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 report on illiquidity premia in equity option markets. An increase in option illiquidity decreases the current option price and predicts higher expected option returns. This effect is statistically and economically significant. It is robust across different empirical approaches and when including various control variables. The illiquidity of the underlying stock affects the option return negatively, consistent with a hedging argument: When stock market illiquidity increases, the cost of replicating the option goes up, which increases the option price and reduces its expected return.

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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. In equity markets, Amihud and Mendelson (1986, 1989), Eleswarapu and Reinganum (1993), Brennan and Subrahmanyam (1996), Amihud (2002), Jones (2002), Pastor and Stambaugh (2003), and Acharya and Pedersen (2005) compare stock market illiquidity to ex-post returns on equities. In bond markets, Amihud and Mendelson (1991), Warga (1992), Boudoukh and Whitelaw (1993), Kamara (1994), Krishnamurthy (2002), Longstaff (2004), Goldreich, Hanke and Nath (2005), and Beber, Brandt and Kavajecz (2009) analyze the impact of bond illiquidity on expected bond returns.

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 (2010) for evidence on the credit default swap market. Vijh (1990) measures liquidity premia 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. However, the literature has been mostly silent so far 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. George and Longstaff (1993) find that 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.

Our contribution is to study the effect of option and stock illiquidity on equity option returns. We document the statistical significance and economic magnitude of the impact of option illiquidity on option returns. We also estimate the effect of illiquidity in the underlying stocks on option returns. 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, then the trading strategy replicating the price of the option is harder to implement and the illiquidity costs of this trade should affect the price and thus return of the option.

We establish our main results using cross-sectional Fama-MacBeth (1973) regressions for daily and weekly returns. We present univariate regressions but also multivariate regressions controlling for stock volatility, stock returns, lagged option returns, and other firm characteristics, as in Duan and Wei (2009). An increase in option illiquidity has a positive and significant impact on next period's option returns, across all moneyness and maturity categories. This evidence is consistent with the existence of an illiquidity premium in the options market, similar to the effect of stock illiquidity on stock returns reported by Amihud (2002). The effect is also economically significant: for example, a two standard deviation shock to out-of-the-money short-term call illiquidity results in a 2.37% change in the next day out-of-the-money short-term call returns. A two standard deviation shock to out-of-the-money short-term put illiquidity results in a 1.61% change in the next day out-of-the-money short-term put returns.

We find that the illiquidity of underlying stocks also has a significant impact on option prices. As expected, this effect is opposite to the effect of option illiquidity on option returns. A positive shock to stock illiquidity decreases next period's option returns. This finding is consistent with trading motivated by hedging considerations. Whenever stock market illiquidity increases, the higher stock transaction costs will increase the cost of replicating the option, which will increase the option price and reduce its expected return. This effect is also economically meaningful, although it is smaller compared to the impact of option illiquidity: for example, a two standard deviation shock to stock illiquidity would result in a 0.87% change in the next day short-term out of the money call returns and a 0.59% change in the next day short-term out of the money put returns. This is consistent with Cetin, Jarrow, Protter and Warachka (2006), who suggest that illiquidity of underlying stocks constitutes a significant part of option prices.

Analyzing the effects of illiquidity in the cross-section of option returns is empirically more challenging than analyzing the cross-section of stock returns, because of the strong dependence of option returns on the returns of the underlying. We therefore investigate the robustness of our results by analyzing the cross-section of implied volatilities in addition to the cross-section of returns. We find that both the illiquidity of the options and the underlying assets help explain the level of implied volatility, and that the sign of the effect is consistent with the evidence from the cross-section of returns. Moreover, option illiquidity significantly affects the slope of the implied volatility curve: the implied volatility curve is steeper for more illiquid option contracts.

Finally, we report time-series evidence for liquidity decile portfolios. We find that a contemporaneous increase in option illiquidity has a significantly negative effect on option prices, consistent with the cross-sectional evidence. This result is again similar to the effect of stock illiquidity on stock returns reported by Amihud (2002). A contemporaneous shock to option illiquidity decreases the current price and increases expected option returns to compensate traders for holding illiquid contracts.

To the best of our knowledge these 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.[1]

The paper is organized as follows. Section 2 lays out our main hypotheses and discusses the theoretical literature on expected option returns. Section 3 describes the data and variables we use, in particular, the construction of option returns and illiquidity measures. Section 4 presents empirical results on the impact of illiquidity on the cross-section of option returns. Section 5 investigates the cross-section of implied volatilities and the slope of the implied volatility curve. Section 6 presents time-series evidence, and Section 7 concludes.

2 Illiquidity and Expected Option Returns

Motivated by the literature on liquidity risk in the bond and equity markets, we investigate the following hypotheses in our empirical work:

1. In the cross-section, illiquid options earn on average higher expected returns, supporting the existence of a positive illiquidity premium.

2. The illiquidity of the underlying stock negatively affects expected option returns, which is consistent with the following hedging argument: Higher stock transaction costs increase the cost of replicating the option, which increases the option price and reduces its expected return.

3. Option illiquidity and the illiquidity of the underlying stock are important determinants of the level and slope of the implied volatility curve.

4. In a time series analysis, lagged option illiquidity predicts future expected option returns and illiquidity shocks are negatively related to contemporaneous option returns, consistent with a positive illiquidity premium.

Before forging ahead with empirical tests of these hypotheses, we briefly review existing theoretical results on expected option returns. These results will be used to provide guidance in the design of the illiquidity tests.

[1] The equity option literature also contains related results on trading activity and demand pressures. Prominent papers include Garleanu, Pedersen, and Poteshman (2009), Easley, O'Hara, and Srinivas (1998), Lakonishok, Lee, and Poteshman (2007), Mayhew (2002), Pan and Poteshman (2006), and Roll, Schwartz, and Subrahmanyam (2010).

Mainstream option valuation theory assumes away illiquidity in option markets as well as in the market for the underlying and bond markets.[2] This is done in order to arrive at option valuation expressions that are deterministic functions of the underlying asset price and the interest rate as well as other variables, including volatility.

In the standard Black and 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 we can write

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

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.

In the Black-Scholes model, the risk-free rate is assumed to be constant across maturities. Bakshi, Cao and Chen (1997) show empirically that allowing for stochastic interest rates does not change the value of the option by much, compared to the simple use of maturity-specific risk-free rates in the Black-Scholes model. Thus we do not control for stochastic interest rates in our empirical analysis below.

The absence of stochastic volatility in the Black-Scholes model is much more critical. Hull and White (1987) and Scott (1987) develop option valuation models with stochastic volatility. 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. Broadie, Chernov, and Johannes (2009) and Duarte and Jones (2007) show that in a standard stochastic volatility model, the expected

[2] 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.

option return is given by

$$E\left[R^O\right] = \left(r + \left(E\left[R^S\right] - r\right)\frac{S}{O}\frac{\partial O}{\partial S} + \lambda\frac{\sigma}{O}\frac{\partial O}{\partial \sigma}\right)dt \tag{2.3}$$

where the sensitivity of the option price to volatility (the option vega), denoted by $\frac{\partial O}{\partial \sigma}$, is positive for all options, and where the price of volatility risk, λ, is negative because the added volatility risk increases the option value.[3] Equation (2.3) shows that it will be important to control for the dynamic volatility of the stock when regressing option returns on illiquidity measures.

The standard option valuation models discussed above do not allow for transactions costs or liquidity risk. A much smaller option valuation literature allows for illiquidity effects in the underlying asset. Prominent papers include Cetin, Jarrow and Protter (2004), Jarrow and Protter (2005), and Cetin, Jarrow, Protter and Warachka (2006). The latter paper shows that the Black-Scholes pricing model holds in the presence of liquidity costs associated with trading the underlying asset, but also that the optimal hedging strategy changes compared to Black-Scholes. Toft (1996) studies option valuation in the presence of trading costs. Constantinides and Perrakis (2002, 2007), Oancea and Perrakis (2007), and Constantinides, Jackwerth, and Perrakis (2009) rely on a stochastic dominance approach to characterize bounds on option prices. As this approach establishes option valuation bounds rather than option prices, expressions for the relationship between expected option returns and liquidity measures are not readily available.

In recent work, Bongaerts, de Jong and Driessen (2010) develop an equilibrium asset pricing model with liquidity risk where the underlying asset is in positive net supply and the derivative asset is in zero net supply. The model contains heterogeneous investors who differ with respect to their degree of risk-aversion, initial wealth and investment horizon. In a linear special case of their model, the expected option return can be derived as

$$E\left[R^O\right] = \delta_1 E\left[R^S\right] + \beta_2 E\left[IL^O\right] + \beta_3 E\left[IL^S\right] \tag{2.4}$$

where IL^O is the illiquidity (in terms of transaction cost) of the option and IL^S is the illiquidity of the underlying stock. Bongaerts, de Jong and Driessen (2010) show that when the less risk-averse investors have long positions in the option, the coefficient on $E\left[IL^O\right]$ is positive and the option buyers will earn a positive illiquidity premium. These investors are more sensitive to transaction costs and will therefore require compensation for illiquidity risk. The model is not conclusive with respect to the sign of the coefficient on $E\left[IL^S\right]$,

[3] The derivation of (2.3) assumes that the diffusion to volatility is linear in the volatility level.

which therefore remains an open question in the empirical analysis, to which we now turn.

3 Data and Variable Construction

3.1 Option Returns

We investigate the impact of option illiquidity as well as stock illiquidity on option returns. The construction of these two measures is complicated by the large number of option contracts and the need to construct stock illiquidity measures using high-frequency data. Moreover, data on option contracts for smaller firms is less readily available when researching longer time periods. We therefore limit ourselves to options data for S&P500 index constituents from OptionMetrics, which includes daily closing bid and ask quotes on American options, as well as their implied volatilities and deltas. By limiting ourselves to S&P500 firms, we bias our results towards not finding evidence of the importance of illiquidity. The sample period is January 1996 to December 2007. We limit the sample to firms that have options trading throughout the entire sample period. We implement this by verifying whether the firms have options trading on the first trading day of each calendar year in the sample, as well as the last day in our sample, December 31, 2007. This yields a sample of 341 firms.

We repeat our analysis for six different option samples. For each firm, we consider put and call options for two maturity categories: short-term, with time to maturity between 20 and 70 days, and long-term, with time to maturity between 71 and 180 days. Each maturity category is in turn divided according to moneyness 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 to the option delta from OptionMetrics,[4] 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 and eliminate 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

[4] For American options, OptionMetrics relies on the Cox, Ross, and Rubinstein (1979) binomial tree model for computing implied volatilities and deltas.

than the minimum tick size which signals a data error. We have also re-run the empirical tests without imposing any filters, and the results are robust.

For all remaining options, our method for computing option returns follows Coval and Shumway (2001). We compute daily returns using 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 each moneyness and maturity category by averaging option returns for all available contracts. For each option category and for each firm, the return from t to $t+1$ is defined by

$$R^O_{t+1} = \frac{1}{N}\sum_{n=1}^{N} \frac{O_{t+1}(K_n, T_n - 1) \times f_{t+1} - O_t(K_n, T_n) \times f_t}{O_t(K_n, T_n) \times f_t} \tag{3.1}$$

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, and f_t is the cumulative adjustment factor for splits or other distribution events, provided by OptionMetrics.

Weekly option returns are constructed similar to daily returns using Friday-to-Friday data wherever possible, and alternatively using a minimum of four daily returns.[5]

Figure 1 plots the daily option returns over time. Figure 1A contains the call option returns and Figure 1B has the put option returns. The short-term returns in the left panels are clearly more volatile than the long-term returns in the right panels. This is true for both calls and puts. 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. Table 1 shows that call returns on average are positive and put returns are negative, for daily data as well as weekly data in all categories. This is as expected from the option deltas as shown in (2.2). The option returns exhibit positive skewness and excess kurtosis in all categories as well, which is also as expected due to option gamma. Returns on OTM options are higher than returns on ITM options. They are also more variable and exhibit higher kurtosis. Returns on short-term options are higher and more variable than returns on long-term options, confirming the visual impression from Figure 1. The option returns display little evidence of serial dependence judging from the first-order autocorrelation, $\rho(1)$, but the absolute return autocorrelation $\rho^{abs}(1)$ is positive

[5] We try the following combinations: Friday-to-Friday, then Friday-to-Thursday, then Thursday-to-Friday, then Thursday-to-Thursday. If none of these are available then we discard the weekly observation for that option.

for all categories, confirming the volatility clustering apparent from Figure 1.

3.2 Illiquidity Measures for Stocks and Options

We investigate the impact on option returns of option illiquidity but also of illiquidity in the underlying stock market. There is an extensive literature on stock market illiquidity as we discussed in the introduction. We follow the convention in the literature and compute stock illiquidity as the effective spread obtained from high-frequency intraday TAQ (Trade and Quote) data. Specifically, for a given stock, the TAQ effective spread on the trade is defined as

$$IL_k^S = 2\left|\ln(P_k) - \ln(M_k)\right|, \tag{3.2}$$

where P_k is the price of the k^{th} trade and M_k 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.

The literature on equity option illiquidity is in its infancy, and therefore it is less clear how to define the option illiquidity measure. Furthermore, transaction prices to estimate effective spreads are not available for options. Similar to conventional illiquidity measures for stocks, we therefore measure illiquidity in the option market with relative quoted bid-ask spreads.[6] This is a transparent measure of illiquidity, and better alternatives are not readily available.[7] We compute relative quoted bid-ask spreads using end-of-day quoted bid and ask prices provided by Ivy DB OptionMetrics.[8] For each contract, we compute the daily relative quoted spread

$$IL_{t,n}^O = \frac{OA_t(K_n, T_n) - OB_t(K_n, T_n)}{O_t(K_n, T_n)} \tag{3.3}$$

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 $O_t(K_n, T_n) = (OA_t(K_n, T_n) + OB_t(K_n, T_n))/2$.

[6] 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).

[7] 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.

[8] We use the following fields in OptionMetrics: "Best bid" defined as the best, or highest, closing bid price across all exchanges on which the option trades. Similarly for "Best offer".

The equally-weighted average spreads are then computed for each option category as

$$IL_t^O = \frac{1}{N} \sum_{n=1}^{N} IL_{t,n}^O \tag{3.4}$$

where N is the number of available contracts that are within the particular category at time t.

