	0.834
	2	0.007	-0.002	0.025	0.026	0.091	0.084	2.330
	3	0.006	0.141	0.044	0.077	0.073	0.066	1.148
	4	-0.069	0.085	0.063	0.124	-0.027	0.041	0.912
	$5.IL^O$	-0.005	0.020	0.157	0.069	0.141	0.146	2.142
	5-1	-0.048	-0.104	0.052	-0.029	0.064		
	t-stat	-0.860	-1.761	0.911	-0.681	1.156		
ITM	$1.IL^O$	0.027	0.027	0.049	0.127	0.047	0.020	0.813
	2	0.020	-0.007	0.044	0.023	0.046	0.026	1.119
	3	0.040	0.007	0.105	0.060	0.061	0.021	0.506
	4	-0.025	-0.016	0.147	0.073	0.108	0.133	2.205
	$5.IL^O$	0.026	0.048	0.104	0.118	0.191	0.165	4.371
	5-1	-0.001	0.021	0.055	-0.009	0.144		
	t-stat	-0.033	0.516	1.573	-0.093	4.448		
ALL	$1.IL^O$	-0.073	-0.039	0.019	-0.085	0.025	0.098	2.676
	2	-0.063	-0.023	-0.025	0.012	0.003	0.066	1.491
	3	-0.064	0.040	-0.012	0.002	0.003	0.068	1.508
	4	-0.081	-0.060	0.135	0.099	0.035	0.117	2.489
	$5.IL^O$	0.095	0.051	0.034	0.179	0.153	0.057	0.948
	5-1	0.169	0.090	0.016	0.264	0.128		
	t-stat	2.893	1.772	0.246	4.280	2.859		

Notes: 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 6. Fama-MacBeth Regressions for Delta-Hedged Option Returns

Panel A: Daily Call Option Returns

	OTM		ATM		ITM		ALL	
	coeff	t-stat	coeff	t-stat	coeff	t-stat	coeff	t-stat
IL^O	0.0171	5.50	0.0098	3.69	0.0069	3.10	0.0121	5.46
IL^S	-1.3259	-1.78	-0.6448	-1.59	-0.1733	-0.67	-0.7840	-2.24
σ	-0.0032	-1.50	0.0009	0.94	-0.0006	-1.04	-0.0004	-0.34
b	0.0030	1.30	0.0033	3.07	0.0003	0.63	0.0029	2.50
log(Size)	-0.0016	-6.16	-0.0003	-2.44	-0.0002	-2.78	-0.0005	-3.37
Leverage	0.0043	3.24	0.0020	3.11	0.0008	2.49	0.0016	2.56
Adjusted R^2	0.035		0.039		0.040		0.038	
# Obs in CS (avr.)	298		315		270		412	
# CS regressions	2118		2118		2055		2118	

Panel B: Weekly Call Option Returns

	OTM		ATM		ITM		ALL	
	coeff	t-stat	coeff	t-stat	coeff	t-stat	coeff	t-stat
IL^O	0.0938	5.07	0.0433	3.49	0.0432	2.77	0.0478	3.81
IL^S	-12.9457	-4.09	-3.6846	-3.10	-0.9554	-1.42	-4.8904	-3.52
σ	0.0042	0.41	-0.0001	-0.03	-0.0042	-2.17	0.0021	0.48
b	0.0226	2.16	0.0146	2.89	0.0008	0.37	0.0143	2.66
log(Size)	-0.0058	-4.38	-0.0011	-2.43	-0.0006	-2.36	-0.0016	-2.67
Leverage	0.0063	1.04	0.0059	2.27	0.0037	2.77	0.0050	1.78
Adjusted R^2	0.035		0.036		0.038		0.035	
# Obs in CS (avr.)	333		347		302		433	
# CS regressions	468		468		468		468	

Notes to Table: We report the results of cross-sectional Fama-Macbeth regressions for daily (Panel A) and weekly (Panel B) delta-hedged call option returns (in percent). The regressions include lagged values of the following variables: option illiquidity, IL^O, stock illiquidity, IL^S, stock volatility σ, the systematic risk proportion b, the logarithm of the firm size log(size), and firm leverage. The sample period covers daily data from January 2004 through December 2012 for the S&P 500 constituents that have options trading throughout the sample period. Reported are coefficients and Fama-Macbeth t-statistics with Newey-West correction for serial correlation (8 lags for daily returns and 3 lags for weekly returns).

