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Illiquidity Premia in the Equity Options Market

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Abstract

Standard option valuation models leave no room for option illiquidity premia. Yet we find the risk-adjusted return spread for illiquid over liquid equity options is 3.4% per day for at-the-money calls and 2.5% for at-the-money puts. These premia are computed using option illiquidity measures constructed from intraday effective spreads for a large panel of U.S. equities, and they are robust to different empirical implementations. Our findings are consistent with evidence that market makers in the equity options market hold large and risky net long positions, and positive illiquidity premia compensate them for the risks and costs of these positions.

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In positive net supply markets, such as in bond or stock markets, it is natural to expect a positive illiquidity premium (Amihud and Mendelson 1986). In zero net supply derivatives markets, market makers absorb buying and selling pressures and the sign of net demand determines if the illiquidity premium is positive or negative. Market makers need to hedge these risky positions (Jameson and Wilhelm 1992; Engle and Neri 2010) and cross-sectional differences in the resultant costs and risks should be reflected in illiquidity measures as well as the cross-section of expected option returns. Lakonishok et al. (2007) and Gârleanu, Pedersen, and Poteshman (2009) document that in the equity option market, end users are net sellers. We therefore expect that in equity option markets, market makers are compensated for the costs of being net long equity options by price discounts and higher expected returns, and that in the cross-section the size of the option return premium is positively related to the option's illiquidity.

We empirically investigate this conjecture. We construct daily illiquidity measures based on effective spreads from a new dataset on intraday option trades and quotes for S&P 500 stocks for the 2004–2012 period. We confirm the existence of selling pressures from end users. We find that expected option returns increase with illiquidity, and we refer to the resultant differences in expected returns as illiquidity premia. To our knowledge, we are the first to use intraday trades and quotes to compute illiquidity using effective spreads for equity options on a large number of underlying stocks. When sorting stocks into quintiles based on this measure of option illiquidity, we find that the option spread portfolio that goes long the most illiquid contracts and short the least illiquid contracts earns a positive and significant premium across moneyness categories. These effects are statistically and also economically significant. Using daily returns, the average risk-adjusted option return spread for at-the-money (ATM) calls is 3.4% and for ATM puts it is 2.5%.

Next, we delve deeper into the relation between effective spreads, their economic determinants, and expected returns. It is natural to think of bid-ask spreads and expected returns as being jointly determined, especially in markets in which market makers play a prominent role. Indeed, the existing literature highlights that the bid-ask spread is an important source of market makers' revenues and that it reflects the costs and risks of market making and the characteristics of the market, which includes investors' liquidity needs and the availability of counterparties.

We therefore investigate observable proxies that capture the risks and costs of market making and the characteristics of the market, and investigate if they affect effective spreads and expected returns. We first document that, consistent with the existing theoretical literature, proxies for asymmetric information, hedging costs, stock illiquidity and inventory risks are significant drivers of effective spreads. Net option order imbalances, which we use as a proxy for shocks to inventory, are also an important driver of effective spreads. When we regress option returns on lagged values of effective spreads as well as proxies of the costs and risks of market making we find that several of these variables are significant determinants of expected returns, but effective spreads remain an economically and statistically significant driver of expected returns even in the presence of these variables. This is not surprising because effective spreads reflect the illiquidity characteristics of options, including inventory carrying and holding costs, volatility risks, the inability to perfectly hedge accumulated inventory, as well as deviations from market makers' preferred inventory position (Amihud and Mendelson 1980), and information asymmetries. These major risks and costs of market making are difficult to measure precisely, but are transmitted into the illiquidity premium and captured by the more precisely measured effective spreads. Because effective spreads encompass these different risks, their effect on expected option returns differs from the relation between net option imbalances and returns documented in the existing literature (Gârleanu et al. 2009; Bollen and Whaley 2004).

Our results are related to various strands of literature. The empirical literature contains a wealth of evidence regarding illiquidity premia in stock and bond markets. It has been shown in both markets that illiquidity affects expected returns, with more illiquid assets having higher expected returns. The illiquidity premium was first documented for the equity market in Amihud and Mendelson (1986), and for the bond market in Amihud and Mendelson (1991).[1] A growing body of evidence investigates the existence of significant illiquidity premia in other markets (see, for instance, Mancini, Ranaldo, and Wrampelmayer 2013 for the FX market and Bongaerts, De Jong, and Driessen 2011 for the credit default swap market).

An extensive theoretical and empirical literature investigates the behavior of market makers and the determination of prices and spreads in these markets. The theoretical analysis of market maker inventory management goes back to Amihud and Mendelson (1980), Stoll (1978), and Ho and Stoll (1981, 1983). Glosten and Milgrom (1985), Kyle (1985), Easley and O'Hara (1987), and Grossman and Miller (1988) consider consider the role of informed traders and asymmetric information. Gârleanu, Pedersen, and Poteshman (2009) develop a demand-based option theory involving market makers who face unhedgeable risks. Hendershott and Seasholes (2007), Comerton-Forde et al. (2010), and Hendershott and Menkveld (2014) empirically study market maker behavior and inventory in stock markets. Duffie, Gârleanu, and Pedersen (2005) emphasize how prices and spreads are jointly determined in a search model as a function of market characteristics and risks that are difficult to measure and quantify, such as investor holding costs and investors' need for immediacy.[2] Option spreads and their determinants have been analyzed in, for example, Vijh (1990), Jameson and Wilhelm (1992), George and Longstaff (1993), Cho and Engle (1999), and de Fontnouvelle, Fishe, and Harris (2003).[3] Finally, Bollen and Whaley (2004), Gârleanu, Pedersen, and Poteshman (2009), and Muravyev (2016) document the impact of inventory shocks and net demand on option prices.[4]

It is important to note that the different strands of the (theoretical) literature emphasize various aspects of the determination of prices and spreads in equity option markets. To the best of our knowledge, no single model incorporates all of the above economic intuition. As a result, any test of the existing theory regarding the determinants of spreads and returns will be somewhat ad hoc, in the sense that it amounts to a reduced-form analysis of the implications of different models, rather than a structural test of an all-encompassing model. Moreover, some of the determinants of prices and spreads suggested by existing models are readily observable, whereas others, such as market makers' inventories, carrying costs, and risks, are difficult to measure. We use effective spreads as a measure of illiquidity because it reflects those determinants that are easily observable but also those that are not.

Our paper differs from the existing literature by empirically studying illiquidity premia in equity option markets. The existing empirical evidence on illiquidity premia and discounts in derivatives markets is limited. Li and Zhang (2011) discuss the zero net supply case and find empirically that buying pressure combined with illiquidity creates price premia for more liquid warrants relative to more illiquid options on the Hang Seng index. Deuskar, Gupta, and Subrahmanyam (2011) find a liquidity price discount in the market for interest rate caps and floors, in which market makers have a net short position. Brenner, Eldor, and Hauser (2001) compare central bank-issued and exchange-traded options and report a 21% illiquidity discount for nontradable central bank-issued options. Consistent with these findings, we show that the combination of selling pressures and illiquidity in equity options on a panel of S&P 500 stocks generates a positive illiquidity premium in expected equity option returns. Net demand from end users is negative on average, and market makers absorb it. Liquidity providers in equity option markets thus hold long positions on average and require higher compensation for more illiquid series, consistent with lower current prices and higher expected returns.

1 Illiquidity and Expected Option Returns

In this section, we first develop hypotheses regarding the relationship between option illiquidity and expected returns. We then construct daily stock and option returns as well as illiquidity measures from intraday trades and quotes. Finally, we define and discuss option order imbalance measures.

1.1 Hypothesis development

An extensive literature documents that higher illiquidity leads to higher subsequent returns in positive net supply markets. Deuskar, Gupta, and Subrahmanyam (2011) and Li and Zhang (2011) discuss and empirically investigate the existence of illiquidity premia and discounts in derivatives markets, which are zero net supply markets. Both papers convincingly argue that it is not obvious ex ante whether one should expect liquidity premia or discounts in derivatives markets. They argue that the *sign* of the illiquidity risk premium should depend on whether the market is characterized by net buying or net selling pressure. Higher illiquidity will be positively correlated with expected returns in derivatives markets in which end users are net sellers, while the correlation will be negative in markets in which end users are net buyers. The existing empirical evidence is consistent with these predictions. Deuskar, Gupta, and Subrahmanyam (2011) find a liquidity price discount in the market for interest rate caps and floors, where market makers have a net short position. Li and Zhang (2011) use data on options and derivative warrants on the Hang Seng index and find price discounts in the more illiquid options.

Our empirical analysis focuses on U.S. individual equity options. Using data on 303 stocks from 1996 to 2001, Gârleanu, Pedersen, and Poteshman (GPP, 2009) find that dealers in U.S. equity option markets face selling pressures. We obtain option data on S&P 500 stocks from 2004 to 2012, and we focus on the effective spread as a measure of illiquidity. We confirm the existence of selling pressures in this market using end users' signed option trading volume on the CBOE and ISE exchanges. Our first and most important testable hypothesis concerns the implications of this aggregate net selling pressure for the cross-section of expected option returns:

- $H_0(1)$: If market makers on average face net selling pressures, then in the cross section more illiquid options will have higher expected returns.

If $H_0(1)$ is confirmed by the data, and we find below that it is, then it becomes of first-order importance to investigate which factors determine option illiquidity as measured by effective spreads, which we denote by ES^O. An extensive literature analyzes and documents the determinants of illiquidity, including the determinants of effective spreads in stock, bond, and derivatives markets. When analyzing these determinants, it is critically important to take market structure into account. In equity option markets, market makers play a very important role. We therefore formulate the following hypothesis:

- $H_0(2)$: In the cross-section, option effective spreads, ES^O, are an increasing function of the costs and risks of market making, including hedging and rebalancing costs and asymmetric information.