Given the data constraints, using quoted spreads as an alternative to effective spreads is reasonable. Battalio, Hatch and Jennings (2004), who use data for January 2000 through June 2002, which is part of our sample period, find that for large stocks the ratio of effective spread to quoted spread fluctuates between 0.8 and 1. Since our sample is limited to S&P500 firms, quoted spreads are a good substitute for effective spreads.

Panel A of Table 2 presents summary statistics for the relative bid-ask spread illiquidity measure using our cross-section of 341 firms. For the option illiquidity, IL^O, we find that short-term contracts are more illiquid than long-term contracts, regardless of whether the options are OTM, ATM, or ITM. For example, the average relative spread of short-term OTM call options is 34.02%, while for long-term OTM calls the average spread is 22.67%.[9]

Table 2 also shows that illiquidity is highest on average for OTM options, followed by ATM options, which in turn are more illiquid than ITM options. We therefore conclude there are strong moneyness and maturity effects in liquidity. In order to control for this, we will run our empirical tests separately on six different moneyness and maturity categories.

An alternative to the use of relative spreads as an illiquidity measure is Amihud's (2002) illiquidity measure, the price impact value, which is also considered by Bongaerts et al. (2010). We construct this measure for options as follows: For each day and for each option category we compute the average return and the average dollar volume across all available contracts. Dollar volume is computed as the bid-ask midpoint multiplied by trading volume. We then compute the ratio of the absolute return to the dollar volume for each day and average it for each week. This is similar Amihud's (2002) implementation, with the difference that we construct a weekly rather than a monthly measure.

Table 3 reports summary statistics for Amihud's illiquidity measure. Across option categories, OTM options have the highest price impact value. This is consistent with the evidence on relative spreads in Table 2, which shows that OTM options are most illiquid. Among other categories, similar to Table 2, ITM options are the least illiquid and ATM options are in between. The cross-sectional correlation between Amihud's price-impact measure and relative quoted bid-ask spreads ranges between 0.20 and 0.33 (not reported). This

[9] To put the magnitudes of these relative spreads in perspective, the average dollar spread in our sample is 22.9 cents for calls and 23.8 cents for puts. This is very similar to the 21.3 cent average dollar spread reported by Vijh (1990).

is comparable to the evidence presented in Goyenko et al. (2009) for stocks.

For our purpose, the disadvantage of Amihud's (2002) price impact measure is that our empirical investigation uses daily and weekly returns on options, because constructing monthly option returns is much less straightforward. Goyenko, Holden, and Trzcinka (2009) argue against aggregating Amihud's (2002) price impact measure at lower than monthly frequencies, on the grounds that it yields a noisy estimate of illiquidity. We therefore use the relative spreads for our main results. Nevertheless, we replicate our main results using Amihud's (2002) measure, and we obtain qualitatively similar results. These results are available from the authors on request.

Trading volume and open interest are sometimes used as illiquidity measures. Table 3 reports on option trading volume and open interest. Table 3 shows that, as is well-known in the empirical option valuation literature, open interest and volume are highest for ATM and OTM options and lower for ITM options. So, while ITM options are the cheapest to trade in a relative bid-ask sense, which is our measure of liquidity, the ATM and OTM options have the highest trading volume. This is consistent with existing literature, which suggests that volume is not informative about illiquidity in option markets. For instance, Mayhew (2002) argues that an option can be liquid even if it has low trading volume. This may occur if other options on the same stock are actively traded. In that case it is easy for a market maker to hedge the low-volume option with actively traded options at other strikes and maturities, as well as to hedge calls with puts and vice versa. Therefore, when thinking of illiquidity in terms of trading costs, one should not expect an obvious relationship between illiquidity and trading volume in option markets. The apparent incongruity between option volume and trading cost also has interesting parallels to the literature on stock market liquidity. Pastor and Stambaugh (2003) discuss the October 19, 1987 crash when the NYSE set a record in trading volume but where the stock market was highly illiquid from a trading cost perspective.

The right-most column in Table 2 shows that in our sample, stocks are on average substantially more liquid than options. The average relative bid-ask spread for stocks is 0.26% in our sample. This is lower than most estimates reported in the literature, which is due to the fact that our sample is limited to S&P500 firms, which are the most liquid. Panel A of Table 2 also indicates that option illiquidity is substantially more volatile than stock illiquidity.

Figure 2A depicts the evolution of our call illiquidity measure over time for all six option categories, and Figure 2B does the same for put illiquidity. For all six option categories, we report the average of the liquidity measure. Option illiquidity clearly declines over the sample period, but not in a monotonic fashion. As in Pastor and Stambaugh (2003), we see occasional large spikes in the illiquidity measures. The largest spike took place on September 17-18, 2001, which were the first days of trading after the September 11 attacks. Smaller spikes occur towards the end of the sample as the credit crisis gets underway.

The top panel of Figure 3 plots stock illiquidity over time. Stock illiquidity clearly decreases over time, which the literature attributes to decreases in tick size, the increase in electronic trading, and decimalization. There are illiquidity spikes associated with the 1997 Asian crisis, the 1998 LTCM collapse, 9/11, and the WorldCom bankruptcy in 2002.

In order to put our liquidity data into perspective, Figure 3 also plots the S&P500 index level (middle panel) and the VIX volatility index from the CBOE (bottom panel). The inverse relationship between market returns and volatility, the so-called "leverage effect" is evident when comparing the S&P500 level with VIX. Figure 3 also shows some evidence of dependence between spikes in stock illiquidity and spikes in the VIX.

Panels B and C of Table 2 show that option illiquidity has a sizeable positive correlation with stock market illiquidity for all option categories, with somewhat higher correlations for call options. This finding suggests co-movement between illiquidity in the two markets. Table 2 also indicates that the illiquidity of OTM call and put contracts is substantially more volatile than the other categories. Illiquidity of OTM short-term calls and puts is highly correlated, at 0.59 (not reported in Table 2). This supports the findings of George and Longstaff (1993), who suggest that traders regard call and put options as substitutes (via put-call parity) with trading activity in calls and puts being positively related to the bid-ask spreads in calls and puts.

3.3 Other Variables

We obtain daily stock returns, prices, and the number of outstanding shares from CRSP. Weekly stock returns are compounded from daily returns. Data on long-term debt and the par value of preferred stock, which are used to compute firm leverage, are from Compustat. The S&P 500 constituents are also from Compustat. The returns on the Fama-French and momentum factors are from Ken French's online data library.

4 Illiquidity and the Cross-Section of Option Returns

We investigate the cross-sectional relationship between option illiquidity and expected option returns. We proceed by running daily and weekly cross-sectional regressions, and subsequently testing the significance of the time-series means of the estimated coefficients, as in Fama and MacBeth (1973).

4.1 Computing Adjusted Option Returns

Variations in the price of the underlying security are by far the biggest determinant of returns, and it is important to account for this when analyzing determinants of option returns as we showed in equation (2.2). The common practice in the literature is to use delta-hedged option returns. While this transformation is appropriate for studying factors affecting option returns other than illiquidity, it creates a bias when testing the effect of illiquidity on option returns. In particular, Cetin, Jarrow, Protter and Warachka (2006) show that in a Black-Scholes economy with frictions, hedging does not eliminate the risk of the underlying stock. The hedging error due to the illiquidity of the underlying stock inflates option prices. Therefore, using delta-hedged returns biases our test results for stock illiquidity. We instead proceed as follows: we first run a cross-sectional regression of option returns on the returns of the underlying stock and their lagged values. We also include squared stock returns to control for the nonlinear dependence between the two variables

$$R^O_{i,t} = \delta_{0,t} + \delta_{1,t} R^S_{i,t} + \delta_{2,t} R^S_{i,t-1} + \delta_{3,t} \left(R^S_{i,t}\right)^2 + \varepsilon_{i,t}, \quad i = 1, 2, ...$$

and we refer to the residuals plus the intercept from these regressions as adjusted option returns, which we denote

$$\tilde{R}^O_{i,t} = \hat{\delta}_{0,t} + \hat{\varepsilon}_{i,t}$$

Below, we regress these adjusted option returns cross-sectionally on the illiquidity measures and a number of control variables.[10]

4.2 Capturing Liquidity Effects

Our treatment of illiquidity as an explanatory variable in the cross-section follows Amihud's (2002) investigation of expected stock returns, which is in turn inspired by the analysis of French, Schwert, and Stambaugh (1987). Table 2 reports average estimates of the first-order autocorrelation of individual illiquidity. The estimated values of $\rho(1)$ clearly indicate a rather persistent process, in line with the results for stock illiquidity reported by Amihud (2002).

We compute the lagged illiquidity measure, $IL^O_{i,t-1}$, as described in Section 3, for every firm in the sample and use it as a measure of expected liquidity.[11] Following Amihud (2002)

[10] For robustness we also run the regressions in one step, i.e. we control for stock return, lagged stock return and squared stock return on the right hand side together with the other control variables. The results are qualitatively similar, but obviously the regression R-square is much higher.

[11] The illiquidity measure, $IL^O_{i,t-1}$, described in Section 3, is based on the contracts available at time $t-1$. However, only contracts with returns available at time t are considered in the computation of $IL^O_{i,t-1}$,

and French, Schwert, and Stambaugh (1987), we use ex-post realized returns as a measure of expected returns. We run cross-sectional regressions of returns between times $t-1$ and t on the liquidity measure at time $t-1$; we also run similar regressions controlling for multiple other return determinants.

Since the illiquidity of the underlying asset can affect trading activity in the option markets via hedging pressures, we also include our measure of stock illiquidity $IL^S_{i,t-1}$.

4.3 Control Variables

We use a number of control variables in the liquidity regressions. To account for stale prices in the daily data, we include the lagged adjusted option return $R^O_{i,t-1}$ in the regression. Another important determinant of expected option returns is volatility, as we showed in equation (2.3). We estimate historical volatility from the daily stock return data using a simple $GARCH(1,1)$ model:

$$R^S_{i,t} = \mu_i + \sigma_{i,t-1} z_{i,t} \tag{4.1}$$

$$\sigma^2_{i,t} = \alpha_{0,i} + \alpha_{1,i}\sigma^2_{i,t-1} + \alpha_{2,i}\sigma^2_{i,t-1} z^2_{i,t-1} \tag{4.2}$$

where $R^S_{i,t}$ is the stock return, μ_i is the conditional mean, $\sigma^2_{i,t}$ is the conditional variance, and $z_{i,t}$ is a standard normal i.i.d. innovation.

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} in the regression, 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). Furthermore, we control for firm-specific characteristics such as size and leverage which have been shown to affect the distribution of options 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. 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.

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ensuring consistency between returns and illiquidity used in the regressions. As a robustness check, we repeat the tests using illiquidity based on all contracts, and the results are qualitatively very similar.

4.4 Firm-Level Results using Daily Returns

Our most general cross-sectional regression is motivated by the theoretical model in Bongaerts, de Jong and Driessen (2010), as discussed in equation (2.4) in Section 2. We run this regression with and without the control variables discussed above. The most general regression we consider is given by

$$\tilde{R}^O_{i,t} = \alpha_t + \beta_{1,t}\tilde{R}^O_{i,t-1} + \beta_{2,t}IL^O_{i,t-1} + \beta_{3,t}IL^S_{i,t-1} + \beta_{4,t}\sigma_{i,t-1} + \beta_{5,t}b_{i,t-1} + \beta_{6,t}\ln(size_{i,t-1}) + \beta_{7,t}lev_{i,t-1} + \varepsilon_{i,t} \tag{4.3}$$

We run this cross-sectional regression on every day t using all firms available for a given moneyness/maturity category, and subsequently compute the time-series averages of the estimated coefficients.[12] These averages are reported in Table 4. To control for serial correlation, the Fama-MacBeth (1973) t-statistics are corrected according to the Newey and West (1987) procedure using twenty-two lags for daily data.

Panel A of Table 4 reports the results for daily call option returns for all moneyness/maturity categories, and Panel B reports on put options. For call contracts, option illiquidity $IL^O_{i,t-1}$ significantly predicts higher option returns the next day at the 1% significance level, across all maturity and moneyness categories. The coefficient on $IL^O_{i,t-1}$ is statistically significant when $IL^O_{i,t-1}$ is the only regressor, but also when including the control variables as in (4.3). Moreover, the $IL^O_{i,t-1}$ coefficient is not much affected when including the control variables. This suggests that option illiquidity is an independent determinant of option returns, and that its effect is not captured by other well-known determinants of option returns.

Ignoring option illiquidity is tantamount to overestimating option prices. The effect is also economically significant. For example, for OTM short-term options, the coefficient on $IL^O_{i,t-1}$ is 0.062. Table 2 indicates that the standard deviation for OTM short-term call option illiquidity is 0.191. Therefore, a two standard deviation positive shock to OTM short-term call option illiquidity would result in a 2.37% increase in the next-day return on the call option. This is a significant magnitude for daily changes in prices. The coefficient on $IL^O_{i,t-1}$ is higher for short-term contracts than for long-term contracts, implying that the illiquidity impact is especially pronounced for short-term options. Short-term OTM contracts have the highest illiquidity risk.

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

[12] In all our tests, we require at least 30 firm-observations with all data available for each time t (day or week or month) to run a cross-sectional regression.

the expected return over the next period. Option markets are characterized by a positive illiquidity premium, because buyers of illiquid contracts seek higher expected returns.

These results have 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 short-term and 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 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.

Our results also have implications for option trading. In the well-known dispersion trade (see Driessen, Maenhout and Vilkov, 2009), investors sell index options, which are relatively expensive, and buy a portfolio of (cheaper) equity options as a hedge. This trade is commonly regarded as being driven mainly by correlation risk: When correlation increases, index options become relatively more expensive, which is bad for the dispersion seller. Our results suggest that this trade is also nontrivially exposed to liquidity risk because the equity options bought are much less liquid than the index options sold.

The illiquidity of the underlying stock $IL^S_{i,t-1}$ has a negative effect on expected call option returns, and this effect is statistically significant for all categories of short-term calls and for long-term ITM calls. Given the positive coefficient on $IL^O_{i,t-1}$, the negative coefficient on $IL^S_{i,t-1}$ is consistent with a hedging argument. When stocks become more illiquid, the higher stock transaction costs will increase the cost of replicating the option, which will increase the option price and reduce its expected return.