Table 6. Fama-MacBeth Regressions for Delta-Hedged Option Returns (Continued)

Panel C: Daily Put Option Returns

	OTM		ATM		ITM		ALL	
	coeff	t-stat	coeff	t-stat	coeff	t-stat	coeff	t-stat
IL^O	0.0159	6.06	0.0031	1.04	0.0090	2.52	0.0100	4.56
IL^S	0.0635	0.12	-0.0943	-0.24	-0.0150	-0.06	0.1619	0.41
σ	0.0049	2.89	0.0032	3.60	0.0003	0.31	0.0033	3.22
b	0.0002	0.11	0.0018	1.99	0.0001	0.20	0.0007	0.66
log(Size)	-0.0005	-2.63	-0.0002	-1.77	-0.0004	-5.11	-0.0002	-1.63
Leverage	-0.0007	-0.71	-0.0009	-1.65	-0.0004	-0.86	-0.0007	-1.29
Adjusted R^2	0.037		0.038		0.040		0.038	
# Obs in CS (avr.)	284		270		191		373	
# CS regressions	2013		2013		2013		2013	

Panel D: Weekly Put Option Returns

	OTM		ATM		ITM		ALL	
	coeff	t-stat	coeff	t-stat	coeff	t-stat	coeff	t-stat
IL^O	0.0739	5.32	0.0295	1.98	0.0640	4.74	0.0597	5.26
IL^S	-2.4446	-1.53	-0.3652	-0.29	-0.6132	-0.99	-0.4170	-0.42
σ	0.0234	2.94	0.0072	1.61	0.0024	0.97	0.0166	3.55
b	-0.0016	-0.19	0.0085	2.29	0.0012	0.64	0.0007	0.16
log(Size)	-0.0001	-0.14	-0.0009	-2.63	-0.0011	-4.80	0.0005	0.98
Leverage	-0.0056	-1.16	-0.0033	-1.47	-0.0035	-3.07	-0.0036	-1.40
Adjusted R^2	0.037		0.038		0.041		0.037	
# Obs in CS (avr.)	310		300		229		395	
# CS regressions	450		450		450		450	

Notes to Table: We report the results of cross-sectional Fama-Macbeth regressions for daily (Panel A) and weekly (Panel B) delta-hedged put option returns (in percent). The regressions include lagged values of the following variables: option illiquidity, IL^O, stock illiquidity IL^S, stock volatility σ, the systematic risk proportion b, the logarithm of the firm size log(size), and firm leverage. The sample period covers daily data from January 2004 through December 2012 for the S&P 500 constituents that have options trading throughout the sample period. Reported are coefficients and Fama-Macbeth t-statistics with Newey-West correction for serial correlation (8 lags for daily returns and 3 lags for weekly returns).

Table 7. Fama-MacBeth Regressions for Delta-Hedged Daily Option Returns. Order-Imbalances Included

Panel A: Daily Call Option Returns

	OTM		ATM		ITM		ALL	
	coeff	t-stat	coeff	t-stat	coeff	t-stat	coeff	t-stat
IL^O	0.0165	5.34	0.0101	3.78	0.0069	3.05	0.0119	5.36
Imbalances	0.0051	4.93	0.0010	3.16	0.0002	1.51	0.0021	4.78
IL^S	-1.3533	-1.81	-0.6584	-1.61	-0.2038	-0.76	-0.7996	-2.27
σ	-0.0036	-1.65	0.0008	0.84	-0.0006	-1.04	-0.0005	-0.51
b	0.0031	1.34	0.0034	3.08	0.0003	0.59	0.0029	2.55
log(Size)	-0.0017	-6.26	-0.0003	-2.49	-0.0002	-2.89	-0.0005	-3.48
Leverage	0.0044	3.32	0.0020	3.17	0.0009	2.63	0.0016	2.57
Adjusted R^2	0.036		0.039		0.040		0.039	
# Obs in CS (avr.)	298		315		270		412	
# CS regressions	2118		2118		2055		2118	