An extensive theoretical literature considers a market maker who manages inventory (Amihud and Mendelson 1980; Stoll 1978; Ho and Stoll 1981, 1983). This literature highlights a variety of costs that result from holding inventory and may determine effective spreads. Some of these determinants are readily observable, but others, such as the availability of counterparties, are more difficult to quantify. Much of this literature on market making is not specifically focused on derivatives markets. Jameson and Wilhelm (1992), Green and Figlewski (1999), and Battalio and Schultz (2011) argue convincingly that inventory costs and risks are much more serious for option market makers than for liquidity providers in stock markets, due to hedging needs, model risk, and uncertain holding periods. In option markets, market makers also incur hedging and rebalancing costs when they are unable to quickly resell illiquid series (Leland 1985; George and Longstaff 1993; de Fontnouvelle, Fishe, and Harris 2003; Engle and Neri 2010). This literature suggests additional determinants of ES^O. Model risk (Green and Figlewski 1999) is another important component of the risks of market making in derivatives markets. Another strand of the literature (Grossman and Miller 1988; Glosten and Milgrom 1985; Kyle 1985) studies the market maker's optimal decisions in reacting to informed traders and asymmetric information and predicts that effective spreads increase as a function of the amount of private information and informed traders in the option market. Several studies argue that informed traders are attracted to option markets because they can obtain higher leverage.

Many variables affect option effective spreads because they determine how the market maker responds to deviations from her optimal inventory level. This, in turn, suggests that one of the most important potential determinants of ES^O is the deviation from optimal inventory.[5] We follow Bollen and Whaley (2004), Gârleanu, Pedersen, and Poteshman (2009), and Muravyev (2016), who use data on net demand, which we refer to as imbalances below. This variable represents a good measure of shocks to inventory and is therefore likely to affect the behavior of the market maker, spreads and expected returns.

Our next hypothesis addresses the effect of net demand on effective spreads. Amihud and Mendelson (1980) predicts that larger deviations from optimal inventory, proxied by imbalances, will lead to higher spreads. O'Hara and Oldfield (1986) show that risk averse market makers adjust spreads as a function of inventory. Comerton-Forde et al. (2010) argue that financing constraints can generate a relation between inventory and spreads with risk-averse market makers. Much of the existing literature is again in the context of the equity market, where the market maker is almost always net long most stocks (Hendershott and Menkveld 2014). In equity option markets, the dealers face net selling pressure, but they also hold short positions for many option classes. We therefore formulate

- $H_0(3)$: In the cross-section, the more imbalanced the net demand for an option, the higher the effective option spread, ES^O.

It is clear that some of the potential determinants of ES^O that capture the cost of market making can be quantified relatively easily, such as option Greeks, but others, such as the probability of informed trading are much more difficult to quantify. In dynamic search models of financial markets (Duffie, Gârleanu, and Pedersen 2005), spreads and prices are functions of factors such as investors' ability to find market makers, financing constraints, as well as the immediacy with which investors require cash, which captures the notion of illiquidity in the most intuitive possible way but is not straightforward to proxy for empirically.[6]

Our final hypothesis conjectures that because of measurement issues, effective option spreads computed from intraday trades and quotes continue to explain expected returns even when standard proxies for various characteristics and determinants of inventory risk and the market maker's environment are taken into account. Hypothesis $H_0(2)$ above predicts that effective option spreads, ES^O, capture the risks and costs of market making. While some aspects of the market maker's environment may primarily affect prices and expected returns rather than spreads and vice versa, for the most part spreads and expected returns are affected by the same variables. As a result the effective spread, which can be measured fairly precisely, is a powerful determinant of expected returns because it encompasses proxies for various market characteristics that are difficult to measure precisely, such as inventory holdings, the costs of managing these inventories, volatility risk, information asymmetries (Goyenko, Ornthanalai, and Tang 2015), and market makers' inability to perfectly hedge accumulated inventory as well as deviations from optimal inventory (Amihud and Mendelson 1980). This line of argument gives:

- $H_0(4)$: Even after controlling for observable drivers of the risks and costs of market making, option effective spreads computed from intraday trades and quotes are a significant driver of expected option returns.

Having developed four hypotheses regarding option returns and illiquidity, we next define and discuss the empirical measures required to carry out the corresponding tests.

1.2 Option returns and stock returns

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

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

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

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

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

The presence of $E\left[R^S\right]$ and $\frac{\partial O}{\partial S}$ on the right-hand side of Equation (2) shows that it is critical to properly control for the return on the underlying stock when regressing option returns on illiquidity measures. We implement this control by using delta-hedged returns computed as

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

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

We now discuss the computation of the raw option returns $R^O_{t+1,n}$, from which we compute the delta-hedged option returns, $\tilde{R}^O_{t+1,n}$. Raw option returns are constructed for all S&P 500 index constituents using intraday trade prices and volumes from LiveVol.

We compute equally weighted average daily returns on a stock-by-stock basis for different moneyness categories by averaging option returns for all available series. For each option moneyness category and for each stock, the delta-hedged return is then computed from Equation (3) as

$$\tilde{R}^O_{t+1}=\frac{1}{N}\sum_{n=1}^{N}\frac{O^{VP}_{t+1}(K_n,T_n-1)-O^{VP}_t(K_n,T_n)}{O^{VP}_t(K_n,T_n)}-R^S_{t+1}S_t\frac{1}{N}\sum_{n=1}^{N}\frac{\Delta_t\left(K_n,T_n\right)}{O^{VP}_t(K_n,T_n)} \tag{4}$$

where N is the number of available series in the particular category at time t that are also in the sample at time $t+1$. Battalio and Schultz (2006) show that end-of-day option quotes are problematic because trades may not have taken place at those quotes. When computing returns we therefore use volume-weighted average intraday trade prices defined by

$$O^{VP}(K_n, T_n) = \frac{\sum_k DolVol_k S_k^P}{\sum_k DolVol_k} \quad (5)$$

where S_k^P is the price for the k^{th} trade and $DolVol_k$ is the associated dollar volume for an option with strike price K_n and maturity T_n.[7] In addition to the equally weighted returns in Equation (4), below we consider open-interest weighted returns as well. In another robustness exercise, we consider returns computed from volume-weighted intraday midpoints, S_k^M, in Equation (7) rather than trade prices, S_k^P, as well as trade prices and midpoints computed at the time of the last trade of the day.

We merge four datasets in our empirical analysis: CRSP, OptionMetrics, TAQ and LiveVol. To be included in our sample, a stock is required to have data available across all four data sources. Our sample period is from January 2004 to December 2012, because for this period we have intraday option prices and quotes from LiveVol.[8] We control for the index composition on a monthly basis. The last month of a stock in the index corresponds to the last month of the stock in our sample. We focus on S&P 500 stocks for reasons of data availability and because of their high liquidity, which biases our results towards not finding evidence of the importance of illiquidity.

For each stock, we consider put and call options with maturity between 30 and 180 days which are the most actively traded. Puts and calls are further divided into moneyness categories. Much of our analysis of the determinants of spreads and returns is done using at-the-money (ATM) options, but we also report results for out-of-the-money (OTM) and ALLoptions. We follow Driessen, Maenhout, and Vilkov (2009) and Bollen and Whaley (2004) and define moneyness according to the option delta from OptionMetrics, which we denote by Δ. OTM options are defined by $0.125 < \Delta \leq 0.375$ for calls and $-0.375 < \Delta \leq -0.125$ for puts and ATM options correspond to $0.375 < \Delta \leq 0.625$ for calls and $-0.625 < \Delta \leq -0.375$ for puts. The ALL option category includes all moneyness categories, including in-the-money (ITM) options and is defined by $0.125 < \Delta \leq 0.875$ for calls and $-0.875 < \Delta \leq -0.125$ for puts.[9]

Following Goyal and Saretto (2009), Cao and Wei (2010), and Muravyev (2016) we apply filters to the option data, eliminating the following series: (1) prices that violate no-arbitrage conditions; (2) observations with ask price lower than or equal to the bid price; (3) options with open interest equal to zero; (4) options with missing prices, implied volatilities or deltas;

(5) options with quoted bid-ask spread above 50% of the mid-quote; and (6) options with mid-point prices below $0.10.[10]

For options that are not part of the penny-pilot program we remove series with prices lower than $3*and* bid-ask spread below $0.05, or prices equal to or higher than $3*and* bid-ask spread below $0.10, on the grounds that the bid-ask spread is lower than the minimum tick size, which signals a data error. For penny-pilot options we remove series with prices equal to or higher than $3*and* bid-ask spreads below $0.05. Finally, we include only stock/day observations with positive volume reported in OptionMetrics. For calls this yields data on 487 option classes on average per day in the ALL category, for puts we have 423 option classes on average per day.

Using equally weighted returns, Figure 1 plots the average across stocks of the daily delta-hedged option returns over time. All the option returns display volatility clustering and strong evidence of nonnormality. As is typical of daily speculative returns, the mean is completely dominated by the dispersion. Outliers are clearly visible as well. Below, we therefore run robustness checks, eliminating the most extreme option returns.