These results for short-term options are consistent with the evidence reported in Cetin, Jarrow, Protter and Warachka (2006), who suggest ITM options are the least exposed to the illiquidity of underlying stocks, since with ITM options most of the rebalancing of option payoff replicating portfolios occurs only as the stock price decreases. This argument suggests the largest effects for OTM options, where the replicating portfolio rebalancing occurs as the stock price changes in either direction, with ATM options somewhere in between. The coefficient on IL^S_{t-1} is more negative for OTM options, -2.077, and the least negative for ITM options, -0.428, with the coefficient for ATM options being in between, -0.873. For long-term calls the effect of stock illiquidity is less pronounced. Our estimate of -2.077 implies that a two standard deviation shock to stock illiquidity results in a 87 basis point change next day for short-term out of the money call returns. Therefore, while the effect of stock illiquidity on call returns is small compared to that of option illiquidity, it is still economically meaningful.

Among other variables, the effect of the lagged option return $\tilde{R}^O_{i,t-1}$ is negative and significant, which indicates negative mean reversion in option returns, consistent with the evidence on stock returns at the daily frequency. The volatility of the underlying also has a negative and significant effect on expected option returns. This finding is consistent with an option pricing model allowing for stochastic volatility and negative volatility risk premium (e.g. Heston, 1993). As discussed in Section 2, in a stochastic volatility model, the expected option return, $E\left[R^O\right]$, is negatively related to volatility through the positive option vega, $\frac{\partial O}{\partial \sigma}$, and the negative price of volatility risk, λ, as in equation (2.3), which we repeat here for convenience

$$E\left[R^O\right] = \left(r + (E\left[R^S\right] - r)\frac{S}{O}\frac{\partial O}{\partial S} + \lambda\frac{\sigma}{O}\frac{\partial O}{\partial \sigma}\right)dt \tag{4.4}$$

Further, the proportion of systematic risk, $b_{i.t-1}$, is typically small and insignificant. Among firm-specific characteristics, size exhibits a strong influence while leverage is typically insignificant.

For the put options in Panel B, we obtain similar results for option illiquidity IL^O_{t-1}, which positively predicts next period put returns. This effect is significant across all moneyness and maturity categories in the univariate regression, but also when controlling for other variables. Also confirming the results for call options, the effect of put illiquidity on expected put returns is more pronounced for the short-term contracts compared to the long-term contracts. For example, the coefficient on $IL^O_{i,t-1}$ for OTM short-term contracts is 0.048, almost twice the coefficient for the long-term contracts, which is 0.023. In economic terms, the coefficient of 0.043 implies that a two standard deviation shock to OTM short-term put illiquidity results in a 1.61% change in the next day put return. This is also an economically meaningful number.

The results for stock illiquidity are also quite robust for the put options. The coefficient on $IL^S_{i,t-1}$ is negative in all six categories and significant in four of six categories.

The total risk $\sigma_{i,t-1}$ has a significant impact on put returns across all moneyness and maturity categories, whereas the effect from the share of systematic risk, b_{t-1}, is small and insignificant. Among other firm characteristics, size and leverage also seem to affect put returns, consistent with the evidence in Dennis and Mayhew (2002).

We verified the robustness of the results in Table 4 by using raw option returns and including current and lagged stock returns as regressors. This yields very similar results for the variables of interest. The resulting R-squares are of course much higher, as the stock return explains a significant part of the variation in option returns.

4.5 Firm-Level Results using Weekly Returns

Daily prices may be subject to problems such as stale quotes and microstructure noise. Table 5 therefore repeats the exercise from Table 4 using weekly data. To control for serial correlation, the Fama-MacBeth (1973) t-statistics are corrected according to the Newey and West (1987) procedure using eight lags. We classify the options as OTM, ATM, or ITM, as well as short-term and long-term according to their average delta and maturity over the week. The weekly results reported in Panel A of Table 5 for call options confirm the results from Panel A of Table 4. The coefficients on lagged option illiquidity, $IL^O_{i,t-1}$, are robustly positive, and the estimates are statistically significant. The coefficients on lagged stock illiquidity, $IL^S_{i,t-1}$, are negative and statistically significant. This is true for the univariate as well as the multivariate regressions.

The evidence on weekly put returns in Panel B of Table 5 also broadly confirms the results from daily returns in Panel B of Table 4. Option illiquidity is significantly positively related to option returns in four of the six categories in the multivariate regression. Stock illiquidity is strongly negatively related with option returns for all categories.

Overall, the evidence in Tables 4 and 5 documents a statistically and economically significant impact of option illiquidity on expected option returns. This effect is similar to the effect of stock illiquidity on expected stocks returns (Amihud, 2002) and suggests a positive illiquidity premium in equity option markets. The call option results are robust to controlling for lagged option returns, stock returns, and stock volatility, as well as stock illiquidity and firm-specific characteristics. Moreover, the illiquidity of the underlying stock has a significantly negative impact on expected call and put option returns.

4.6 Portfolio Results

In the regression approach used in Tables 4 and 5, noise in returns on individual option contracts may weaken inference. It is therefore of interest to confirm the results using different empirical techniques. A simple alternative approach is to sort firms in liquidity portfolio baskets, and investigate the resulting patterns in portfolio returns. This portfolio approach can reduce the noise in returns on individual contracts. Panel A of Table 6 presents portfolio results for daily call returns, and Panel B for daily put returns. Table 7 presents results for weekly data. At time $t-1$ (day or week) all options are sorted into liquidity deciles. Subsequently we compute the average option return, stock return, illiquidity and market capitalization for each decile portfolio at time t.

Consistent with the liquidity premium hypothesis, option returns are monotonically increasing from the most liquid decile portfolio to the most illiquid decile portfolio for both calls and puts. For the call options in Panel A, stock returns are increasing across decile portfolios, for daily as well as weekly data; for the put options in panel B, stock returns are decreasing across decile portfolios, as expected. Consistent with liquidity co-movement between stock and option markets, stock illiquidity monotonically increases with option illiquidity for both calls and puts, for weekly as well as daily data. It is also seen that the more illiquid firms are on average smaller.

We can use portfolios to investigate whether returns on different horizon investments outweigh the substantial transaction costs. Similar to Amihud and Mendelson (1986), we compute returns net of transaction costs, using the bid and ask quotes. The net return R^O_{net}-*Long* is computed as $(\text{bid}_t - \text{ask}_{t-1})/\text{ask}_{t-1}$ and R^O_{net}-*Short* is computed as $(\text{-ask}_t + \text{bid}_{t-1})/\text{bid}_{t-1}$. Not surprisingly, the net returns after-trading costs for both long and short option positions are negative, clearly indicating that at short horizons liquidity premia are absorbed by market frictions.

5 Illiquidity and Implied Volatility

In Section 4, we study the impact of option illiquidity on the cross-section of option returns. This is a natural starting point, because it is straightforward to build intuition for illiquidity's expected effects on returns. The existing literature on illiquidity in bond and stock markets also investigates the effects of illiquidity on returns, and provides a natural reference point. However, there are some obvious differences between the analysis of options markets and stock markets, and we have to keep these in mind when interpreting our results. Most importantly, even though an analysis of the effect of illiquidity on stock returns also needs to control for other return determinants, in the case of option returns an overriding concern is that the return on the underlying is the first-order determinant of option returns (see equation (2.2)). As explained above, we control for this in our empirical work in Section 4 by either using the residuals from a regression on stock returns in our analysis, or alternatively by including stock returns in the regression. But it is worthwhile to investigate if our results are robust to an alternative empirical setup.

For equity options, an alternative approach is provided by the analysis of implied volatilities. This is interesting from two perspectives. First, the analysis of implied volatilities is well-established in the option literature. In fact, the importance of some of the control variables used in (4.3) was previously demonstrated in the context of the study of the structure of implied volatilities, see for instance Bakshi, Kapadia, and Madan (2003) and Duan and Wei (2009). Deuskar, Gupta, and Subrahmanyam (2011), who study the effect of liquidity on bond options, exclusively use implied volatilities as left-side variables, presumably because of potential problems with the analysis of returns. Second, because the structure of implied volatilities can simply be thought of as a (nonlinear) transformation of the structure of option prices, its analysis can be easily linked to the illiquidity literature, which often presents its arguments in terms of prices rather than returns. For example, Amihud (2002) investigates the hypothesis that higher expected liquidity raises expected returns, which lowers prices, assuming that liquidity does not affect corporate cash flows.

We therefore investigate whether option illiquidity affects the structure of implied volatilities. Following Duan and Wei (2009), we investigate several aspects of the implied volatility curve by first estimating the following model for each firm i for each moneyness and maturity category used in Section 4

$$iv_{i,t}(\chi_k, T_k) = \kappa_{i,t} + \theta_{i,t}(\chi_k - \bar{\chi}_k) + \eta_{i,t}(T_k - \bar{T}_k) + u_{i,t}^k, \qquad k = 1, 2, ..., K \tag{5.1}$$

where $iv_{i.t}(\chi_k, T_k)$ is the implied volatility for option k with maturity T_k and moneyness χ_k defined as the strike price over the stock price at time t. To ensure that sufficient contracts are available, we run the regression every month. Implied volatility and option characteristics are provided by Ivy DB OptionMetrics. We include only months with more than ten contracts available. $\bar{T}_k$ and $\bar{\chi}_k$ are the average time to maturity and moneyness, respectively, for each category. Using these regressions, we obtain for each firm i a monthly time series $\kappa_{i,t}$ which corresponds to the estimated level of implied volatility, and a monthly time series $\theta_{i,t}$ which corresponds to the estimated moneyness slope of the implied volatility. We define $\widetilde{\kappa}_{i,t}$ as the residuals plus the intercept from the cross-sectional regression of $\kappa_{i,t}$ on the monthly volatility, estimated by the square root of the sum of squared daily returns for the month. This is needed in order to eliminate the first-order determinant of implied volatility, similar to the use of adjusted option returns in Section 4.

Using both call and put contracts, we first estimate the illiquidity impact on the level of implied volatility by running monthly cross-sectional Fama-MacBeth regressions for the following model

$$\widetilde{\kappa}_{i,t} = a_{0,t} + a_{1,t}IL_{i,t}^O + a_{2,t}IL_{i,t}^S + a_{3,t}R_{i,t}^S + a_{4,t}b_{i,t} + a_{5,t}\ln(size_{i,t}) + a_{6,t}lev_{i,t} + \varepsilon_{i,t}^k \tag{5.2}$$

where $R_{i,t}^S$ is the firm's stock return, $IL_{i,t}^O$ is the average for the month of daily option illiquidity, and $IL_{i.t}^S$ is the dollar-volume weighted average of daily stock illiquidity, respectively. The proportion of systematic risk averaged throughout the month is denoted by $b_{i,t}$ and defined as in Duan and Wei (2009). To capture size we use the last daily observation each month and to capture leverage we use the observation available in the previous quarter. As in Section 4, the regression is run using all firms available for a given moneyness/maturity category.

Table 8 presents the results of this approach for calls and puts respectively. Option illiquidity IL_t^O negatively affects the level of implied volatility at the 1% significance level across all moneyness and maturity categories. These results are consistent with the positive predictive impact of option illiquidity IL_{t-1}^O on option returns in Tables 4 and 5. An increase in illiquidity decreases current prices, and therefore also the level of implied volatility, and increases expected option returns. Moreover, stock illiquidity, IL_t^S, has a positive and significant impact on the level of implied volatility, which is also consistent with the results in Tables 4 and 5, and with a hedging argument. An increase in stock illiquidity facilitates trading in options to hedge long/short positions in more illiquid stocks. This causes an increase in contemporaneous option prices, i.e. the level of implied volatility. These findings suggest illiquidity spillovers between stock and option markets. Overall, we observe a strong and statistically significant effect of both option illiquidity and stock illiquidity on the level of implied volatility across all option categories. The robustness of this effect across all option categories suggests a systematic impact of illiquidity on option prices.

We next examine the effect of option illiquidity on the moneyness slope of the implied volatility curve. It is well known that the data exhibit a smile or smirk in the moneyness dimension, implying that the slope is sometimes negative and sometimes positive. We test the hypothesis that illiquidity increases the absolute value of the slope by estimating

$$|\theta_{i,t}| = c_{0,t} + c_{1,t} IL_{i,t}^O + c_{2,t} IL_{i,t}^S + c_{3,t} R_{i,t}^S + c_{4,t} b_{i,t} + c_{5,t} \ln(size_{i,t}) + c_{6,t} lev_{i,t} + \varepsilon_{i,t}^k \tag{5.3}$$

where $\theta_{i,t}$ is obtained from equation (5.1).

Table 9 reports the regression results. Option illiquidity IL_t^O significantly increases the implied volatility moneyness slope, while the effect of stock illiquidity IL_t^S is less robust.

Overall, the results of Tables 8 and 9 suggest that option illiquidity is an important determinant of the structure of implied volatilities. Stock illiquidity is also an important determinant of the level and slope of implied volatility.

6 Option Illiquidity: Time Series Evidence

The cross-sectional results in Sections 4 and 5 provide substantial evidence of the importance of both option and stock illiquidity for option returns at the firm level. We now present time series evidence for portfolios. Portfolio-level time-series evidence can potentially yield additional insights as firm-specific risks are largely diversified away in this case. We use the time-series framework of French, Schwert, and Stambaugh (1987) and Amihud (2002).

Conducting portfolio-level time series analyses is more involved for options than for stocks. We proceed as follows. For each firm i and for each period t, we compute the option return $R_{i,t}^{O}$ as the equally-weighted average return in (3.1) for all eligible contracts available at time t. For these contracts we also compute the average illiquidity at time t, denote it $IL_{i,t}$. Some contracts are not available at both times $t-1$ and time t, due to the data filters. Therefore, the illiquidity at time $t-1$ is only computed for the option contracts with quotes available to compute their returns at time t, which ensures that $R_{i,t}^{O}$, $IL_{i,t}$ and $IL_{i,t-1}$ are based on the same contracts. As in the cross-sectional regressions, we adjust option returns for variation in the price and volatility of the underlying stock. We do so by regressing the raw option return on the current and lagged stock return and squared stock return and using the residuals from this regression instead of the raw option returns.