Panel B: Daily Put Option Returns

	OTM		ATM		ITM		ALL	
	coeff	t-stat	coeff	t-stat	coeff	t-stat	coeff	t-stat
IL^O	0.0155	5.84	0.0030	1.03	0.0087	2.41	0.0098	4.45
Imbalances	0.0020	2.70	0.0007	3.08	0.0001	0.45	0.0009	3.57
IL^S	0.0858	0.16	-0.1040	-0.27	-0.0272	-0.11	0.1695	0.44
σ	0.0050	2.95	0.0032	3.63	0.0003	0.40	0.0032	3.12
b	0.0002	0.13	0.0019	2.06	0.0001	0.22	0.0006	0.57
log(Size)	-0.0005	-2.60	-0.0002	-1.77	-0.0004	-5.15	-0.0002	-1.68
Leverage	-0.0007	-0.69	-0.0009	-1.58	-0.0004	-0.73	-0.0007	-1.24
Adjusted R^2	0.037		0.039		0.041		0.039	
# Obs in CS (avr.)	283.7		269.7		191.5		373.1	
# CS regressions	2013		2013		2013		2013	

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 (in percent). The regressions include lagged values of the following variables: option illiquidity, IL^O, option order imbalances, stock illiquidity, IL^S, stock volatility σ, the systematic risk proportion b, the logarithm of the firm size log(size), and firm leverage. The sample period covers daily data from January 2004 through December 2012 for the S&P 500 constituents that have options trading throughout the sample period. Reported are coefficients and Fama-Macbeth t-statistics with Newey-West correction for serial correlation (8 lags for daily returns and 3 lags for weekly returns).

Table 8. Option Illiquidity Coefficients from Fama-Macbeth Regressions. Various Robustness Checks

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

		Trim 1% of Returns	Add $R^S(t+1)$	Add other Variables	Trim 1% of Returns, add Imbalances	Add $R^S(t+1)$ and Imbalances	Add other Vars. incl. Imbalances
OTM	Coeff	0.0132	0.0190	0.0231	0.0128	0.0186	0.0226
	T-stat	9.2025	8.4876	9.7494	8.9077	8.2803	9.5037
	Adj R^2	0.0371	0.1235	0.1677	0.0377	0.1241	0.1683
ATM	Coeff	0.0133	0.0140	0.0212	0.0136	0.0143	0.0215
	T-stat	8.7207	5.5304	8.3372	8.8314	5.6073	8.4453
	Adj R^2	0.0371	0.1182	0.1616	0.0377	0.1188	0.1621
ITM	Coeff	0.0087	0.0090	0.0134	0.0087	0.0090	0.0133
	T-stat	6.6125	4.0897	6.2803	6.6180	4.0413	6.2530
	Adj R^2	0.0364	0.0967	0.1718	0.0370	0.0975	0.1723
ALL	Coeff	0.0097	0.0130	0.0155	0.0096	0.0128	0.0153
	T-stat	10.1385	7.5844	8.9790	10.0437	7.4365	8.8494
	Adj R^2	0.0382	0.1103	0.1601	0.0388	0.1111	0.1609