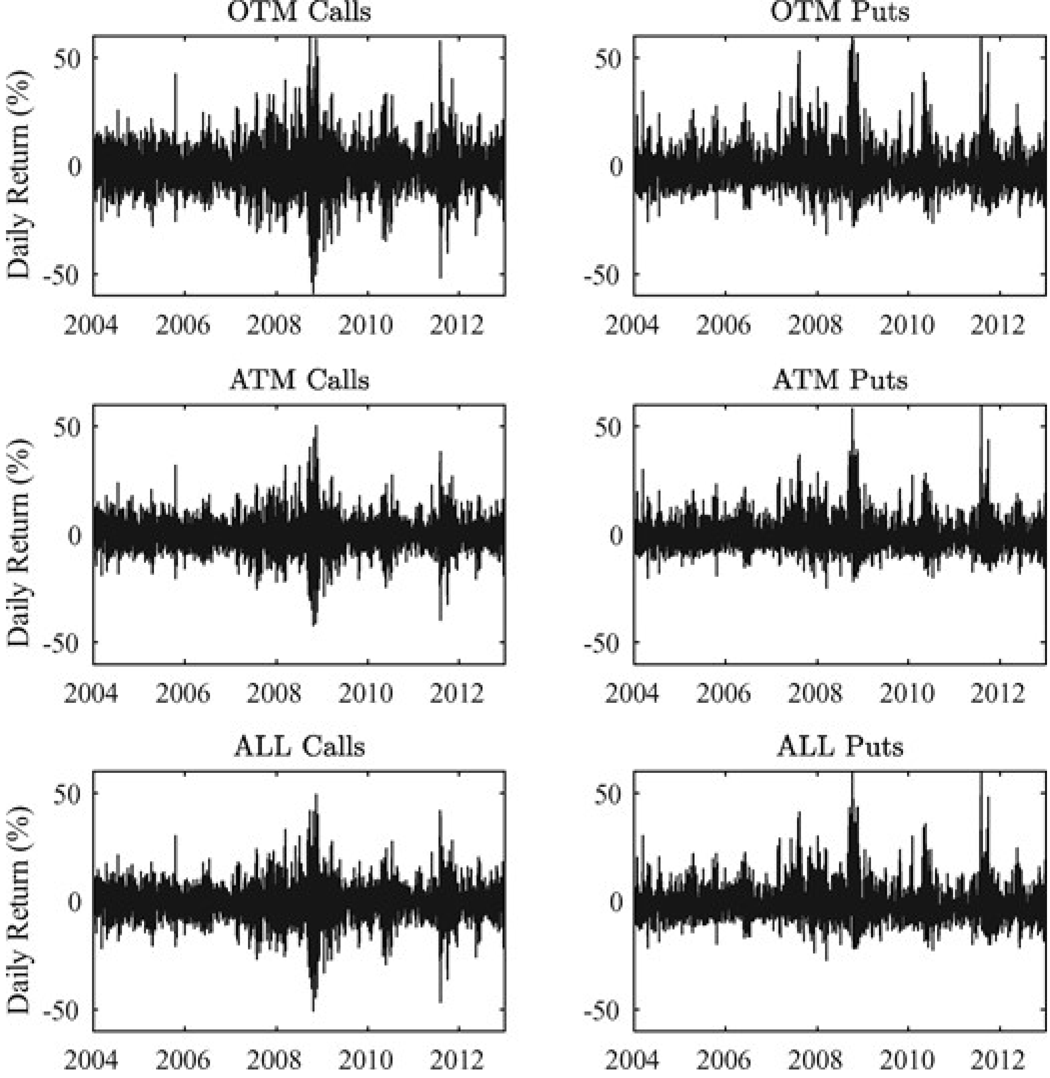

Figure 1 **Average daily delta-hedged option returns, 2004–2012**

We plot the daily delta-hedged returns on portfolios of equity options equally weighted across option classes. Option returns are computed from volume-weighted intraday trade prices. OTM refers to out-of-the-money; ATM refers to at-the-money; and ALL includes all strikes. The sample starts in January 2004 and ends in December 2012.

Table 1 reports summary statistics for daily delta-hedged option returns. We first compute the respective statistics for each option class and report the average across option classes. Despite our focus on large capitalization stocks, we have less than 500 option classes available because of the stringent filters we use. We also report the average number of option series per option class for each moneyness category.

Table 1
Descriptive statistics of daily delta-hedged option returns and stock returns as a percentage

	A. Daily delta-hedged call returns			*B. Daily delta-hedged put returns*			*C. Daily stock returns*	
	OTM	**ATM**	**ALL**	**OTM**	**ATM**	**ALL**		
Average	−2.11	0.32	−0.36	−2.57	0.14	−0.94	Average	0.04

SD	27.18	18.91	19.72	22.65	19.11	19.45	SD	2.40
Skewness	2.14	1.69	1.86	1.78	1.79	1.68	Skewness	0.49
Kurtosis	38.01	29.79	38.18	22.86	27.82	27.55	Kurtosis	19.60
$\rho(1)$	−0.17	−0.20	−0.18	−0.10	−0.12	−0.08	$\rho(1)$	−0.04
abs [$\rho(1)$]	0.12	0.16	0.15	0.11	0.13	0.12	abs [$\rho(1)$]	0.21
Avg # stocks	379	390	487	359	339	423	Avg # stocks	498
Avg # series	3.16	2.96	7.03	3.56	2.65	6.28		

We provide descriptive statistics for daily stock returns and delta-hedged option returns computed from volume-weighted intraday trade prices. First, we compute the descriptive statistics for each stock and then we take the cross-sectional averages of these statistics. We report the mean (as a percentage), standard deviation (as a percentage), skewness, kurtosis, first-order autocorrelation of delta-hedged returns $\rho(1)$, and first-order autocorrelation of the absolute value of delta-hedged returns, abs[$\rho(1)$]. OTM (out-of-the-money) corresponds to $0.125 < \Delta \leq 0.375$ for calls and $-0.375 < \Delta \leq -0.125$ for puts, where Δ is the Black-Scholes delta. ATM (at-the-money) corresponds to $0.375 < \Delta \leq 0.625$ for calls and $-0.625 < \Delta \leq -0.375$ for puts. Options are aggregated across maturities between 30 and 180 days. The option data are from LiveVol. The sample includes the S&P 500 constituents with valid traded options data from January 2004 to December 2012.

The delta-hedged return averages are fairly large and negative for OTM options and small and positive for ATM options. The option returns exhibit positive skewness and excess kurtosis in all categories, which is expected due to the option payoff convexity. The option returns display evidence of rapid mean-reversion as evidenced by the negative first-order autocorrelation. These reversals are suggestive of the importance of liquidity provision in this market. The absolute return autocorrelation is positive for all categories and nontrivial in panels A and B, confirming the volatility clustering apparent in Figure 1.

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

1.3 Illiquidity measures from trades and quotes

We document the impact of option illiquidity on option returns, but also investigate if illiquidity in the underlying stock market affects option returns. We rely on the effective relative spread, which is a conventional measure of illiquidity that measures the direct costs that dealers charge for transactions, reflecting their costs of market making. The effective spread captures both the informational and noninformational components of trading costs (Bessembinder and Venkataraman 2010).

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 relative spread on a trade k is defined as

$$ES_k^S = \frac{2|S_k^P - S_k^M|}{S_k^M}, \quad (6)$$

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

$$ES^S = \frac{\sum_k DolVol_k ES_k^S}{\sum_k DolVol_k}$$

where the dollar-volume, $DolVol_k$, is the stock price multiplied by the trading volume. Below, we compute ES^S for each stock on each day for the 2004–2012 sample.[11]

Intraday options trading data are reported by all equity options exchanges via the Options Price Reporting Authority (OPRA).

We obtain data from LiveVol, a commercial data vendor that uses the raw OPRA data to create files for each stock on each day with information about each option trade during the day, including the national best bid and offer quotes prevailing at the time of the trade, execution price, and trading volume of each trade. The LiveVol data start in January 2004 and our sample goes through the end of 2012.

Our sample contains all trades and matched quotes for all option series on S&P 500 stocks. Using intraday data, we compute the effective relative option spread associated with the k^{th} trade as

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

where O_k^P is the price of the k^{th} trade and O_k^M is the midpoint of the consolidated (from different exchanges) best bid and offer prevailing at the time of the k^{th} trade.[12] The daily effective option spread, ES^O, is the volume-weighted average of all ES_k^O computed over all trades during the day

$$ES^O = \frac{\sum_k Vol_k ES_k^O}{\sum_k Vol_k}$$

where the volume, Vol_k, is the number of contracts transacted in the k^{th} trade.[13] For every day in the sample, we compute ES^O for all series traded on any of the available option classes in the sample. The ES^O measure is then averaged across series within the same moneyness category for each stock, using equal weights. To the best of our knowledge we are the first to construct option illiquidity measures from TAQ-type data on an extensive sample of stocks for an extended time period.

Panel A of Table 2 presents summary statistics of our liquidity measures for calls and puts across different moneyness categories. Effective relative spreads are higher on average for calls, at 6.41% (ATM), compared with puts, at 5.25%. OTM options have the highest effective spreads for both calls and puts. Note that the average effective spread on stocks is much smaller at 0.09%.

Table 2

Descriptive statistics on illiquidity measures

A. Descriptive statistics on option and stock effective relative spreads

Calls	OTM	ATM	ALL	Puts	OTM	ATM	ALL	
Mean	12.58	6.41	8.03	Mean	9.77	5.25	7.01	Mean
SD	7.59	4.02	4.95	SD	6.54	3.62	4.76	SD
Min	0.34	0.20	0.46	Min	0.28	0.11	0.21	Min
Max	63.61	39.79	47.78	Max	56.57	34.46	45.31	Max
$\rho(1)$	0.27	0.33	0.34	$\rho(1)$	0.27	0.28	0.30	$\rho(1)$
Avg # stocks	379	390	487	Avg # stocks	359	339	423	Avg # stocks
Avg volume	740	759	1595	Avg volume	646	453	1098	
Avg # trades	36	41	87	Avg # trades	28	23	53	
Avg imbalance	–20.72	–15.78	–15.61	Avg imbalance	–13.63	–7.62	–10.72	

Avg imbalance (Δ)	−6.15	−7.65	−6.55	Avg imbalance (Δ)	−3.43	−3.97	−4.10	
	B. Correlations of call option and stock illiquidity						*C. Correlations of p option and stock illiquidity*	
	OTM	ATM	ALL	Stocks		OTM	ATM	ALL
ATM	0.48	1.00			ATM	0.45	1.00	
ALL	0.88	0.70	1.00		ALL	0.89	0.68	1.00
Stocks	0.17	0.18	0.17	1.00	Stocks	0.15	0.12	0.14

The table presents summary statistics for the illiquidity measures (as a percentage) and order imbalances in panelA and the correlations between the illiquidity measures for call and put options (in panels B and C, respectively). Option and stock illiquidity measures are estimated from intraday data as the volume-weighted average of the effective relative spread for each day. For each stock and on each day, we compute the average illiquidity of all the available options in a given category and then we compute across time the mean, the minimum, the maximum, the standard deviation, and the first-order autocorrelation, ρ (1). Finally, we report the across stock averages of these statistics in panel A. Panel A also reports the average option volume (in number of contracts), the average number of trades per stock per day, and the average order imbalance (end user buy minus sell orders as a percentage of total) equal and delta-weighted. We compute the cross-sectional correlations between the illiquidity measures on each day and report the time-series averages of these correlations in panel B for call options and panel C for put options. The sample includes the S&P 500 constituents with valid traded options data from January 2004 to December 2012. Imbalances are available only from 2005.