Then, as in Section 4.6, we rank the returns into deciles based on $IL_{i,t-1}$, and for each decile, we compute the equally weighted average of $R_{i,t}^{O}$, $IL_{i,t}$ and $IL_{i,t-1}$. We also compute the equally weighted average of lagged stock illiquidity $IL_{i,t-1}^{S}$ for each decile portfolio.

We are interested in the time series dynamics of the effect of option illiquidity on option returns at the portfolio level. Following the methodology in Amihud (2002), we test the predictive power of option illiquidity on option returns as well as the effect of a contemporaneous and unexpected shock to option illiquidity on option returns. We estimate the illiquidity shock of each decile, j, in the following time series regression in logarithms, using weekly data:

$$\ln\left(IL_{j,t}\right) = \omega_{j,0} + \omega_{j,1}\ln\left(IL_{j,t-1}\right) + v_{j,t}^{IL} \tag{6.1}$$

We use the residuals from this regression as a proxy for unexpected shocks to option illiquidity, defined as $IL_{j,t}^{u} \equiv v_{j,t}^{IL}$. The effect of option illiquidity on option returns is subsequently estimated for each decile portfolio using the following regression

$$\widetilde{R}_{j,t}^{O} = \gamma_0 + \gamma_1 \ln\left(IL'_{j,t-1}\right) + \gamma_2 IL_{j,t}^{u} + \gamma_3 \ln\left(IL_{j,t-1}^{S}\right) + v_{j,t} \tag{6.2}$$

Based on our cross-sectional findings, we expect γ_1 to be positive and significant. Moreover, we expect γ_1 to monotonically increase from less illiquid to more illiquid portfolios since we expect the illiquidity impact to be higher for more illiquid assets, similar to Amihud's (2002) findings for stocks. Given that lagged illiquidity has a positive impact, the contemporaneous unexpected shock should have a negative effect on option returns, i.e. an unexpected positive illiquidity shock should decrease current option prices and thus increase expected option returns. Similar to the evidence on the impact of illiquidity on stock market returns (Amihud, 2002), we also expect the effect of γ_2 to be stronger, i.e. more negative, for more illiquid portfolios.

Finally, the expected sign for the effect of stock illiquidity on expected option returns can be motivated by the discussion in Cetin et al (2006). A positive illiquidity shock in the stock market increases the cost of the replicating portfolio and therefore increases the current option price. Since options become more expensive for more illiquid stocks, the expected return on these options decrease. Moreover, they decrease more for more illiquid options. We therefore expect γ_3 to be negative.

The illiquidity portfolio level results for all option categories are reported in Table 10. The results are more pronounced for the call options reported in Panel A. For both short-term and long-term OTM calls, γ_1 is positive and significant and increases with portfolio illiquidity. This coefficient is higher for short-term contracts, suggesting higher illiquidity premia for short-term calls. The unexpected illiquidity has a significantly negative effect on short-term OTM calls and the magnitude of this effect is monotonically increasing in portfolio illiquidity. This is similar to the effect of stock illiquidity on stock returns (Amihud, 2002). The unexpected illiquidity shock is only significant for high-illiquidity portfolios and for long-term OTM calls but its coefficient has the expected negative sign and monotonically increases in absolute value with portfolio illiquidity. The results on option illiquidity are qualitatively similar across ATM and ITM short-term and long-term contracts, but the effect is more pronounced for short-term contracts. This is consistent with Amihud and Mendelson's (1986) clientele effect, where the holders of longer term assets are able to amortize illiquidity costs due to longer holding periods and thus require lower compensation for bearing illiquidity costs. This assumes of course that long-term options are indeed held for longer periods on average.

We obtain similar results for put options in Panel B, but with the exception of OTM put options, the results for call options are stronger in terms of magnitude and significance than for put options. Even though the two are linked via put-call parity, for ATM and ITM contracts, call options appear to be more exposed to illiquidity in the option and stock markets.

Finally, we find that stock illiquidity has a negative and significant impact on expected option returns across both calls and puts and for different maturity and moneyness categories. The pattern of γ_3 across illiquidity portfolios is not monotone. It is higher in absolute value for medium-illiquidity portfolios and lower for extreme decile portfolios. This suggests that even though stock illiquidity does affect option returns, it represents a different type of risk than option illiquidity.

7 Conclusion

We present evidence on illiquidity premia in equity option markets. Using cross-sectional and time series evidence, we find an economically and statistically significant positive impact of option illiquidity on expected option returns. The cross-sectional results obtain in univariate regressions, as well as in multivariate regressions controlling for returns and volatility of the underlying equity, lagged option returns, and a variety of other variables. The results are robust across six different moneyness and maturity categories, and estimates obtained using the cross-section of implied volatilities confirm the positive impact of option illiquidity on option returns. Our results are similar to the findings of Amihud (2002), who 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 traders for holding illiquid contracts.

The illiquidity of the underlying stocks also has an economically significant impact on option returns. A positive shock to stock illiquidity increase current option prices and decreases expected option returns. This effect is consistent with an increase in hedging trades due to higher stock illiquidity: Whenever stock market illiquidity increases, the higher stock transaction costs increase the cost of replicating the option, which in turn increases the option price and reduces its expected return.

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Figure 1A
Daily Call Option Returns

We plot daily returns on equally-weighted portfolios of call options. Option returns are computed from closing bid-ask price midpoints. For call options, OTM (out-of-the-money) corresponds to $0.125 < \Delta \leq 0.375$, ATM (at-the-money) corresponds to $0.375 < \Delta \leq 0.625$, and ITM (in-the-money) corresponds to $0.625 < \Delta \leq 0.875$. Short-term options have maturities between 20 and 70 days, whereas long-term options have maturities between 71 and 180 days. The option data are from Ivy DB OptionMetrics. The sample includes the S&P 500 constituents as of December 31, 2007 for which options trade throughout the entire sample period, which is from January 1996 through December 2007.

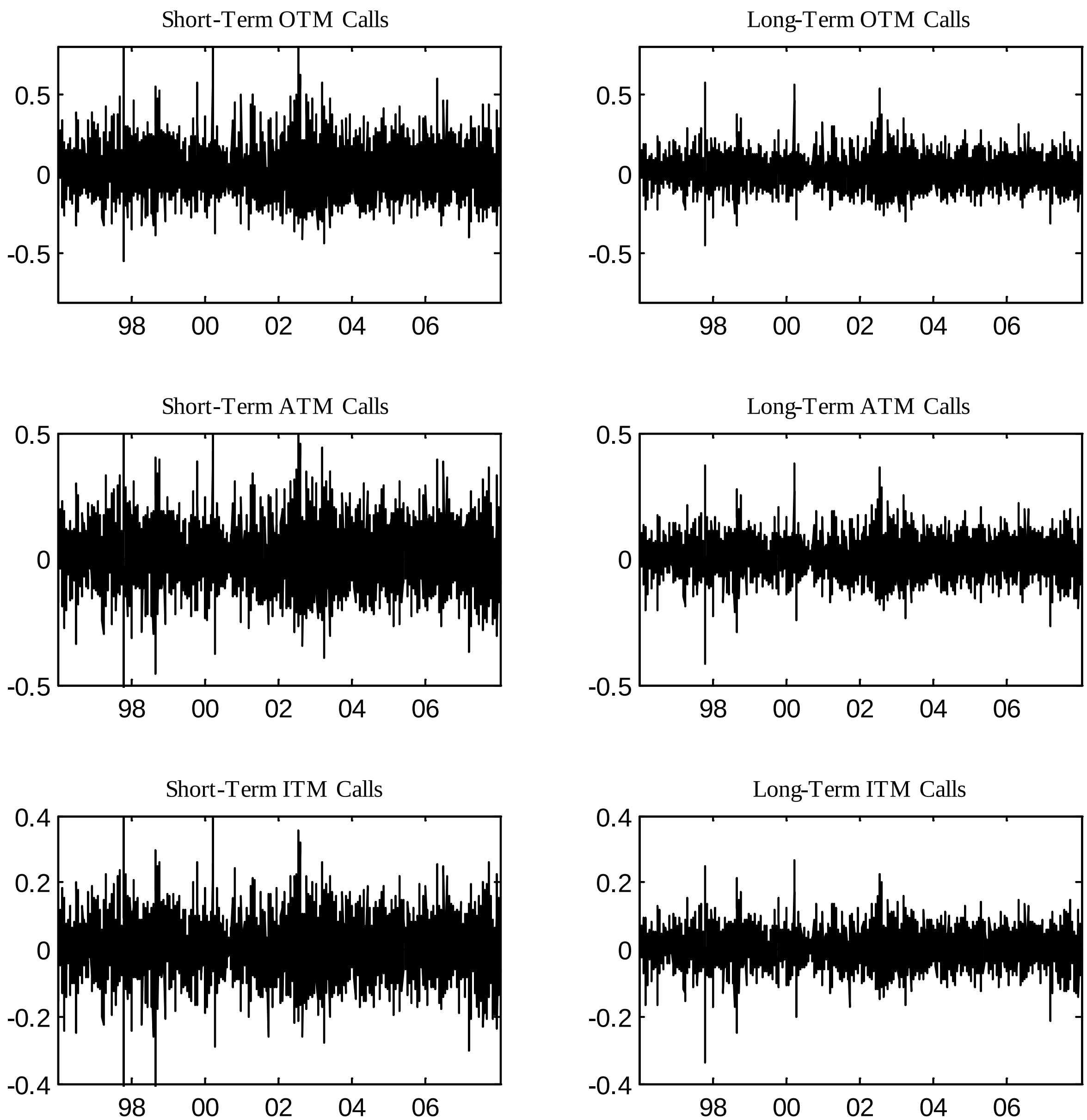

Figure 1B
Daily Put Option Returns

We plot daily returns on equally-weighted portfolios of put options. Option returns are computed from closing bid-ask price midpoints. For put options, OTM (out-of-the-money) corresponds to $-0.375 < \Delta \leq -0.125$, ATM (at-the-money) corresponds to $-0.625 < \Delta \leq -0.375$, and ITM (in-the-money) corresponds to $-0.875 < \Delta < -0.625$. Short-term options have maturities between 20 and 70 days, whereas long-term options have maturities between 71 and 180 days. The option data are from Ivy DB OptionMetrics. The sample includes the S&P 500 constituents as of December 31, 2007 for which options trade throughout the entire sample period, which is from January 1996 through December 2007.

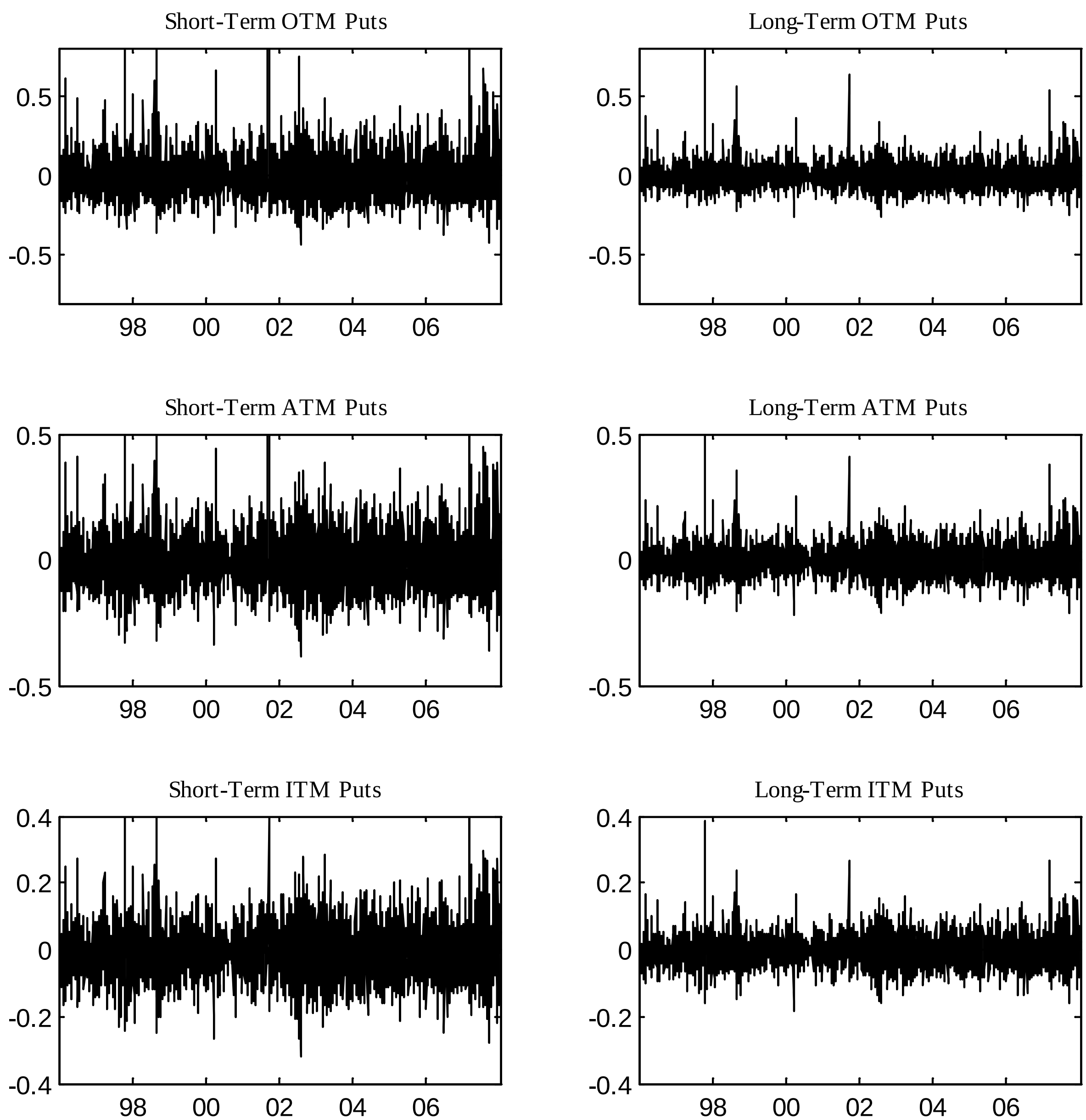

Figure 2A
Aggregate Illiquidity for Call Options

We plot aggregate daily illiquidity measures for call options. The illiquidity measure is based on the average relative bid-ask spread, where ask and bid are end-of-day closing quoted ask and bid prices available from Ivy DB OptionMetrics. The sample includes the S&P 500 constituents as of December 31, 2007 for which options trade throughout the entire sample period, which is from January 1996 through December 2007.