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

		Trim 1% of Returns	Add $R^S(t+1)$	Add other Variables	Trim 1% of Returns, add Imbalances	Add $R^S(t+1)$ and Imbalances	Add Imbal. and other Variables
OTM	Coeff	0.0142	0.0205	0.0251	0.0139	0.0201	0.0245
	T-stat	10.4641	8.0444	9.8013	10.2606	7.7953	9.5032
	Adj R^2	0.0406	0.1529	0.1958	0.0411	0.1532	0.1961
ATM	Coeff	0.0099	0.0078	0.0151	0.0099	0.0078	0.0151
	T-stat	6.1520	2.9392	5.2195	6.1622	2.9221	5.1850
	Adj R^2	0.0395	0.1243	0.1684	0.0398	0.1248	0.1688
ITM	Coeff	0.0096	0.0114	0.0152	0.0094	0.0110	0.0149
	T-stat	6.4044	3.4824	6.4808	6.2610	3.3388	6.3406
	Adj R^2	0.0394	0.1038	0.1749	0.0398	0.1044	0.1754
ALL	Coeff	0.0101	0.0123	0.0154	0.0099	0.0121	0.0151
	T-stat	10.3273	5.8987	7.1166	10.1392	5.7743	6.9789
	Adj R^2	0.0407	0.1276	0.1753	0.0414	0.1284	0.1760

Notes to Table: We reports the coefficients on option illiquidity from Fama-Macbeth regressions on daily option returns for different option categories (OTM, ATM, ITM, and ALL). The regressors in Table 6 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 2004 to December 2012. Each column corresponds to a different robustness check described in the text. "Other 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. Imbalances refer to the difference between buy and sell option volume weighted by delta.

Table 9. Determinants of Daily Option Spreads

	Panel A. Call Option Effective Spreads				Panel B. Call Option Quoted Spreads			
	Coeff	T-stat	Coeff	T-stat	Coeff	T-stat	Coeff	T-stat
Lagged Option Spread	0.196	46.5	0.189	46.7	0.252	42.7	0.243	42.7
ILS	-4.723	-10.7	-5.070	-11.6	-6.886	-14.7	-7.236	-15.7
1/(Option Price)	0.065	90.3	0.065	90.5	0.075	121.7	0.075	123.2
σ	-0.024	-19.2	-0.021	-17.2	-0.026	-17.8	-0.022	-15.7
Stock Return			6.2E-03	1.3			-7.9E-03	-1.5
Option Volume			-1.0E-06	-33.3			-1.2E-06	-32.7
Imbalances	0.006	12.4	6.7E-03	13.9	0.004	9.5	5.3E-03	11.4
Vega*ILS	0.947	25.3	0.981	27.3	1.173	29.0	1.221	31.8
Adj. R^2	0.487		0.490		0.556		0.559	
# firms	387		387		387		387	
# cs obs	2208		2208		2208		2208	

	Panel C. Put Option Effective Spreads				Panel D. Put Option Quoted Spreads			
	Coeff	T-stat	Coeff	T-stat	Coeff	T-stat	Coeff	T-stat
Lagged Option Spread	0.188	38.3	0.184	38.6	0.248	36.3	0.242	36.5
ILS	-1.537	-3.8	-1.865	-4.6	-2.608	-5.6	-2.907	-6.3
1/(Option Price)	0.059	80.9	0.060	80.7	0.071	114.8	0.071	115.2
σ	-0.007	-6.5	-0.006	-5.5	-0.010	-7.1	-0.007	-5.6
Stock Return			2.0E-02	4.6			1.8E-02	4.0
Option Volume			-6.6E-07	-20.3			-9.6E-07	-21.4
Imbalances	0.006	19.3	6.0E-03	20.1	0.004	12.4	4.5E-03	13.2
Vega*ILS	0.737	23.0	7.6E-01	24.2	0.932	29.1	9.7E-01	31.1
Rsqr	0.449		0.451		0.533		0.536	
#firms	336		336		336		336	
#cs obs	2093		2093		2093		2093	

Notes to Table: We report the results of cross-sectional Fama-MacBeth regressions for daily volume-weighted average effective and quoted call option and put option spreads. The regressions include lagged values of the dependent variable as well as the following variables: option order imbalances, stock illiquidity, ILS, stock volatility, σ, the underlying stock returns, option volume, inverse option volume-weighted average daily price, and the product of option vega and stock illiquidity, Vega*ILS. The sample period covers daily data from January 2004 through December 2012 for the S&P 500 constituents that have options trading throughout the sample period. Reported are coefficients and Fama-MacBeth t-statistics with Newey-West correction for serial correlation (8 lags).