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

Figure 2 shows the time series of effective relative spreads for each moneyness category averaged across option classes. All spreads significantly spike up during the 2008–2009 credit crisis, and less so during the European debt crisis from 2010 to 2011.[14] All series are trending down throughout the sample, as the option markets become more efficient.[15]

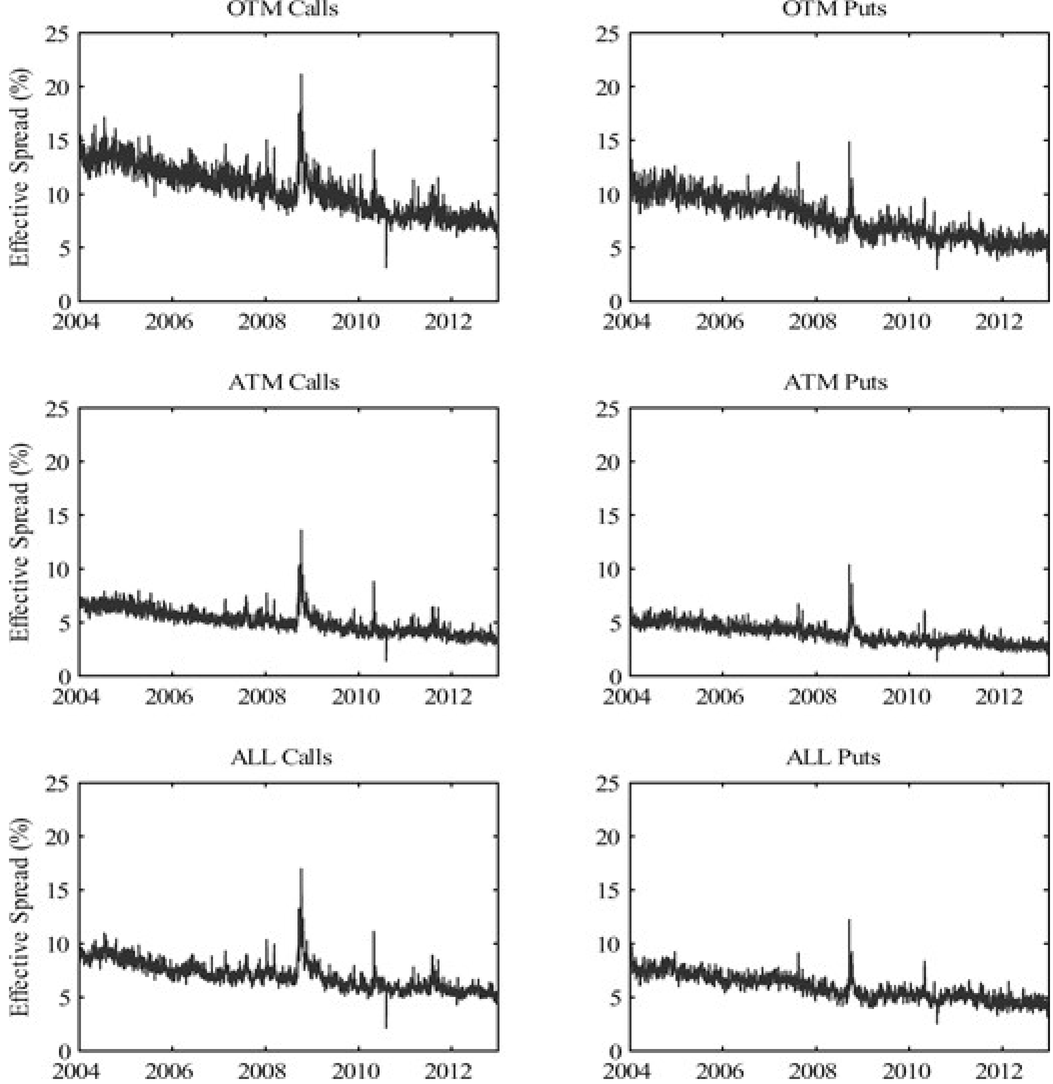

Figure 2 **Average effective relative equity option spreads, 2004–2012**

Average daily option illiquidity is computed as the equally weighted average across option classes of the effective relative spread. The underlying trade and quote data are from LiveVol and include the S&P 500 constituents for which options trade during our sample. The sample period is January 2004 to December 2012.

The top panel of Figure 3 plots stock effective relative spreads over time. There is no obvious downward trend, because liquidity in stock markets had already increased significantly prior to the beginning of our sample. Figure 3 also plots the S&P 500 index level (middle panel) and the VIX volatility index (bottom panel). Note that when effective spreads spike in the recent financial crisis, the S&P 500 drops and the VIX also increases.

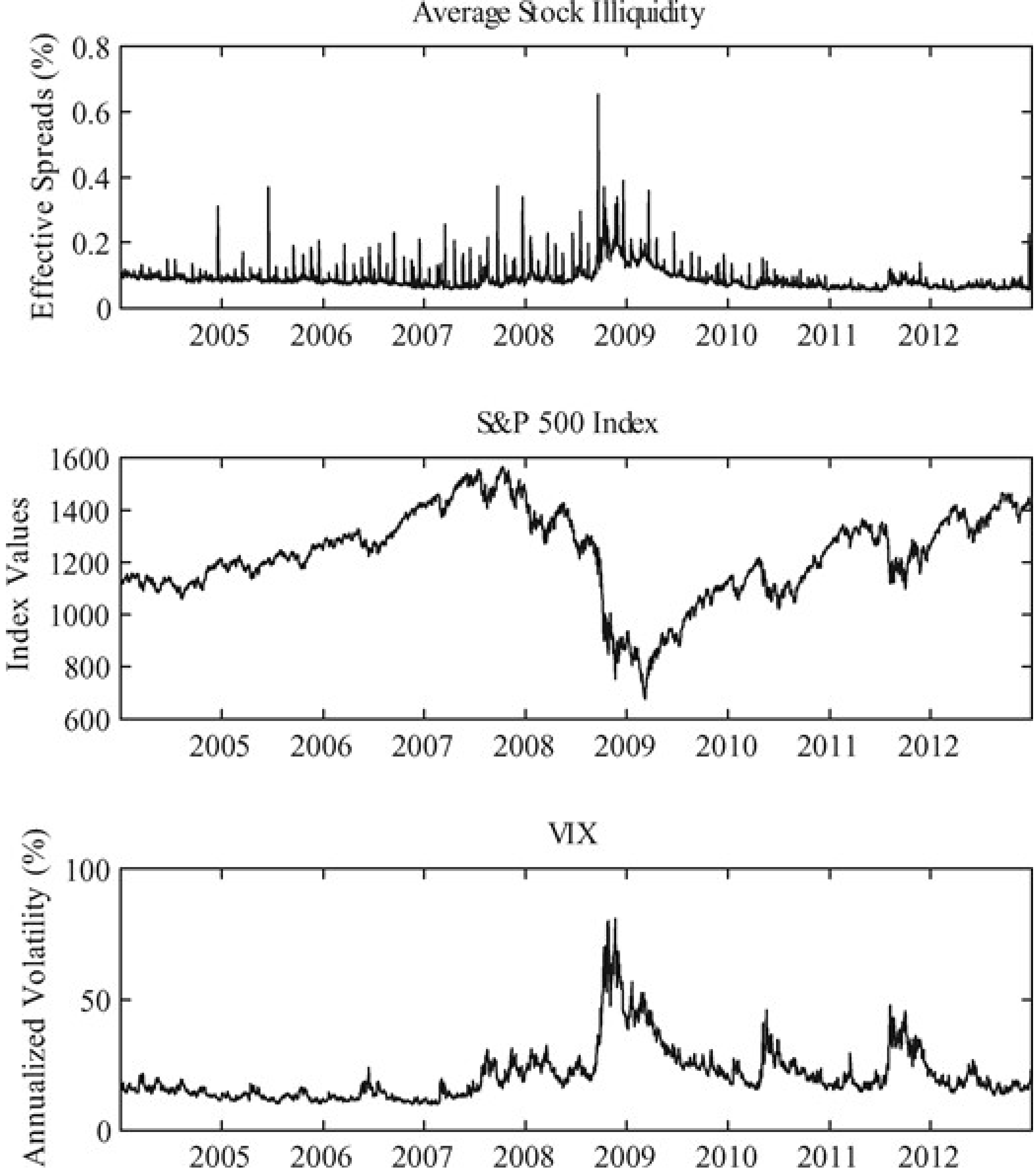

Figure 3 **Daily average stock effective relative spreads, S&P 500 index, and the VIX**

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

Panels B (for calls) and C (for puts) in Table 2 report cross-sectional correlations between ES^O for OTM, ATM, and ALL options as well as ES^S. We compute the cross-sectional correlations between the illiquidity measures on each day and report the time-series averages of these correlations. The correlation of different ES^O categories with stock illiquidity ranges between 12% and 18%. The correlation between OTM and ATM ES^O is 48% for calls and 45% for puts. The correlation between ALL ES^O and the ES^O of the separate moneyness categories is not surprisingly large and positive.