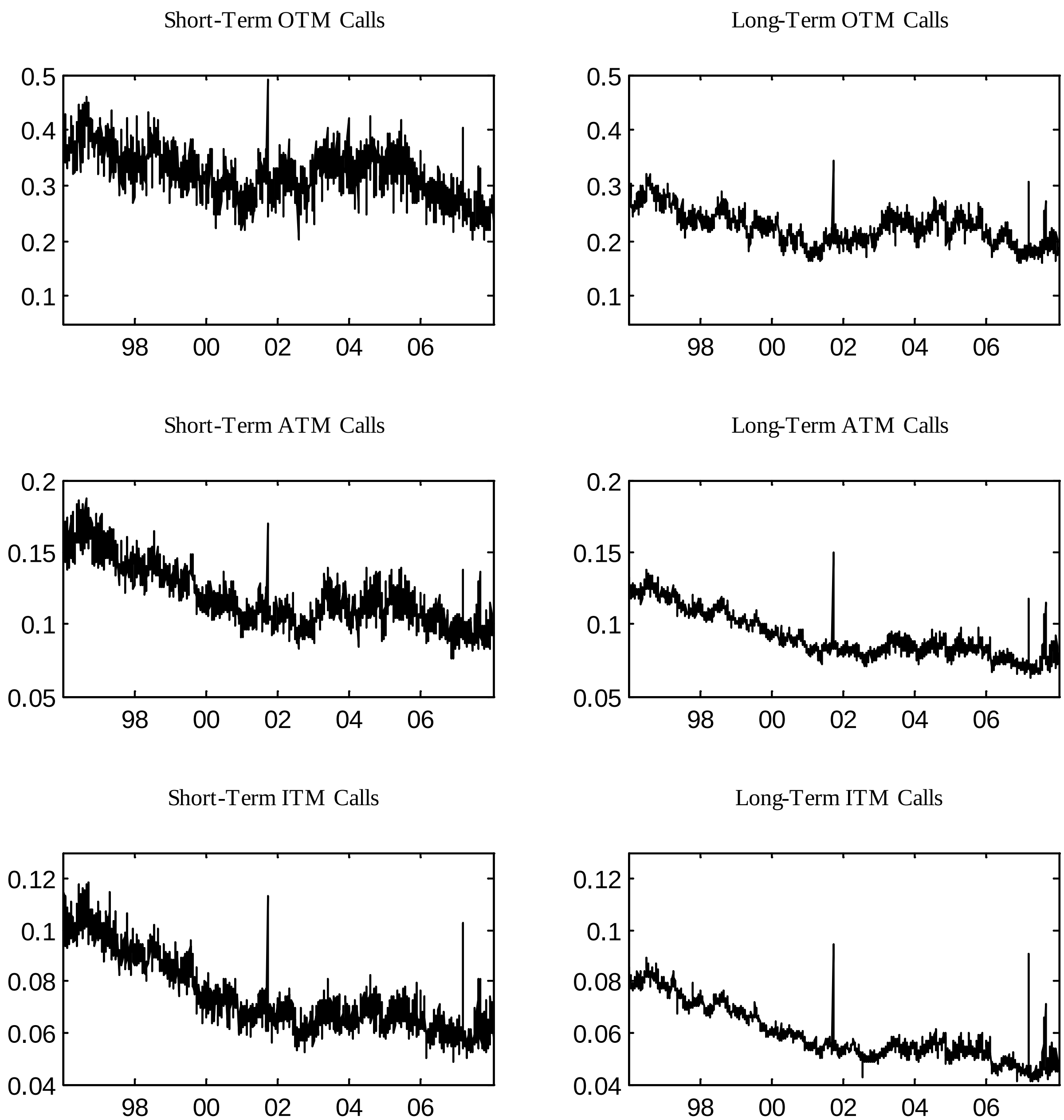

Figure 2B
Aggregate Illiquidity for Put Options

We plot aggregate daily illiquidity measures for put options. The illiquidity measure is based on the average relative bid-ask spread, where ask and bid are end of day closing quoted ask and bid prices available from Ivy DB OptionMetrics. The sample includes the S&P 500 constituents as of December 31, 2007 for which options trade throughout the entire sample period, which is from January 1996 through December 2007.

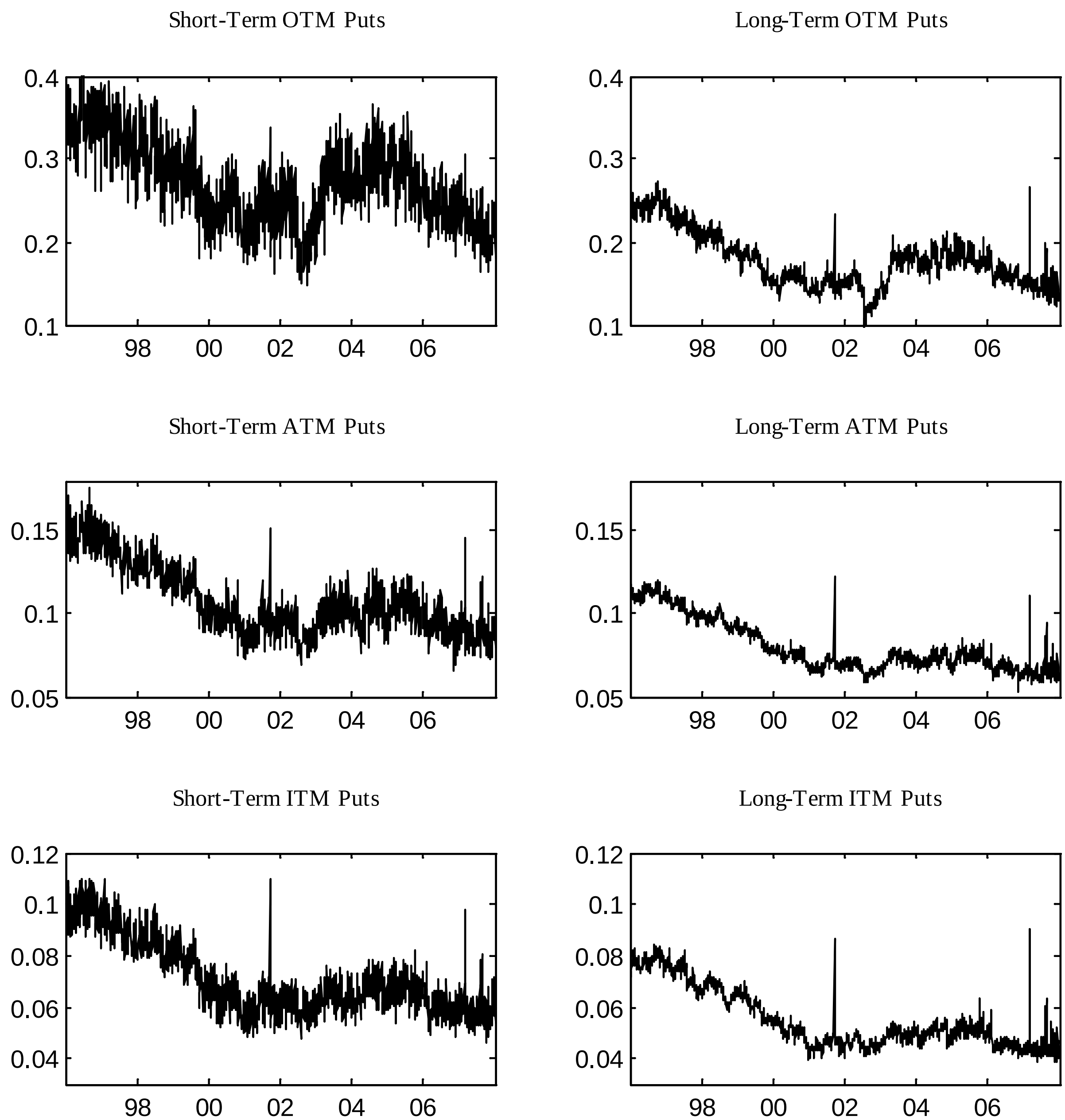

Figure 3
Aggregate Stock Illiquidity, S&P 500 Index, and VIX

We plot the aggregate stock illiquidity measure, the level of 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 1996 through December 2007.

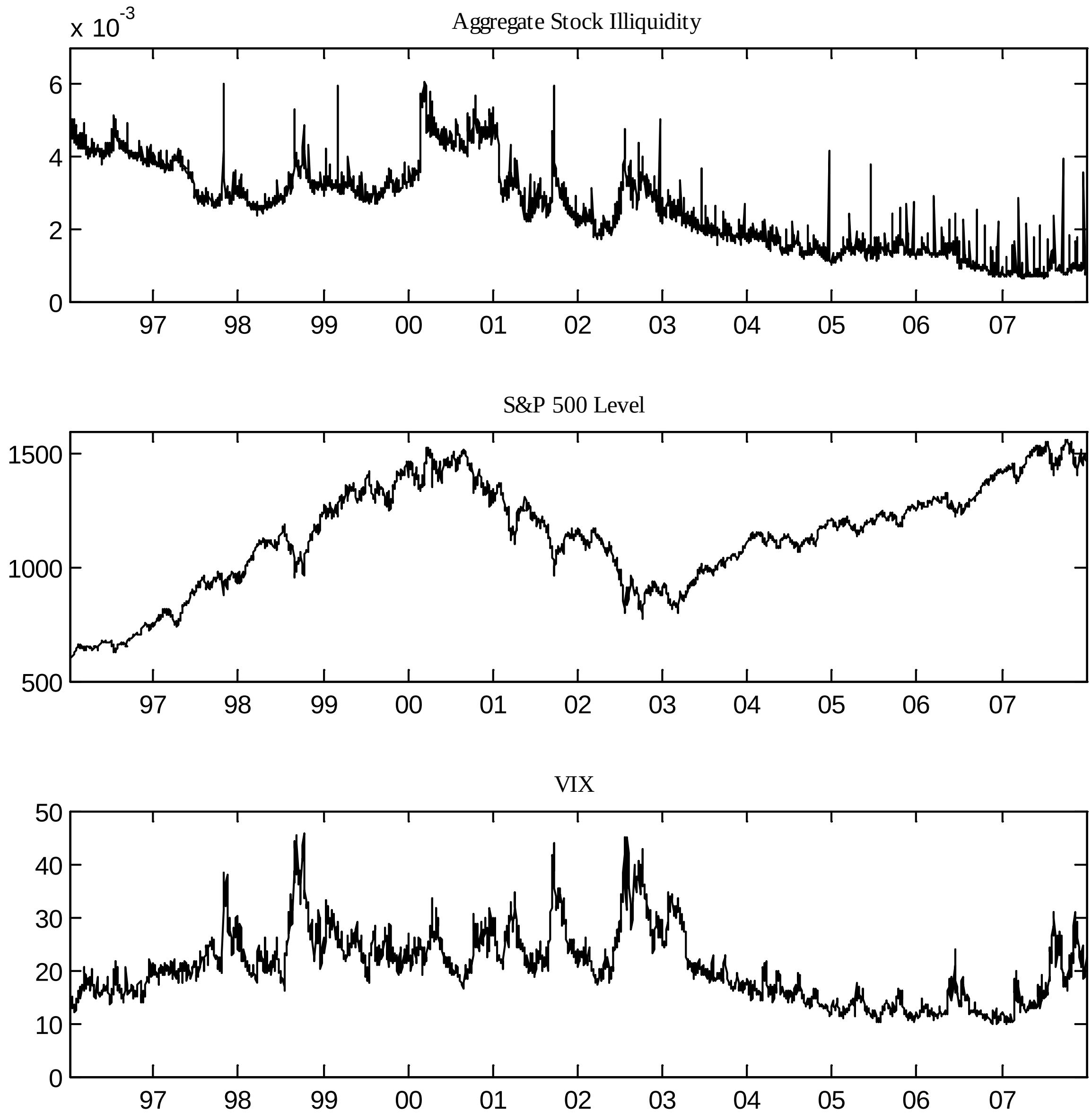

Table 1
Descriptive Statistics

We provide descriptive statistics for daily and weekly option 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 percentages), the standard deviation, the skewness, the kurtosis, the first-order autocorrelation of returns $\rho(1)$, and the first-order autocorrelation of absolute value of returns, $\rho^{abs}(1)$. 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. 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. Short-term options have maturity between 20 and 70 days, whereas long-term options have maturity between 71 and 180 days. The option data are from Ivy DB OptionMetrics. The sample includes the S&P 500 constituents as of December 31, 2007 for which options trade throughout the entire sample period, which is from January 1996 through December 2007.