1.4 Order imbalances

We now discuss our proxy for deviations from optimal inventory. We obtain data on open and close positions, and buy versus sell orders from end users, that is, non-market-makers, from the CBOE and the ISE. These are the two largest option exchanges and they capture more than 60% of overall trading volume. Data are available starting in January 2005. Therefore, when analyzing the impact of imbalances on effective spreads and expected returns, our sample starts in January 2005 instead of January 2004.

The exchanges provide end-user-initiated open-buy, open-sell, close-buy, and close-sell volumes for each series. We use this data to construct an option order imbalance measure for each option class and moneyness category, in the spirit of Bollen and Whaley (2004):

$$IMBAL = \frac{\sum_s |\Delta_s| (OpenBuy_s + CloseBuy_s - OpenSell_s - CloseSell_s)}{\sum_s (OpenBuy_s + CloseBuy_s + OpenSell_s + CloseSell_s)}, \tag{7}$$

where s denotes the option series, and where we weigh each series in the sum by its absolute delta, $|\Delta_s|$, so that the $IMBAL$ variable is measured in the number of underlying shares.

This measure has several advantages: (1) it provides signed volume so that we do not need to use the otherwise prevalent Lee and Ready (1991) algorithm to sign trades, and (2) the data do not include dealer volume, and, as a result, allow us to directly observe the aggregate inventory pressures on dealers.

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

Figure 4 plots weekly delta-weighted order imbalances averaged across option classes. For each of the six option categories, order imbalances are persistent. Note also that the order imbalances for calls are strongly negative throughout the period, confirming that end users consistently are net sellers of equity call options. For put options the picture is more mixed. Put order imbalances are mostly negative throughout the sample, but often close to zero or even positive. In our empirical results below we document how these patterns affect expected returns, bid-ask spreads, and the cross-sectional relation between returns and ES^O.

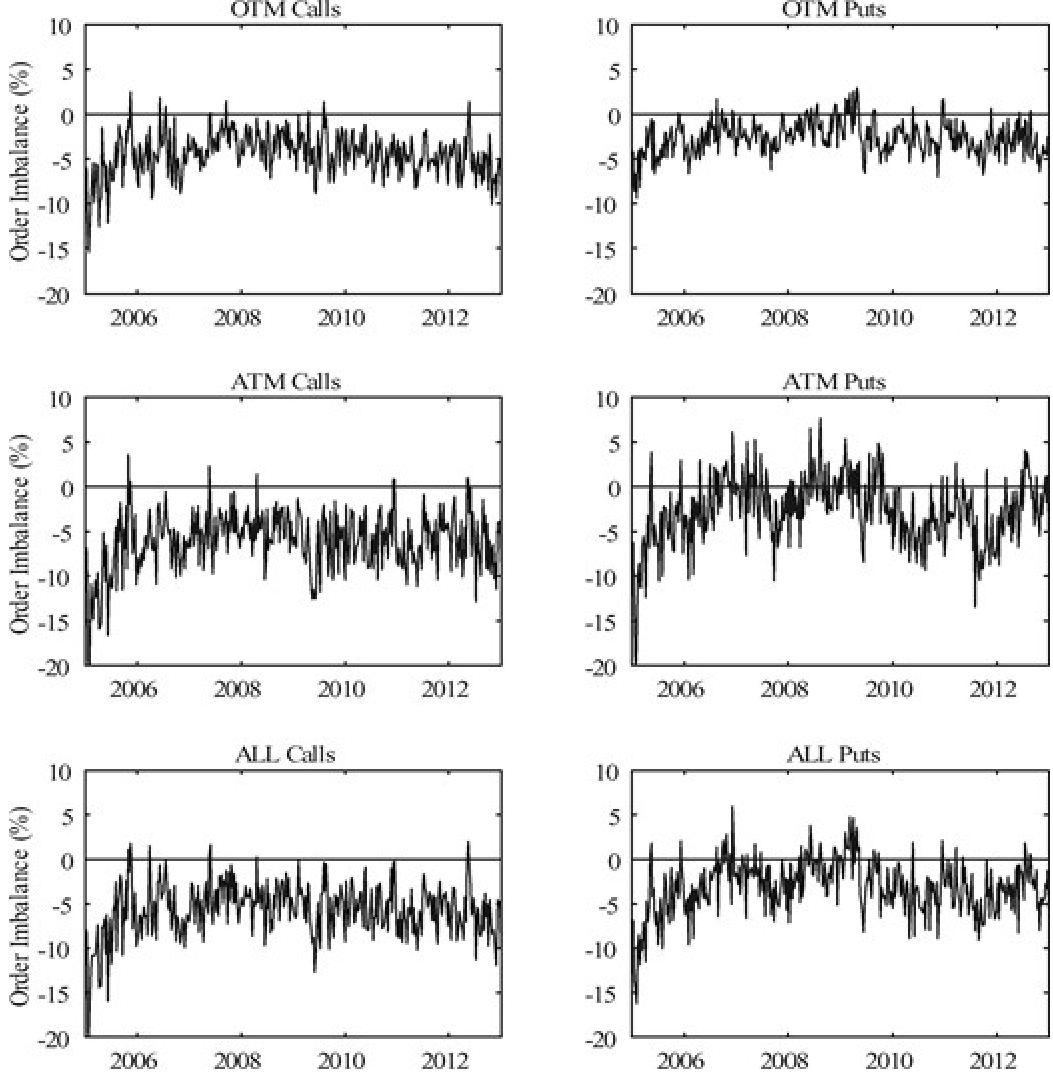

Figure 4 **Option order imbalances**

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

2 Illiquidity and the Cross-section of Expected Option Returns

We now investigate the cross-sectional relationship between option illiquidity and expected option returns. We first discuss simple univariate portfolio sorts on option illiquidity as measured by effective relative spreads. We then present a number of robustness checks.

2.1 Sorting on option illiquidity

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

Following Amihud (2002) and French, Schwert, and Stambaugh (1987), we use ex post realized returns as a measure of expected returns. To remove the first-order effects from the underlying asset, we transform the ex post returns to delta-hedged returns using Equation (4). To alleviate potential asynchronicity biases, for our main results we follow Goyal and Saretto's (2009) analysis of option returns and skip one day between the computation of illiquidity measures and the computation of returns.[16] Our analysis thus requires that an option series is available on three consecutive days. We also report results without skipping a day. We report these results for robustness, but also because we will refer to them in Section 4.

Panels A and B of Table 3 report our main results when skipping a day. The table reports portfolio sorting results for delta-hedged call and put returns. The sample period is from January 2004 to December 2012 and corresponds to the availability of LiveVol data. We sort option classes into quintiles based on lagged option illiquidity. For each quintile, we report the percentage average return as well as the corresponding alpha from the Carhart (1997) model.[17] We compute *t*-statistics using a Newey and West (1987) correction for serial correlation, using 8 lags.

Table 3
Portfolio returns and alphas: Sorting on option illiquidity

		A. Daily call option returns at $t+2$						***B. Daily put opti***	
		1	**2**	**3**	**4**	**5**	**5−1**	**1**	**2**
OTM	Mean	−2.828	−1.889	−1.212	−0.471	1.492	4.331	−2.427	−1.779
	Alpha	−2.673	−1.732	−1.050	−0.311	1.669	4.349	−2.491	−1.846
	t-stat	−17.420	−11.140	−5.980	−1.570	7.060	26.370	−11.620	−8.190
ATM	Mean	−1.182	−0.442	−0.050	0.554	2.238	3.422	−1.128	−0.542
	Alpha	−1.082	−0.341	0.054	0.661	2.359	3.440	−1.185	−0.600
	t-stat	−10.030	−3.150	0.440	4.630	12.070	26.210	−7.730	−3.920
ALL	Mean	−1.266	−0.769	−0.388	−0.017	0.813	2.084	−1.472	−0.922
	Alpha	−1.158	−0.655	−0.273	0.107	0.950	2.112	−1.530	−0.982

	t-stat	−9.480	−4.970	–1.770	0.620	4.540	16.890	−8.410	–4.920
		C. Daily call option returns at t+1						*D. Daily put optic*	
		1	2	3	4	5	5−1	1	2
OTM	Mean	−2.924	−2.117	–1.745	–0.830	2.883	5.806	−2.560	–2.021
	Alpha	−2.765	−1.958	–1.580	–0.665	3.065	5.826	−2.626	–2.090
	t-stat	–17.320	–12.190	–9.280	–3.430	11.920	29.560	–12.030	–9.320
ATM	Mean	−1.190	−0.585	–0.251	0.357	2.723	3.917	−1.315	–0.700
	Alpha	−1.089	−0.480	–0.145	0.467	2.846	3.938	−1.374	–0.758
	t-stat	−9.730	−4.360	–1.200	3.320	14.160	28.490	−8.890	–4.810
ALL	Mean	−1.013	−0.692	–0.685	–0.409	1.089	2.101	−1.365	–1.014
	Alpha	−0.901	−0.578	–0.566	–0.282	1.232	2.133	−1.424	–1.076
	t-stat	−7.100	−4.340	–3.730	–1.680	5.690	16.890	−7.750	–5.480

The table reports portfolio results for daily delta-hedged call and put returns and alphas (as a percentage). In panels A and B, we sort stocks into quintiles based on their twice lagged option illiquidity and in panels C and D based on once lagged illiquidity. Option illiquidity is obtained as volume-weighted effective spreads from intraday LiveVol data. For each quintile, we report the mean, the alpha from the Carhart model and its *t*-statistic with Newey-West correction for serial correlation, using eight lags. The sample includes the S&P 500 constituents with valid traded options data from January 2004 to December 2012.

Throughout the paper we report separate results for calls and puts. Note that put-call parity does not hold for American style equity options nor when spreads are nontrivial as they are in this market. Note also that the option-based predictability literature often exploits the differential information in call and put equity option prices, suggesting at least partial segmentation of these markets.[18] We want to avoid any loss of information by aggregating calls and puts and so keep them separate throughout our analysis.

Panel A of Table 3 reports the results for daily delta-hedged returns on calls. Daily put option returns are in panel B. We report average returns and alphas for all call or put options jointly (ALL), as well as for the two moneyness categories (ATM and OTM) separately. In panel A, the 5–1 portfolio that goes long the most illiquid calls and short the least illiquid calls earns a large, positive and significant premium in all categories. The Carhart alphas are not very different from the average returns. The daily alpha spread is 3.4% for ATM calls and 4.3% for OTM calls. The call returns and alphas are monotonically increasing across the option spread quintiles for all categories of options.

Panel B of Table 3 reports the results for daily delta-hedged returns on puts. The daily alpha spread is 2.5% for ATM puts and 1.9% for OTM puts. The premia for puts are smaller than for calls but they are still large, positive, and significant. Note that the put returns and alphas are also monotonically increasing across the option spread quintiles for all categories of options.

Panels C and D of Table 3 report results for future returns without skipping a day. The main conclusion from panels C and D is that they confirm the conclusions from panels A and B, but the results are economically even larger.

Although the alphas in Table 3 may appear unrealistically large, from Table 2, we know that bid-ask spreads are large as well. Therefore, these alphas are not readily earned by investors who must pay the spread.[19]

Overall we conclude that the illiquidity premium is positive and significant for calls and puts. This confirms hypothesis $H_0(1)$.

2.2 Robustness checks on option illiquidity sorts

It is natural to ask if the single-sort results in Table 3 are robust to various permutations in the empirical design. Table 4 reports on these robustness checks. Several robustness checks use alternative return definitions. The Online Appendix reports and discusses descriptive statistics for these returns. To save space Table 4 only reports the results for the 5–1 quintile spread returns in ATM options. The Online Appendix reports more detailed results for the alternative return definitions.

Table 4
Daily ATM option return spreads: Various robustness checks

A. Returns from average intraday trade prices

		Base case from Table 3	**OI-weighted returns**	**Only nonfinancial stocks**	**100 stocks with largest option volume**	**Trim 1 % of of returns in each tail**	**Returns using only last price of each day**
ATM	Mean	3.422	3.349	3.394	3.450	3.375	1.724
Calls	Alpha	3.440	3.366	3.408	3.448	3.392	1.757
	t-stat	26.210	25.500	25.780	16.420	26.250	14.980
ATM	Mean	2.517	2.437	2.570	2.156	1.560	1.656
Puts	Alpha	2.506	2.427	2.557	2.159	1.560	1.627
	t-stat	14.400	14.440	14.310	14.130	17.980	9.540
		B. Returns from average intraday midpoint quotes					
		Equally-weighted	OI-weighted returns	Only nonfinancial stocks	100 stocks with largest option volume	Trim 1 % of of returns in each tail	Returns using only last price of each day
ATM	Mean	2.551	2.378	2.498	1.829	1.674	1.592
Calls	Alpha	2.570	2.396	2.515	1.827	1.676	1.629
	t-stat	23.780	23.230	23.410	24.230	24.910	15.020
ATM	Mean	2.156	2.005	2.189	1.235	1.350	1.636
Puts	Alpha	2.140	1.991	2.173	1.238	1.346	1.602
	t-stat	12.770	12.610	12.730	16.200	16.290	9.260

We report daily t+2 return spreads and alphas for delta-hedged ATM call and puts. Stocks are sorted into quintiles based on their lagged option illiquidity. For the 5–1 quintiles, we report (as a percentage) the mean, the alpha from the Carhart model, and its t-statistic with Newey-West correction for serial correlation using eight lags. The sample includes the S&P 500 constituents with valid traded options data from January 2004 to December 2012. Each column corresponds to a different robustness check described in the text.

The first column in panel A of Table 4 contains the base case sorting results from panels A and B in Table 3. They are repeated here for convenience.

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

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

The fourth column in panel A of Table 4 only relies on the top 100 option classes by average daily option trading volume. They account for approximately 61% of option trading volume in ATM calls and 58% of volume in ATM puts in our sample. Note that the long-short option spreads are close to the base case from Table 3. The option illiquidity spread is therefore not driven by options with low trading volumes.

The fifth column in panel A of Table 4 trims away the 1% largest positive and 1% largest (in magnitude) negative returns in each category. For calls we see that the results are virtually unchanged whereas for puts the average returns and alphas drop. They are however still very large, positive, and strongly significant.

The final column of panel A uses returns computed from only the last traded price on each day. While the long-short option return spread is smaller when we use this more noisy return definition, the spread is still fairly large and highly significant.

The use of trade prices may lead to well-known biases such as the bid-ask bounce (Blume and Stambaugh 1983). One way to address some of these biases is the use of midpoints rather than trade prices. Panel B of Table 4 repeats the analysis in panel A but we now use intraday midpoints S_k^M, as defined in Section 1.3, to compute option returns instead of intraday trade prices. Equation (5) thus gets replaced by

$$O^{VM}(K_n, T_n) = \frac{\sum_k DolVol_k S_k^M}{\sum_k DolVol_k}.$$

Comparing panel B with panel A, we see that the illiquidity premia are generally smaller when using intraday midpoint quotes, in particular for the top 100 option classes by trading volume and when trimming the extreme returns. However, the illiquidity premia remain positive, very large, and strongly statistically significant. Note also that the alphas in Table 4 are close to the raw returns everywhere. This also matches the base case results from Table 3.

The last column of panel B of Table 4 reports on returns computed from midpoint quotes, but it exclusively uses the quotes corresponding to the last trade of the day. These returns are similar in construction to the ones based on OptionMetrics data used by many existing studies.[20] The last columns of panels A and B suggest that using the last quotes of the day yields results that are similar to using the last trade price of the day. The caveat is that these returns in the last column may be noisy. When using the averages in the other columns of Table 4, the differences between panel A and panel B are somewhat bigger.

ATM options are of particular interest, because they provide investors with substantial exposure to volatility in the underlying stock. In Table 5, we therefore investigate the robustness of the daily ATM results in panels A and B of Table 3 when we narrow the width of the moneyness interval. Throughout we keep the moneyness interval centered on $\Delta = +0.5$ for calls and $\Delta = -0.5$ for puts. Table 5 shows that the illiquidity premium is highly robust to changing the width of the moneyness interval from the original $\Delta \in (0.375; 0.625]$ in Table 3 to intervals ranging from $\Delta \in (0.4; 0.6]$ to $\Delta \in (0.49; 0.51]$.

Table 5

ATM portfolio returns and alphas using various moneyness intervals: Sorting on option illiquidity

		A. Daily ATM call option returns							*B. D*
	Delta interval	**1**	**2**	**3**	**4**	**5**	**5−1**	**Delta interval**	**1**
Mean		–1.096	–0.476	0.030	0.550	2.193	3.291		–1.0
Alpha	(0.4; 0.6]	–0.997	–0.375	0.131	0.657	2.312	3.307	(−0.6 ; −0.4]	–1.1
t-stat		–9.260	–3.520	1.090	4.680	12.270	26.200		–7.4
Mean	(0.425; 0.575]	–1.015	–0.455	0.052	0.553	2.185	3.203	(−0.575 ; −0.425]	–1.0
Alpha		–0.916	–0.354	0.153	0.657	2.302	3.218		–1.0
t-stat		–8.740	–3.370	1.300	4.810	12.590	25.430		–7.2

Mean	(0.45; 0.55]	–0.950	–0.441	0.028	0.577	2.304	3.254	(−0.55; −0.45]	–0.96
Alpha		–0.851	–0.340	0.130	0.680	2.419	3.269		–1.0
t-stat		–8.230	–3.330	1.110	5.090	12.750	23.310		–6.9
Mean	(0.475; 0.525]	–0.820	–0.355	0.042	0.576	2.334	3.154	(−0.525; −0.475]	–0.7
Alpha		–0.724	–0.254	0.146	0.679	2.447	3.171		–0.8
t-stat		–6.800	–2.350	1.190	4.950	13.120	22.150		–5.5
Mean	(0.49; 0.51]	–0.689	–0.406	0.024	0.525	2.418	3.116	(−0.51; −0.49]	–0.7
Alpha		–0.594	–0.303	0.130	0.626	2.533	3.137		–0.8
t-stat		–4.980	–2.330	0.950	4.250	11.350	16.440		–5.2

The table reports portfolio results for delta-hedged ATM call and put t+2 returns and alphas. We sort stocks into quintiles based on their lagged option illiquidity. For each quintile, we report in percentage the mean, the alpha from the Carhart model, and its t-statistic with Newey-West correction for serial correlation, using eight lags. The sample includes the S&P 500 constituents with valid traded options data from January 2004 to December 2012.

Finally, to investigate the robustness of the results over the sample period, for each nonoverlapping six-month period, the top row of Figure 5 plots the average 5−1 option return spread when sorting on ES^O. The bottom row plots the six-month averages of the 5−1 difference in the ES^O themselves. The 5−1 return spreads in the top row and the 5−1 differences in effective relative spreads in the bottom row display similar patterns, including a somewhat negative trend. We conclude that Figure 5 suggests a close correspondence between the 5−1 effective bid-ask spread and the 5−1 option return spread.