	Short-term			Long-term		
	OTM	ATM	ITM	OTM	ATM	ITM
Daily Call Returns						
Mean	1.740	0.496	0.173	0.864	0.414	0.258
Std	0.361	0.256	0.177	0.217	0.157	0.110
Skew	2.941	1.347	0.742	1.940	1.107	0.667
Kurt	34.621	10.487	8.044	22.097	12.518	12.997
$\rho(1)$	-0.009	-0.005	-0.011	-0.013	-0.009	-0.009
$\rho^{abs}(1)$	0.061	0.065	0.082	0.087	0.093	0.105
Avr. Nb. Firms	221	213	236	262	291	300
Daily Put Returns						
Mean	-0.137	-0.460	-0.643	-0.138	-0.199	-0.229
Std	0.313	0.227	0.166	0.175	0.129	0.098
Skew	4.039	1.466	0.645	3.555	1.411	0.748
Kurt	74.910	17.852	9.315	86.911	22.639	14.844
$\rho(1)$	-0.001	-0.002	-0.010	0.001	0.000	-0.002
$\rho^{abs}(1)$	0.065	0.065	0.073	0.086	0.087	0.087
Avr. Nb. Firms	232	199	194	301	274	227
Weekly Call Returns						
Mean	10.020	2.572	0.172	4.287	1.975	1.148
Std	0.887	0.581	0.380	0.497	0.344	0.238
Skew	3.213	1.616	0.803	2.257	1.248	0.658
Kurt	22.379	8.766	5.273	16.497	8.249	5.537
$\rho(1)$	0.003	-0.008	-0.022	-0.011	-0.025	-0.035
$\rho^{abs}(1)$	0.019	0.013	0.020	0.032	0.031	0.039
Avr. Nb. Firms	244	243	260	280	306	312
Weekly Put Returns						
Mean	-0.874	-3.585	-4.627	-1.072	-1.363	-1.572
Std	0.739	0.508	0.357	0.398	0.284	0.212
Skew	3.668	1.713	0.796	2.980	1.354	0.722
Kurt	31.715	10.998	5.584	31.259	10.487	6.780
$\rho(1)$	0.015	0.011	0.002	0.005	-0.006	0.003
$\rho^{abs}(1)$	0.034	0.023	0.014	0.052	0.039	0.041
Avr. Nb. Firms	252	229	220	311	290	245

Table 2
Illiquidity Measures

We present summary statistics for the illiquidity measures in percentages (in Panel A) and the correlations between the illiquidity measures for call and put options (in Panels B and C respectively). Stock illiquidity IL^S is estimated from TAQ (Trade and Quote) intra-day data as the dollar-volume weighted average of the effective relative spread for each day. The option illiquidity measure IL^O is based on the average relative bid-ask spread, where ask and bid are end-of-day closing quoted ask and bid prices available from Ivy DB OptionMetrics. For each firm and for each day, we compute the average of the relative bid-ask spreads 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, $\rho(1)$, of these averages. We report the cross-sectional averages of these statistics in Panel A. 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 option data are from Ivy DB OptionMetrics. The sample includes the S&P 500 constituents as of December 31, 2007 for which options trade throughout the entire sample period, which is from January 1996 through December 2007.

Panel A: Descriptive Statistics

	Options						Stocks
	Short-term			Long-term			
	OTM	ATM	ITM	OTM	ATM	ITM	
IL_t^O for call options							IL_t^S
Mean	34.02	12.97	7.86	22.67	9.48	6.05	0.26
Min	3.89	2.18	1.56	2.74	1.78	1.23	0.03
Max	123.40	48.33	30.85	91.45	35.35	22.54	3.85
Std	19.10	6.10	3.32	12.25	3.96	2.33	0.21
$\rho(1)$	0.61	0.65	0.69	0.70	0.69	0.76	0.58
IL_t^O for put options							
Mean	29.21	11.72	7.46	18.12	8.23	5.52	
Min	3.62	2.07	1.54	2.55	1.59	1.18	
Max	115.51	45.09	29.03	76.15	31.53	20.93	
Std	16.78	5.52	3.12	9.60	3.44	2.23	
$\rho(1)$	0.67	0.69	0.68	0.77	0.74	0.75	

Panel B: Correlation Matrix for Call Options

		IL_t^O Short-term			IL_t^O Long-term		
		OTM	ATM	ITM	OTM	ATM	ITM
IL_t^O	ATM	0.66					
Short-term	ITM	0.58	0.65				
IL_t^O	OTM	0.58	0.62	0.60			
Long-term	ATM	0.59	0.67	0.67	0.67		
	ITM	0.64	0.70	0.74	0.67	0.74	
IL_t^S		0.24	0.25	0.26	0.30	0.26	0.29

Panel C: Correlation Matrix for Put Options

		IL_t^O Short-term			IL_t^O Long-term		
		OTM	ATM	ITM	OTM	ATM	ITM
IL_t^O	ATM	0.69					
Short-term	ITM	0.60	0.64				
IL_t^O	OTM	0.69	0.69	0.64			
Long-term	ATM	0.65	0.69	0.67	0.72		
	ITM	0.64	0.67	0.70	0.70	0.75	
IL_t^S		0.23	0.21	0.20	0.24	0.22	0.19

Table 3
Descriptive Statistics for Volume, Open Interest and Amihud's Illiquidity Measure

We present summary statistics for option volume, open interest and Amihud's Illiquidity measure for call options (Panel A) and put options (Panel B). For each firm and each day, we compute the average volume and open interest for all available options in a given category, and then we take the mean, the minimum, the maximum, the standard deviation and the first-order autocorrelation $\rho(1)$ of these averages. We compute Amihud's illiquidity measure on a weekly basis for each firm, and we take the mean, the minimum, the maximum, the standard deviation and the first-order autocorrelation $\rho(1)$ of these weekly measures. We report the cross-sectional averages of these statistics. The sample includes the S&P 500 constituents as of December 31, 2007 for which options trade throughout the entire sample period, which is from January 1996 through December 2007.

Panel A: Call Options

	Short-term			Long-term		
	OTM	ATM	ITM	OTM	ATM	ITM
Amihud's Illiquidity Measure						
Mean	3.527	0.736	0.309	1.815	0.352	0.165
Min	0.004	0.001	0.000	0.002	0.001	0.000
Max	105.010	22.586	8.231	49.345	8.256	3.583
Std	8.729	1.846	0.727	4.072	0.691	0.329
$\rho(1)$	0.077	0.126	0.107	0.117	0.156	0.118
Volume						
Mean	198	271	108	88	114	34
Min	0	0	0	0	0	0
Max	10222	11246	8385	7004	8824	5261
Std	516	633	364	294	365	171
$\rho(1)$	0.20	0.24	0.17	0.14	0.15	0.12
Open Interest						
Mean	2295	2418	1743	2493	2587	1483
Min	2	3	1	2	12	3
Max	31024	30416	27355	27964	29252	22486
Std	3586	3731	3164	3443	3541	2497
$\rho(1)$	0.84	0.85	0.86	0.89	0.91	0.89

Panel B: Put Options

	Short-term			Long-term		
	OTM	ATM	ITM	OTM	ATM	ITM
Amihud's Illiquidity Measure						
Mean	2.492	0.644	0.313	1.117	0.296	0.152
Min	0.003	0.001	0.001	0.002	0.000	0.000
Max	76.468	18.916	7.684	28.185	6.808	2.641
Std	6.421	1.666	0.761	2.448	0.623	0.304
$\rho(1)$	0.072	0.100	0.084	0.100	0.112	0.087
Volume						
Mean	141	151	59	56	54	16
Min	0	0	0	0	0	0
Max	9639	8598	5750	6309	6064	3045
Std	433	441	242	233	231	99
$\rho(1)$	0.19	0.19	0.14	0.12	0.13	0.10
Open Interest						
Mean	1689	1537	1075	1809	1580	940
Min	2	1	1	7	2	1
Max	27047	25244	20654	23298	22106	16473
Std	2835	2725	2179	2757	2567	1811
$\rho(1)$	0.86	0.84	0.83	0.91	0.91	0.87

Table 4
Fama-MacBeth Regressions for Daily Adjusted Option Returns

We report the results of cross-sectional Fama-MacBeth regressions for daily adjusted call and put option returns ($\widetilde{R}^{O}$), i.e. the residuals plus the intercept from the regression of option returns on stock returns, lagged stock returns and squared stock returns. We include the lagged values of the following regressors: option illiquidity IL^{O}, the illiquidity of the underlying asset IL^{S}, the conditional volatility, which is estimated using a GARCH(1,1) model, the systematic risk proportion b, which corresponds to the square root of the R^2 from the regression of stock returns on Fama-French and momentum factors, and the logarithm of size and firm leverage. The option illiquidity measure IL^{O} is based on the average relative bid-ask spread, where ask and bid are end-of-day closing quoted ask and bid prices available from Ivy DB OptionMetrics. Stock illiquidity is obtained as the dollar-volume average of the effective relative spreads from TAQ. The sample includes the S&P 500 constituents as of December 31, 2007 for which options trade throughout the entire sample period, which is from January 1996 through December 2007. The symbols *, † and ‡ denote, respectively, significance at the 10%, 5% and 1% levels using Fama-MacBeth t-statistics with Newey-West correction for serial correlation, using 22 lags.

	Panel A: Call Options						**Panel B: Put Options**					
	Short-Term			Long-Term			Short-Term			Long-Term		
	OTM	ATM	ITM	OTM	ATM	ITM	OTM	ATM	ITM	OTM	ATM	ITM
IL^{O}_{t-1}	0.062‡	0.038‡	0.046‡	0.027‡	0.019‡	0.026‡	0.045‡	0.025‡	0.034‡	0.020‡	0.014‡	0.020‡
Adj R^2	0.012	0.013	0.018	0.010	0.010	0.013	0.011	0.013	0.015	0.011	0.012	0.014
# Obs in CS (avr.)	220	213	236	262	290	300	232	199	194	301	274	227
# CS regressions	2984	2984	2984	2982	2982	2982	2984	2983	2984	2982	2982	2982
IL^{S}_{t-1}	-4.071‡	-2.149‡	-0.761‡	-1.216‡	-0.721‡	-0.280‡	-2.913‡	-2.109‡	-0.249	-0.982‡	-0.589‡	-0.169†
Adj R^2	0.009	0.010	0.009	0.008	0.010	0.010	0.010	0.013	0.014	0.009	0.012	0.014
# Obs in CS (avr.)	220	213	236	261	290	299	231	199	193	300	273	227
# CS regressions	2984	2984	2984	2982	2982	2982	2984	2983	2984	2982	2982	2982
IL^{O}_{t-1}	0.062‡	0.035‡	0.045‡	0.030‡	0.022‡	0.033‡	0.048‡	0.023‡	0.027‡	0.023‡	0.012‡	0.021‡
IL^{S}_{t-1}	-2.077‡	-0.873‡	-0.428‡	-0.598‡	-0.223‡	-0.205‡	-1.399‡	-1.109‡	-0.064	-0.416‡	-0.238‡	-0.084
$\tilde{R}^{O}_{t-1}$	-0.032‡	-0.015‡	-0.010‡	-0.031‡	-0.014‡	-0.011‡	-0.030‡	-0.013‡	-0.011‡	-0.027‡	-0.014‡	-0.012‡
σ_{t-1}	-0.112‡	-0.049‡	-0.014‡	-0.041‡	-0.018‡	-0.005‡	-0.064‡	-0.031‡	-0.007‡	-0.019‡	-0.011‡	-0.003†
b_{t-1}	-0.002	0.000	0.001	0.000	0.000	0.000	-0.003*	-0.004‡	-0.001	-0.002	-0.001	0.000
ln $(size_{t-1})$	0.004‡	0.002‡	0.001‡	0.001‡	0.001‡	0.001‡	0.004‡	0.002‡	0.000‡	0.001‡	0.000‡	0.000‡
lev_{t-1}	-0.001	0.000	-0.001†	-0.001	0.000	0.002	-0.002†	-0.002†	0.000	-0.001	0.000	0.000
Adj R^2	0.060	0.075	0.080	0.057	0.071	0.080	0.065	0.087	0.094	0.067	0.088	0.098
# Obs in CS (avr.)	189	179	207	240	270	283	204	166	163	285	252	206
# CS regressions	2968	2968	2968	2965	2965	2965	2968	2965	2965	2965	2965	2965

Table 5
Fama-MacBeth Regressions for Weekly Adjusted Option Returns

We report the results of cross-sectional Fama-MacBeth regressions for weekly adjusted call and put option returns ($\widetilde{R}^{O}$), i.e. the residuals plus the intercept from the regression of option returns on stock returns, lagged stock returns and squared stock returns. We include the lagged values of the following regressors: option illiquidity IL^{O}, computed from relative daily quoted bid-ask spreads, IL^{S} , the dollar-volume weighted average of daily stock illiquidity for the previous week, the conditional volatility of returns, computed as the square root of the sum of squared daily returns for the previous week, *b*, the average of daily systematic risk proportion for the previous week, the logarithm of the firm size and the firm leverage. We use the size observed on the last day of the previous week, and the leverage from the previous quarter. The sample includes the S&P 500 constituents as of December 31, 2007 for which options trade throughout the entire sample period, which is from January 1996 through December 2007. The symbols *, † and ‡ denote, respectively, significance at the 10%, 5% and 1% levels using Fama-MacBeth t-statistics with Newey-West correction for serial correlation, using 8 lags.

	Panel A: Call Options						**Panel B: Put Options**					
			Short-Term			Long-Term			Short-Term			Long-Term
	OTM	ATM	ITM	OTM	ATM	ITM	OTM	ATM	ITM	OTM	ATM	ITM
IL^{O}_{t-1}	0.211‡	0.101‡	-0.004	0.076‡	0.059‡	0.048‡	0.159‡	0.012	-0.081‡	0.059‡	0.000	-0.023
Adj R^2	0.015	0.009	0.015	0.008	0.008	0.012	0.012	0.010	0.014	0.008	0.011	0.013
# Obs in CS (avr.)	244	243	260	279	305	311	251	229	220	311	290	244
# CS regressions	622	622	622	622	622	622	622	622	622	622	622	622
IL^{S}_{t-1}	-23.676‡	-11.526‡	-6.029‡	-9.116‡	-5.307‡	-2.422‡	-17.129‡	-9.846‡	-2.625‡	-5.925‡	-3.371‡	-0.895*
Adj R^2	0.010	0.011	0.011	0.012	0.012	0.013	0.011	0.012	0.013	0.012	0.014	0.018
# Obs in CS (avr.)	244	242	259	279	305	311	251	228	220	310	290	244
# CS regressions	622	622	622	622	622	622	622	622	622	622	622	622
IL^{O}_{t-1}	0.262‡	0.193‡	0.073‡	0.122‡	0.132‡	0.105‡	0.192‡	0.055*	-0.100‡	0.091‡	0.041*	-0.032
IL^{S}_{t-1}	-20.355‡	-7.431‡	-3.664‡	-9.239‡	-3.888‡	-1.872‡	-14.206‡	-5.626‡	-0.151	-4.969‡	-2.169‡	-0.173
$\tilde{R}^{O}_{t-1}$	0.003	0.001	-0.007‡	-0.011‡	-0.006‡	-0.007‡	-0.002	-0.001	-0.004†	-0.008†	-0.009‡	-0.008‡
σ_{t-1}	-0.213‡	-0.102‡	-0.039‡	-0.051‡	-0.028‡	-0.017‡	-0.078‡	-0.047‡	-0.025‡	-0.008	-0.014‡	-0.011‡
b_{t-1}	-0.015	-0.004	-0.004	-0.012	-0.005	-0.001	-0.042‡	-0.034‡	-0.010*	-0.015†	-0.008†	-0.001
ln $(size_{t-1})$	0.024‡	0.013‡	0.005‡	0.008‡	0.005‡	0.002‡	0.019‡	0.009‡	0.002‡	0.007‡	0.003‡	0.001*
lev_{t-1}	0.049‡	0.025‡	0.005†	0.021‡	0.006‡	0.002	0.028‡	0.014‡	0.011‡	0.007†	0.003*	0.002
Adj R^2	0.058	0.050	0.054	0.049	0.054	0.060	0.055	0.057	0.060	0.052	0.066	0.071
# Obs in CS (avr.)	200	199	222	252	284	294	215	184	176	293	266	217
# CS regressions	621	621	621	621	621	621	621	621	621	621	621	621

Table 6
Daily Portfolio Strategies

We show portfolio sorting results for call options (Panel A) and put options (Panel B). Each day, we sort the firms into deciles based on their lagged option illiquidity IL^O. For each decile, we report (in percentages) the time-series average of raw option returns R^O, the net (after transaction costs) option returns, R^O_{net}-Long for the long position and R^O_{net}-Short for the short position, stock returns R^S, the option quoted relative bid-ask spread IL^O, the effective relative bid-ask spread IL^S for the stock, and size in millions of dollars. The sample includes the S&P 500 constituents as of December 31, 2007 for which options trade throughout the entire sample period, which is from January 1996 through December 2007.