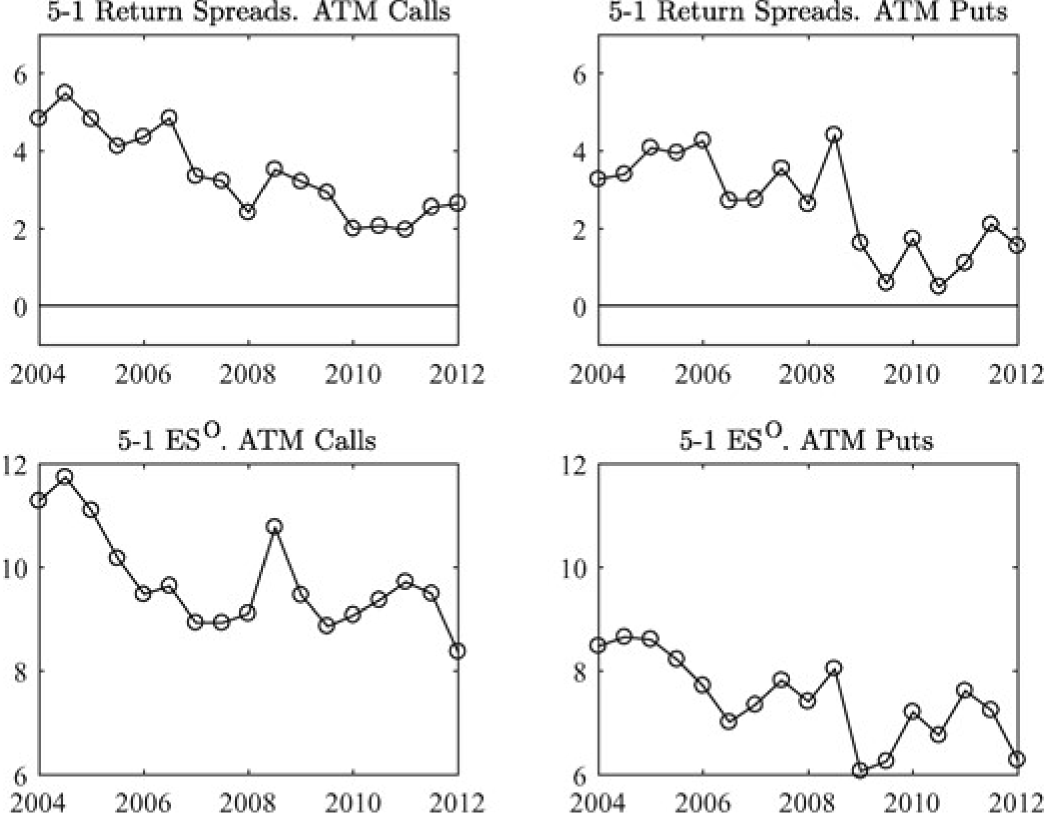

Figure 5 **Long-short return spreads and effective relative spreads. ATM calls and puts**

We sort option classes into quintiles based on lagged option illiquidity measured by effective relative spreads (ES^O). For each six-month period, we plot in the top row the average 5–1 option return spread when sorting on ES^O. The bottom row plots the six-month averages of the 5–1 difference in ES^O themselves. ATM calls are shown in the left column and ATM puts are shown in the right column. The sample includes S&P 500 constituents with available options data from 2004 to 2012.

3 Determinants of Effective Spreads

So far we have determined that the effective spread ES^O is a robust determinant of expected option returns. This clearly begs the question: what are the determinants of ES^O? There is an extensive theoretical and empirical literature on the determinants of spreads in securities markets, and this work has inspired a growing empirical literature on the determinants of spreads in option markets. We first discuss this literature and then we use the variables suggested by these papers to explain the cross-sectional variation in the ES^O measure in our sample. Our investigation uses a more extensive sample compared to the data used in existing studies, with the exception of Goyenko, Ornthanalai, and Tang (2015), who use a similar data set. Whereas we focus on option returns, they document implications for stock returns and investigate the importance of asymmetric information by focusing on earnings announcements.

3.1 Existing literature

The literature considers several distinct major components of bid-ask spreads. Market makers face fixed order processing costs set by the exchange, costs due to asymmetric information, inventory costs, and hedging costs.[21] Compared to liquidity providers in stock markets, inventory costs pose a much bigger problem for option market makers because of the volatility of the option position due to leverage, the stochastic risk exposure, and the nature of the imbalances in the option market (Jameson and Wilhelm 1992; Battalio and Schultz 2011).

These theories on the determinants of spreads in security markets all suggest variables that ought to affect bid-ask spreads in option markets. Information asymmetry theories (Copeland and Galai 1983) suggest that spreads should decrease with market activity and increase when the probability of informed trading is higher. In option markets evidence of informed trading has been presented by Easley, O'Hara, and Srinivas (1998) and Pan and Poteshman (2006).

Inventory models analyze market makers who manage deviations from optimal inventory and predict a negative relation between spreads and the price of the security (Ho and Stoll 1983) and a positive relation between spreads and the security's volatility (Biais 1993). These models also predict that spreads change with market maker risk aversion, which of course is difficult to measure. In option markets, Bollen and Whaley (2004) and Muravyev (2016) use order imbalances as a proxy for deviations from optimal inventory.

Several studies discuss the importance of hedging costs. Cetin et al. (2006) and Figlewski (1989) argue that delta hedging invokes model misspecification risks in option markets. Jameson and Wilhelm (1992), George and Longstaff (1993), and de Fontnouvelle, Fishe, and Harris (2003) find that inability to continuously rebalance the hedge increases options spreads. Battalio and Schultz (2011) document that option spreads increased dramatically during the September 2008 short-sale ban due to the inability of market makers to hedge their position in options on short-sale-restricted stocks. Finally, Evans et al. (2009) show that the difficulty of borrowing shares (specialness) increases option bid-ask spreads. See also Muravyev, Pearson, and Pollet (2016) on the impact of uncertainty regarding stock lending fees.

These hedging costs can be thought of as inventory costs; alternatively Engle and Neri (2010) argue that hedging costs can be viewed as a separate class of costs that affects bid-ask spreads and they document that market makers in equity options face hedging costs that constitute a large part of the overall spread.

Duffie, Gârleanu, and Pedersen (2005) specify a dynamic model with investors and market makers. Effectively the role of market makers' inventory is ignored in their model, which allows the authors to highlight the relation between market structure and characteristics, the characteristics of the search process and spreads and returns. Spreads are affected by standard variables such as hedging costs, but also by variables that are difficult to measure, such as the expected arrival rate of counterparties and investors' liquidity needs.

3.2 Option effective spreads regressions

We now turn to a detailed analysis of the determinants of ES^O for our sample based on the variables suggested in the existing literature. We proceed by conducting a Fama and MacBeth (1973) regression analysis with ES^O as the regressand and with contemporaneous regressors that have been documented to affect liquidity in the literature. We also include standard control variables and lags of ES^O to capture persistence.

Table 6 contains the ES^O regression results. Recall that ES^O is the effective relative option spread. We report two sets of regressions each for ATM calls and puts: One that includes positive and negative imbalances separately, and another that uses the absolute value of imbalances. The use of the imbalances variable is motivated by Bollen and Whaley (2004) and imbalances are defined in Equation (7) above. The most important results in Table 6 are as follows.

Table 6
Option effective spread (ES^O) regressions

	A. Daily ATM call options				*B. Daily ATM put options*			
	Coeff	***t*-stat**	**Coeff**	***t*-stat**	**Coeff**	***t*-stat**	**Coeff**	***t*-stat**
Positive imbalances	0.0015	4.67			0.0026	9.9		
Negative imbalances	–0.0040	−14.6			–0.0016	−7.21		
|Imbalances|			0.0085	23.26			0.0072	23.76
ES^S	2.3156	9.78	2.0351	7.85	1.3001	6.19	0.8618	3.80
PIN	0.0188	13.62	0.0200	12.62	0.0213	15.08	0.0214	13.62
Gamma*σ	0.2962	44.38	0.3133	23.20	0.1943	34.31	0.2201	21.15

Vega*ES^S	–0.0067	–0.52	0.0243	1.65	–0.0080	–0.66	0.0144	1.09
log(option volume)	–0.0013	–35.94	–0.0012	–24.24	–0.0004	–12.6	–0.0005	–13.95
<u>Controls</u>								
ES^O(t-1)	0.3097	91.49	0.2962	81.94	0.3076	84.39	0.2921	71.99
ES^O(t-2)	0.2357	76.43	0.2311	63.04	0.2420	71.36	0.2329	63.59
σ	–0.0468	–57.21	–0.0480	–26.64	–0.0411	–55.78	–0.0420	–27.78
b	–0.0014	–3.51	–0.0023	–4.53	–0.0026	–7.08	–0.0031	–8.16
log(size)	–0.0032	–41.59	–0.0031	–28.09	–0.0027	–36.55	–0.0027	–27.12
Leverage	0.0049	21.32	0.0050	17.17	0.0038	19.53	0.0041	17.23
log(stock volume)	–0.0004	–4.31	–0.0003	–2.76	–0.0003	–3.29	–0.0001	–0.47
|Delta|	–0.0222	–27.57	–0.0805	–63.73	–0.0150	–21.04	–0.0591	–45.04
Adjusted R^2	0.507		0.524		0.455		0.469	
# CS regressions	2009		2009		2009		2009	
# Obs in CS (avg)	327		327		263		263	

We report the results of cross-sectional Fama-Macbeth regressions for daily ATM call option ES^O (panel A) and put option (panel B) ES^O. The regressors are described in the text. Reported are coefficients and Fama-Macbeth t-statistics with Newey-West correction for serial correlation using eight lags. We also provide the adjusted R^2, the number of cross-sectional (CS) regressions, and the average number of observations in each cross-sectional regression. The sample starts in January 2005 and ends in December 2012, following the availability of the imbalance variable.

Leland (1985), Boyle and Vorst (1992), and Constantinides and Perrakis (2007) analyze the effect of illiquidity in the underlying asset on option prices. In the ES^O regressions in Table 6 the coefficient on ES^S is significantly positive. It is more expensive to manage option inventory for stocks with higher ES^S, which drives up relative option spreads.

The probability of informed trading (PIN) measure from Easley, Hvidkjaer, and O'Hara (2002) is a significant driver of ES^O. A high PIN indicates high asymmetric information, which, in turn, increases ES^O. Note that PIN is only available at the quarterly frequency.

Engle and Neri (2010) suggest using the interaction of option Gamma and stock return volatility ($Gamma * \sigma$) to capture hedging costs. Note from Table 6 that the slope on $Gamma * \sigma$ is significantly positive as expected. Higher hedging costs increase ES^O.

Following Leland (1985) and Boyle and Vorst (1992), we apply a commonly used proxy for market makers' inventory rebalancing costs, the product of the option $Vega$ and the relative spread of the underlying stock ($Vega * ES^S$). The effect from $Vega * ES^S$ is not significant in Table 6, perhaps because ES^S is also included in the regression.