Panel A: Call Options

		Short-Term					Long-Term				
Decile		$2. Low$	4	6	8	$10. High$	$2. Low$	4	6	8	$10. High$
OTM	R^O_t	0.17	0.93	0.71	1.49	5.72	0.46	0.73	1.10	0.87	1.94
	R^O_{net}-Long	-12.67	-17.21	-23.77	-31.47	-51.34	-9.25	-12.45	-16.24	-23.01	-42.02
	R^O_{net}-Short	-15.01	-23.50	-33.88	-52.89	-165.82	-11.27	-16.12	-22.55	-33.28	-96.73
	R^S_t	0.07	0.08	0.07	0.09	0.21	0.05	0.07	0.11	0.06	0.10
	IL^O_t	15.87	21.92	30.92	42.55	77.80	11.01	14.62	19.48	28.00	57.50
	IL^S_t	0.22	0.23	0.26	0.28	0.35	0.22	0.24	0.26	0.30	0.39
	$size_t$	33189	23496	19543	13868	7880	38163	26299	18749	13073	7000
ATM	R^O_t	0.06	0.26	0.43	0.54	1.43	0.34	0.41	0.45	0.46	0.84
	R^O_{net}-Long	-6.32	-8.02	-9.92	-12.76	-22.42	-5.01	-6.34	-7.85	-10.02	-16.34
	R^O_{net}-Short	-6.88	-9.33	-12.08	-16.03	-34.53	-6.00	-7.68	-9.57	-12.24	-22.29
	R^S_t	0.07	0.05	0.07	0.07	0.09	0.05	0.07	0.07	0.06	0.08
	IL^O_t	7.33	9.07	11.24	14.63	27.70	5.87	7.12	8.70	11.01	18.51
	IL^S_t	0.22	0.23	0.24	0.27	0.37	0.22	0.24	0.25	0.29	0.38
	$size_t$	38866	26397	19811	14445	7202	39591	26969	18087	12266	6447
ITM	R^O_t	0.11	0.13	-0.08	0.39	0.47	0.24	0.19	0.16	0.28	0.45
	R^O_{net}-Long	-4.29	-5.45	-6.81	-8.21	-13.39	-3.28	-4.36	-5.42	-6.56	-10.60
	R^O_{net}-Short	-4.71	-6.05	-7.17	-9.87	-16.95	-3.90	-4.97	-6.09	-7.65	-13.05
	R^S_t	0.05	0.03	0.02	0.06	0.03	0.06	0.04	0.02	0.06	0.06
	IL^O_t	4.82	5.88	7.03	9.00	14.79	3.75	4.74	5.77	7.01	11.46
	IL^S_t	0.21	0.23	0.25	0.28	0.35	0.21	0.24	0.26	0.29	0.39
	$size_t$	41649	29545	21687	14415	7302	40327	27161	19072	12798	5874

Table 6 (continued)
Daily Portfolio Strategies

Panel B: Put Options

		Short-Term					Long-Term				
Decile		$2. Low$	4	6	8	$10. High$	$2. Low$	4	6	8	$10. High$
OTM	R_t^O	-0.51	-0.30	-0.15	-0.13	3.02	0.15	0.05	0.06	-0.01	0.47
	R_{net}^O-Long	-11.70	-15.77	-20.68	-28.39	-47.97	-8.14	-10.90	-14.06	-18.89	-35.23
	R_{net}^O-Short	-12.24	-18.38	-26.44	-40.75	-127.51	-9.27	-12.55	-16.83	-23.94	-63.84
	R_t^S	0.06	0.05	0.03	0.05	-0.06	0.03	0.04	0.05	0.05	0.05
	IL_t^O	13.42	18.46	24.93	35.78	69.90	9.16	11.99	15.62	21.49	45.29
	IL_t^S	0.22	0.23	0.25	0.28	0.33	0.22	0.24	0.25	0.28	0.36
	$size_t$	36242	28023	21599	15759	8667	36849	27907	20584	13984	7312
ATM	R_t^O	-0.50	-0.41	-0.50	0.01	-0.50	0.02	-0.11	-0.11	-0.12	-0.05
	R_{net}^O-Long	-6.31	-7.88	-9.88	-11.99	-21.71	-4.65	-6.02	-7.32	-9.31	-14.94
	R_{net}^O-Short	-5.68	-7.72	-9.94	-13.76	-27.77	-4.93	-6.20	-7.71	-10.08	-17.85
	R_t^S	0.05	0.06	0.06	0.02	0.08	0.03	0.05	0.06	0.06	0.06
	IL_t^O	6.57	8.14	10.24	13.04	25.08	5.06	6.24	7.55	9.67	15.99
	IL_t^S	0.22	0.23	0.25	0.27	0.36	0.23	0.24	0.26	0.28	0.36
	$size_t$	39024	30491	22602	16936	8830	38333	30040	21287	14210	7229
ITM	R_t^O	-0.30	-0.51	-0.27	-0.43	-0.60	-0.06	-0.14	-0.17	-0.19	-0.23
	R_{net}^O-Long	-4.49	-5.83	-6.69	-8.46	-13.68	-3.24	-4.33	-5.35	-6.55	-10.46
	R_{net}^O-Short	-4.08	-5.14	-6.62	-8.37	-14.77	-3.23	-4.26	-5.31	-6.62	-11.32
	R_t^S	0.06	0.11	0.07	0.10	0.13	0.05	0.06	0.08	0.08	0.11
	IL_t^O	4.60	5.67	6.71	8.44	14.08	3.38	4.39	5.36	6.54	10.69
	IL_t^S	0.23	0.24	0.26	0.28	0.35	0.23	0.25	0.27	0.30	0.38
	$size_t$	40702	32555	25423	17446	8847	40411	32022	23561	16917	7070

Table 7
Weekly Portfolio Strategies

We show portfolio sorting results for calls (Panel A) and puts (Panel B). Each week, we sort the firms into deciles based on their lagged illiquidity IL^O. For each decile, we report (in percentages) the time-series average of raw option returns R^O, the net (after transaction costs) option returns (R^O_{net}-Long for the long position and R^O_{net}-Short for the short position), stock returns R^S, the option quoted relative bid-ask spread IL^O, the stock effective relative bid-ask spreads IL^S, and size, in millions of dollars. The sample includes the S&P 500 constituents as of December 31, 2007 for which options trade throughout the entire sample period, which is from January 1996 through December 2007.

Panel A: Call Options

		Short-Term					Long-Term				
Decile		$2. Low$	4	6	8	$10. High$	$2. Low$	4	6	8	$10. High$
OTM	R^O_t	3.02	4.85	6.80	10.62	25.97	3.09	3.12	3.76	4.92	7.82
	R^O_{net}-Long	-10.20	-13.52	-18.16	-23.25	-35.59	-6.82	-10.37	-13.88	-19.56	-37.04
	R^0_{net}-Short	-18.24	-27.61	-40.37	-62.64	-195.71	-14.12	-18.85	-25.54	-38.03	-104.13
	R^S_t	0.25	0.41	0.56	0.69	1.28	0.30	0.32	0.37	0.47	0.61
	IL^0_t	22.53	29.01	38.38	49.78	75.22	12.47	16.77	22.05	31.39	59.16
	IL^S_t	0.21	0.23	0.25	0.28	0.34	0.21	0.23	0.26	0.30	0.39
	$size_t$	35487	24695	20669	15097	8559	39044	26609	19270	13631	7386
ATM	R^O_t	2.10	1.98	2.45	1.92	3.22	1.61	2.22	1.66	2.48	2.57
	R^O_{net}-Long	-4.49	-6.58	-8.31	-11.88	-21.36	-3.81	-4.64	-6.76	-8.22	-14.98
	R^O_{net}-Short	-9.14	-11.37	-14.56	-18.03	-37.57	-7.35	-9.62	-10.90	-14.53	-24.51
	R^S_t	0.32	0.33	0.35	0.34	0.46	0.32	0.38	0.30	0.39	0.40
	IL^0_t	9.28	11.47	14.44	18.99	35.18	6.23	7.51	9.24	11.65	20.10
	IL^S_t	0.22	0.23	0.24	0.27	0.37	0.22	0.23	0.25	0.28	0.39
	$size_t$	39486	27685	20045	14555	7511	40679	27471	18667	12519	6614
ITM	R^O_t	0.63	0.79	0.20	0.18	0.08	0.95	1.31	1.17	1.43	1.69
	R^O_{net}-Long	-3.82	-4.85	-6.60	-8.48	-13.96	-2.62	-3.30	-4.47	-5.49	-9.45
	R^0_{net}-Short	-5.29	-6.79	-7.53	-9.73	-16.80	-4.65	-6.16	-7.17	-8.89	-14.41
	R^S_t	0.25	0.28	0.21	0.25	0.29	0.29	0.35	0.33	0.37	0.42
	IL^0_t	5.29	6.45	7.78	10.12	17.37	3.89	4.88	5.91	7.17	11.63
	IL^S_t	0.21	0.23	0.25	0.28	0.36	0.21	0.23	0.25	0.29	0.39
	$size_t$	41875	29476	21757	14436	7531	41879	27644	19737	12853	5928

Table 7 (continued)
Weekly Portfolio Strategies

Panel B: Put Options

		Short-Term					Long-Term				
Decile		$2.Low$	4	6	8	$10.High$	$2.Low$	4	6	8	$10.High$
OTM	R_t^O	-3.81	-3.29	-2.08	-1.64	7.87	-0.77	-1.34	-1.22	-0.98	-0.40
	R_{net}^O-Long	-14.94	-18.66	-22.48	-29.51	-43.02	-9.12	-12.33	-15.38	-19.98	-36.19
	R_{net}^0-Short	-8.84	-15.23	-24.25	-38.43	-129.43	-8.43	-11.21	-15.62	-23.16	-64.01
	R_t^S	0.34	0.31	0.17	0.14	-0.34	0.28	0.32	0.29	0.28	0.28
	IL_t^0	19.03	25.58	33.23	45.79	74.32	10.25	13.47	17.58	24.21	50.16
	IL_t^S	0.21	0.23	0.24	0.28	0.33	0.22	0.23	0.25	0.28	0.36
	$size_t$	36413	28377	22343	16838	9556	37853	28216	20604	14338	7768
ATM	R_t^O	-2.93	-3.66	-3.20	-3.59	-5.11	-0.92	-1.38	-1.40	-1.25	-1.99
	R_{net}^O-Long	-8.77	-11.10	-12.58	-15.63	-26.20	-5.61	-7.29	-8.61	-10.44	-16.83
	R_{net}^0-Short	-3.28	-4.44	-7.26	-10.26	-23.17	-4.00	-4.92	-6.41	-8.95	-15.95
	R_t^S	0.32	0.38	0.31	0.29	0.37	0.26	0.35	0.35	0.32	0.37
	IL_t^0	8.18	10.13	13.07	17.37	33.38	5.39	6.59	8.01	10.27	17.42
	IL_t^S	0.22	0.23	0.24	0.27	0.35	0.22	0.23	0.25	0.28	0.36
	$size_t$	39778	31261	22381	16994	8937	39042	29917	21032	14001	7340
ITM	R_t^O	-3.19	-4.28	-4.09	-4.66	-5.75	-1.20	-1.47	-1.64	-1.60	-1.96
	R_{net}^O-Long	-7.35	-9.49	-10.36	-12.54	-18.60	-4.40	-5.66	-6.80	-7.90	-12.15
	R_{net}^0-Short	-1.16	-1.25	-2.64	-3.98	-9.46	-2.12	-2.92	-3.82	-5.17	-9.63
	R_t^S	0.41	0.55	0.46	0.47	0.53	0.35	0.40	0.39	0.41	0.44
	IL_t^0	5.19	6.35	7.59	9.80	17.50	3.58	4.58	5.57	6.74	11.11
	IL_t^S	0.22	0.24	0.25	0.27	0.35	0.23	0.24	0.26	0.29	0.38
	$size_t$	42684	33442	25285	17437	8929	41827	33106	23666	16708	7021

Table 8
Fama-MacBeth Regressions for the Level of Implied Volatility

For each month and for each category, we run the following regression using all observed options within the month. The regression is run separately for call and put options

$$iv_{i,t}(\chi_k, T_k) = \kappa_{i,t} + \Theta_{i,t}(\chi_k - \bar{\chi}_k) + \eta_{i,t}(T_k - \bar{T}_k) + \varepsilon_{i,t}^k, \quad k = 1,2,\ldots.K$$

where $iv_{i,t}(\chi_k, T_k)$ is the implied volatility for an option with moneyness χ_k and maturity T_k. The subscripts *t*, *i* and *k* correspond to month *t*, firm *i* and contract *k*, respectively. *K* is the number of contracts available for a given month and category. We consider only months for which *K* is larger than ten. For each firm *i*, we obtain a monthly time series for $\kappa_{i,t}$ which corresponds to the estimated level of implied volatility. Then, for each month *t*, we run the following regression

$$\tilde{\kappa}_{i,t} = a_{0,t} + a_{1,t}IL_{i,t}^O + a_{2,t}IL_{i,t}^S + a_{3,t}R_{i,t}^S + a_{4,t}b_{i,t} + a_{5,t}\ln(size_{i,t}) + a_{6,t}lev_{i,t} + \varepsilon_{i,t}, \quad i = 1,2,\ldots I$$

where $\tilde{\kappa}_{i,t}$ is the residual plus the intercept from the cross-sectional regression of $\kappa_{i,t}$ on the volatility σ_t. IL_t^O is the monthly average of daily option illiquidity for the K contracts used to run the first regression, and IL_t^S is the dollar-volume weighted average of daily stock illiquidity. R_t^S is the monthly stock return. The option illiquidity is the relative bid-ask spread and the stock illiquidity is the effective bid-ask spread estimated from TAQ data. b_t is the systematic risk proportion, which corresponds to the square root of the R^2 from the regression of stock returns on Fama-French and momentum factors. We use the monthly average of the daily systematic risk proportion. $\ln(size_t)$ and lev_t are respectively the logarithm of firm size and the firm leverage. We use the firm size observed on the last day of the month and leverage from the last available quarter. The sample includes the S&P 500 constituents as of December 31, 2007 for which options trade throughout the entire sample period, which is from January 1996 through December 2007. The symbols *, † and ‡ denote, respectively, significance at the 10%, 5% and 1% levels using Fama-MacBeth t-statistics with Newey-West correction for serial correlation, with 8 lags.

Panel A: Call Options

	Short-Term			Long-Term		
	OTM	ATM	ITM	OTM	ATM	ITM
IL_t^O	-0.102‡	-0.381‡	-0.803‡	-0.121‡	-0.547‡	-1.006‡
IL_t^S	13.418‡	11.651‡	13.956‡	11.880‡	11.490‡	13.174‡
R_t^S	-0.030‡	-0.025†	-0.040‡	-0.008	-0.018	-0.025*
b_t	-0.002	0.012	0.018*	-0.001	0.009	0.013
$\ln(size_t)$	-0.018‡	-0.019‡	-0.019‡	-0.015‡	-0.018‡	-0.017‡
lev_t	-0.012‡	-0.014‡	-0.007	-0.017‡	-0.013‡	-0.005
Adj R^2	0.191	0.195	0.190	0.170	0.190	0.186
# Obs in CS (avr.)	272	257	276	289	310	313
# CS regressions	144	144	144	144	144	144

Panel B: Put Options

	Short-Term			Long-Term		
	OTM	ATM	ITM	OTM	ATM	ITM
IL_t^O	-0.129‡	-0.417‡	-0.733‡	-0.204‡	-0.673‡	-0.958‡
IL_t^S	12.665‡	11.507‡	14.199‡	11.755‡	10.689‡	11.849‡
R_t^S	-0.017	-0.006	-0.008	-0.002	0.005	0.026†
b_t	0.020*	0.016†	0.012	0.009	0.012	0.007
$\ln(size_t)$	-0.018‡	-0.020‡	-0.021‡	-0.015‡	-0.019‡	-0.019‡
lev_t	-0.011*	-0.015‡	-0.009†	-0.007	-0.013‡	-0.016‡
Adj R^2	0.172	0.204	0.213	0.165	0.214	0.215
# Obs in CS (avr.)	274	241	234	314	296	248
# CS regressions	144	144	144	144	144	144

Table 9
Fama-MacBeth Regressions for the Moneyness-Slope of Implied Volatility

For each month and for each option category, we run the following regression using all observed options within the month. The regression is run separately for call and put options

$$iv_{i,t}(\chi_k, T_k) = \kappa_{i,t} + \theta_{i,t}\,(\chi_k - \bar{\chi}_k) + \eta_{i,t}\,(T_k - \bar{T}_k) + \varepsilon_{i,t}^k, \quad k = 1,2,\dots.K$$

where $iv_{i,t}(\chi_k, T_k)$ is the implied volatility for an option with moneyness χ_k and maturity T_k. The subscripts *t*, *i* and *k* correspond to month *t*, firm *i* and contract *k*, respectively. *K* is the number of contracts available for the considered month and category. We consider only months for which *K* is larger than ten. For each firm *i*, we obtain a monthly time series for $\theta_{i,t}$ which corresponds to the estimated moneyness-slope of implied volatility. Then, for each month *t*, we run the following regression

$$|\theta_{i,t}| = c_{0,t} + c_{1,t}IL_{i,t}^O + c_{2,t}IL_{i,t}^S + c_{3,t}R_{i,t}^S + c_{4,t}b_{i,t} + c_{5,t}\ln(size_{i,t}) + c_{6,t}lev_{i,t} + \varepsilon_{i,t}, \quad i = 1,2,\dots I$$

where IL_t^O is the average across the month of daily option illiquidity of the K contracts used to run the first regression, and IL_t^S is the dollar-volume weighted average of daily stock illiquidity. R_t^S is the monthly stock return. The option illiquidity is the relative bid-ask spread, and the stock illiquidity is the effective bid-ask spread estimated from TAQ data. b_t is the systematic risk proportion, which corresponds to the square root of the R^2 from the regression of stock returns on Fama-French and momentum factors. We take the monthly average of the daily systematic risk proportion. ln $(size_t)$ and lev_t are respectively the logarithm of firm size and the firm leverage. We use the firm size observed on the last day of the month and the leverage from the last available quarter. The sample includes the S&P 500 constituents as of December 31, 2007 for which options trade throughout the entire sample period, which is from January 1996 through December 2007. The symbols *, † and ‡ denote, respectively, significance at the 10%, 5% and 1% levels using Fama-MacBeth t-statistics with Newey-West correction for serial correlation, using 8 lags.

Panel A: Call Options

	Short-Term			Long-Term		
	OTM	ATM	ITM	OTM	ATM	ITM
IL_t^O	0.516‡	1.188‡	2.221‡	0.273‡	0.953‡	1.353‡
IL_t^S	26.359‡	20.333‡	32.015‡	-3.671†	-0.040	10.682‡
R_t^S	-0.033	-0.045	0.093†	0.050†	-0.040‡	-0.044†
b_t	-0.110‡	-0.128‡	-0.109‡	-0.031†	-0.020*	0.005
ln $(size_t)$	0.022‡	0.024‡	0.056‡	0.001	0.013‡	0.022‡
lev_t	0.125‡	0.094‡	0.137‡	0.057‡	0.063‡	0.108‡
Adj R^2	0.125	0.074	0.078	0.101	0.080	0.090
# Obs in CS (avr.)	272	257	276	289	310	313
# CS regressions	144	144	144	144	144	144

Panel B: Put Options

	Short-Term			Long-Term		
	OTM	ATM	ITM	OTM	ATM	ITM
IL_t^O	0.231‡	1.122‡	3.289‡	0.171‡	0.893‡	2.088‡
IL_t^S	33.532‡	21.504‡	32.683‡	11.647‡	1.365	5.363†
R_t^S	-0.042	-0.083†	-0.199‡	-0.056‡	-0.032*	0.008
b_t	-0.081*	-0.123‡	-0.136‡	0.003	-0.017	-0.034‡
ln $(size_t)$	0.039‡	0.017‡	0.035‡	0.020‡	0.009‡	0.002
lev_t	0.158‡	0.097‡	0.116‡	0.099‡	0.056‡	0.048‡
Adj R^2	0.071	0.060	0.108	0.085	0.072	0.124
# Obs in CS (avr.)	274	241	234	314	296	248
# CS regressions	144	144	144	144	144	144

Table 10
Time-Series Regressions for Weekly Option Returns

Each week, we sort the firms into deciles based on their lagged option illiquidity. The lagged illiquidity corresponds to the average of relative bid-ask spreads on the previous Friday of the contracts used to compute returns for the week. For each decile j, we take the average across firms of illiquidity, lagged illiquidity, and adjusted option returns, which are the residuals from time-series regression of option returns on current and lagged stock returns and squared stock returns. We thus obtain a weekly time-series for $IL_{j,t}$, and $\tilde{R}^{O}_{j,t}$ over the entire sample period. Then we run the following regression:

$$\ln\left(IL^{O}_{j,t}\right) = \omega_{j,0} + \omega_{j,1}\ln\left(IL^{O}_{j,t-1}\right) + v^{IL}_{j,t}.$$

Defining the unexpected illiquidity by $IL^{u}_{j,t} = v^{IL}_{j,t}$, we estimate the following time-series regression:

$$\tilde{R}^{O}_{j,t} = \gamma_0 + \gamma_1 \ln\left(IL^{O}_{j,t-1}\right) + \gamma_2 IL^{u}_{j,t} + \gamma_3 \ln\left(IL^{S}_{j,t-1}\right) + v_{j,t}$$

where $IL^{S}_{j,t-1}$ is lagged stock illiquidity.

The sample includes the S&P 500 constituents as of December 31, 2007 for which options trade throughout the entire sample period, which is from January 1996 through December 2007. The symbols *, † and ‡ denote, respectively, significance at the 10%, 5% and 1% levels with Newey-West correction for serial correlation, using 8 lags.

Panel A: Call Options

		Short-Term					Long-Term				
Decile		2. *Low*	4	6	8	10. *High*	2. *Low*	4	6	8	10. *High*
OTM	$\ln\left(IL^{O}_{j,t-1}\right)$	0.195‡	0.262‡	0.405‡	0.388‡	0.446‡	0.093‡	0.135‡	0.183‡	0.207‡	0.191‡
	$IL^{u}_{j,t}$	-0.053†	-0.061†	-0.089†	-0.149‡	-0.342‡	-0.012	-0.034	-0.027	-0.078†	-0.139‡
	$\ln\left(IL^{S}_{j,t-1}\right)$	-0.098‡	-0.119‡	-0.152‡	-0.121‡	-0.098‡	-0.038‡	-0.056‡	-0.070‡	-0.061‡	-0.030‡
	Adj R^2	0.177	0.195	0.230	0.195	0.203	0.121	0.154	0.144	0.160	0.121
	# Obs	621	621	621	621	621	621	621	621	621	621
ATM	$\ln\left(IL^{O}_{j,t-1}\right)$	0.062‡	0.111‡	0.136‡	0.196‡	0.103‡	0.034‡	0.054‡	0.072‡	0.126‡	0.073‡
	$IL^{u}_{j,t}$	-0.053‡	-0.070‡	-0.095‡	-0.120‡	-0.177‡	-0.009	-0.025	-0.052†	-0.077‡	-0.112‡
	$\ln\left(IL^{S}_{j,t-1}\right)$	-0.053‡	-0.070‡	-0.086‡	-0.087‡	-0.039‡	-0.022‡	-0.034‡	-0.043‡	-0.048‡	-0.012‡
	Adj R^2	0.124	0.173	0.204	0.210	0.227	0.070	0.117	0.136	0.160	0.150
	# Obs	621	621	621	621	621	621	621	621	621	621
ITM	$\ln\left(IL^{O}_{j,t-1}\right)$	0.030‡	0.038‡	0.047‡	0.073‡	0.034	0.014‡	0.025‡	0.040‡	0.056‡	0.038*
	$IL^{u}_{j,t}$	-0.029	-0.058†	-0.077‡	-0.114‡	-0.170‡	-0.017	-0.043†	-0.047†	-0.075‡	-0.104‡
	$\ln\left(IL^{S}_{j,t-1}\right)$	-0.022‡	-0.030‡	-0.035‡	-0.038‡	-0.018‡	-0.010‡	-0.017‡	-0.019‡	-0.022‡	-0.009†
	Adj R^2	0.065	0.094	0.127	0.195	0.287	0.045	0.097	0.086	0.128	0.163
	# Obs	621	621	621	621	621	621	621	621	621	621

Table 10 (continued)
Time-Series Regressions for Weekly Option Returns

Panel B: Put Options

		Short-Term					Long-Term				
Decile		$2. Low$	4	6	8	$10. High$	$2. Low$	4	6	8	$10. High$
OTM	$\ln(IL^{O}_{j,t-1})$	0.107‡	0.156‡	0.188‡	0.185‡	0.266‡	0.032‡	0.044‡	0.060‡	0.069‡	-0.001
	$IL^{u}_{j,t}$	-0.101‡	-0.130‡	-0.183‡	-0.211‡	-0.388‡	-0.112‡	-0.115‡	-0.149‡	-0.186‡	-0.274‡
	$\ln(IL^{S}_{j,t-1})$	-0.053‡	-0.067‡	-0.075‡	-0.063‡	-0.034†	-0.011*	-0.023‡	-0.029‡	-0.018‡	0.008
	Adj R^2	0.160	0.210	0.248	0.235	0.217	0.079	0.143	0.176	0.227	0.327
	# Obs	621	621	621	621	621	621	621	621	621	621
ATM	$\ln(IL^{O}_{j,t-1})$	0.041‡	0.031‡	0.055‡	0.013	-0.007	0.018‡	0.020‡	0.020†	0.011	0.002
	$IL^{u}_{j,t}$	-0.084‡	-0.126‡	-0.139‡	-0.168‡	-0.232‡	-0.067‡	-0.122‡	-0.132‡	-0.156‡	-0.195‡
	$\ln(IL^{S}_{j,t-1})$	-0.033‡	-0.040‡	-0.047‡	-0.034‡	-0.011	-0.014‡	-0.013‡	-0.017‡	-0.013†	-0.002
	Adj R^2	0.119	0.182	0.177	0.272	0.338	0.067	0.103	0.129	0.141	0.269
	# Obs	621	621	621	621	621	621	621	621	621	621
ITM	$\ln(IL^{O}_{j,t-1})$	0.001	-0.007	-0.010	-0.029†	-0.091‡	0.002	-0.001	-0.009	-0.024‡	-0.036‡
	$IL^{u}_{j,t}$	-0.076‡	-0.088‡	-0.128‡	-0.154‡	-0.206‡	-0.037*	-0.062*	-0.108‡	-0.132‡	-0.198‡
	$\ln(IL^{S}_{j,t-1})$	-0.010†	-0.004	-0.010	-0.001	0.006	-0.006†	-0.005	-0.004	0.003	0.012‡
	Adj R^2	0.062	0.060	0.132	0.193	0.367	0.021	0.029	0.086	0.103	0.248
	# Obs	621	621	621	621	621	621	621	621	621	621