The effect of option volume on ES^O is negative which is not surprising. High volume leads to lower order processing costs and lower inventory holding costs.

As suggested by Duan and Wei (2009), we investigate the effect of systematic equity risk (using the square root of R^2 from the Carhart four-factor model) and also stock return volatility using a simple symmetric GARCH(1,1) model (Bollerslev 1986).[22] The coefficients on these variables are both negative which is perhaps surprising. But recall that GARCH volatility increases the option price, which is in the denominator of ES^O. Systematic equity risk may increase the price of the option through the market variance risk premium as well. Stock volume effects are weak as stock illiquidity is likely captured better by ES^S. The absolute value of delta is included to control for moneyness differences inside each category.

We also control for firm size and leverage following, for instance, Dennis and Mayhew (2002) and Duan and Wei (2009). We measure size using the log of market capitalization. We define leverage as the sum of long-term debt and the par value of preferred stock, divided by the sum of long-term debt, the par value of preferred stock, and the market value of equity. Because leverage is available only at a quarterly frequency, we use leverage computed over the previous quarter. Size has a significantly negative relationship and leverage has a significantly positive relationship with ES^O in Table 6. As expected, smaller and more highly leveraged firms are more risky and more expensive to hedge.

We provide two sets of results with imbalances to illustrate the critical role of the sign of the imbalances. In the first regression specification, the coefficient on imbalances is positive and statistically significant when imbalances are positive, while it is negative and statistically significant when imbalances are negative. This finding obtains for both calls and puts. It is intuitively plausible because it means that spreads widen when imbalances are more extreme. This finding motivates our use of absolute imbalances as a proxy for option inventory risk in the second regression specification (see also Chordia, Roll, and Subrahmanyam 2002). Note the large and significant positive slope on absolute imbalances for both call and put option spreads.

We conclude that the results in Table 6 provide support for several theories on the determinants of spreads and illiquidity. Stock illiquidity, asymmetric information, and hedging costs increase ES^O, confirming the $H_0(2)$ hypothesis. Consistent with inventory theories, absolute order imbalances increase ES^O because market makers face buying or selling pressures in the equity options market. This confirms the $H_0(3)$ hypothesis.

The R^2s in the regressions are around 50%. About half of the cross-sectional variation in ES^O is explained by known factors in a linear regression while about half remains unexplained. Can these R^2s be further improved upon by allowing for nonlinear regression specifications? Because of the large number of variables in Table 6, we do not embark on a fully fledged nonparametric analysis as the curse of dimensionality presents serious challenges. Instead Figure 6 simply scatter plots six of the key variables in Table 6 against ES^O using quintile averages. Figure 6 suggests that the scope for allowing for nonlinear specifications in Table 6 is generally modest, with the exception of the $Vega * ES^S$ variable, which was not significant in Table 6. We conclude that the linear regression specifications in Table 6 provide a reliable analysis of the key drivers of ES^O.

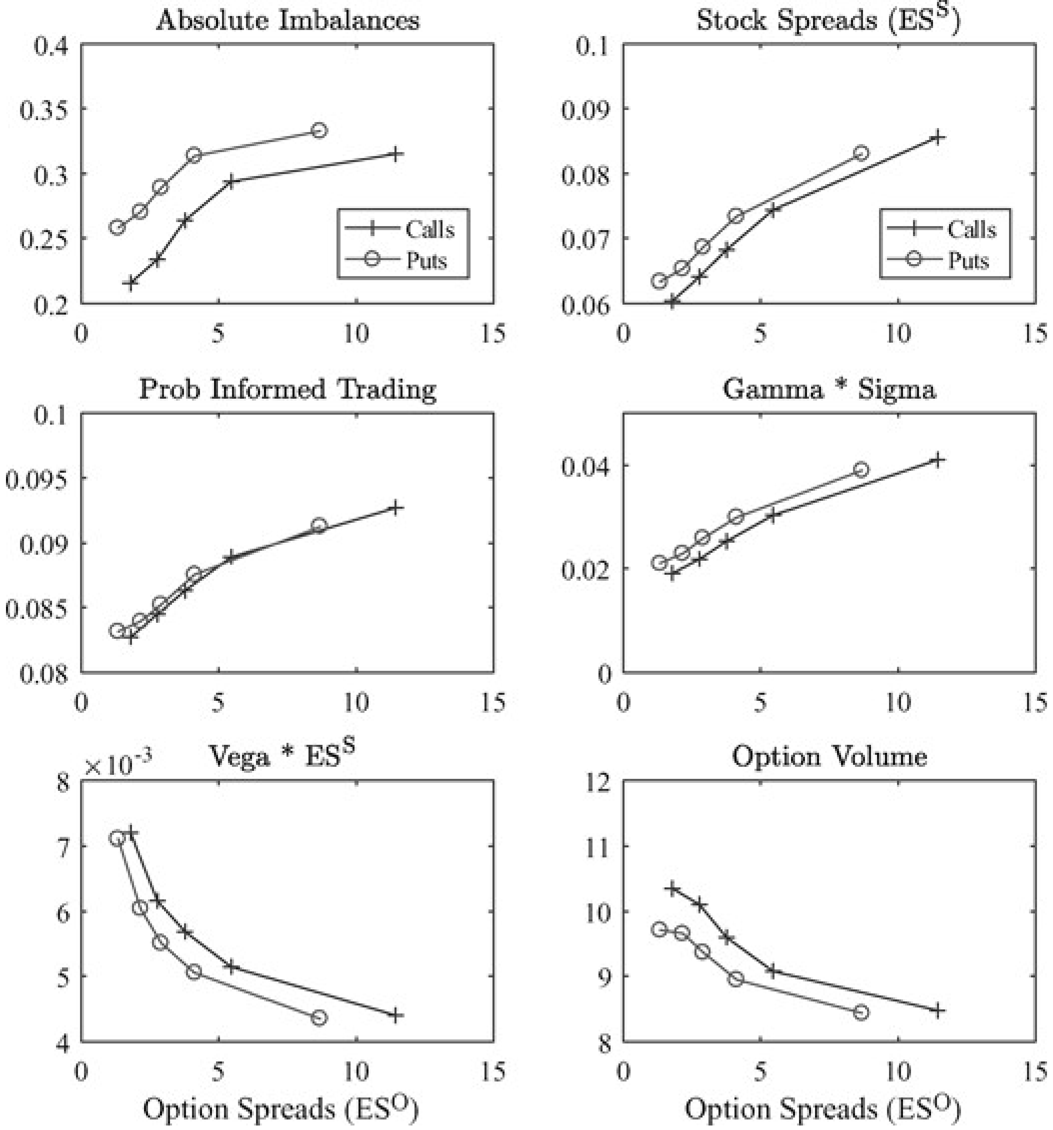

Figure 6 **Scatter plots of various variables against ES^O**

We first sort each variable on ES^O. We then plot the mean value of the variable for each quintile against the mean value of ES^O for each quintile. The sample period is January 2005 to December 2012.

4 Determinants of Expected Option Returns

We have determined that ES^O is a robust determinant of expected option returns using univariate sorts. We then investigated the determinants of ES^O in equity option markets, and we obtain results that are consistent with the existing theoretical and empirical literature. These determinants include measures of asymmetric information, hedging costs, and imbalances, which is a proxy for inventory shocks.

These variables all capture the risks and costs of market making. It is likely that these costs are reflected in expected returns as well as effective spreads, because expected returns and spreads together constitute market makers' remuneration for taking on these risks. Indeed, one can view the spread as a down payment and the expected return as a daily fee charged by the dealer to manage or accept the risk of a position.[23] The existing literature indeed suggests that some of the variables used in the effective spread regressions in Table 6 are determinants of option returns.

In this section we investigate if ES^O remains an important determinant of returns after controlling for the determinants of ES^O studied in Section 3. We first document how the different proxies for the costs and risks of market making are related to expected returns using univariate sorts. We then use multivariate regressions and report robustness checks. We give special attention to the relation between imbalances and returns.

4.1 Univariate sorts

We first consider the direct impact of proxies for the costs and risks of market making on expected option returns using univariate sorts. We consider the variables used in the ES^O regressions in Table 6 and proceed with univariate sorts like we did for ES^O in Table 3.

Table 7 documents the univariate relation between the proxies for the costs and risks of market making and expected option returns. We present results for the next day's return.[24] The first row of Table 7 repeats the results for returns at $t+1$ based on ES^O sorts from panels C and D in Table 3. The signs are as expected for most variables. Future returns are higher for options on more illiquid stocks (ES^S). They are also higher for higher volatility σ, systematic risk b, and option and stock volume. Size and leverage have different effects for puts and calls, but some of this evidence is not very significant statistically. Higher hedging costs $Gamma * \sigma$ and $Vega * ES^S$ also lead to higher returns. The last row indicates that higher imbalances lead to lower returns. We provide a more detailed discussion of the results for imbalances in Section 4.3 below.

Table 7

Option returns from portfolio sorts on various variables: ATM calls and puts

	A. Daily ATM call option returns at t+1							*B. Daily ATM*	
	1	**2**	**3**	**4**	**5**	**5−1**	**5−1 *t*-stat**	**1**	**2**
ES^O	–1.089	–0.480	–0.145	0.467	2.846	3.938	28.490	–1.374	–0.75
ES^S	0.269	0.335	0.267	0.274	0.430	0.161	1.810	–0.502	–0.37
σ	0.232	0.216	0.322	0.342	0.456	0.221	2.120	–0.662	–0.28

b	0.195	0.268	0.349	0.312	0.448	0.248	2.580	–0.207	–0.21
log(size)	–0.030	0.216	0.379	0.501	0.511	0.540	4.830	0.171	–0.15
Leverage	0.284	0.305	0.284	0.295	0.414	0.129	1.530	–0.029	–0.15
|Delta|	–0.188	0.181	0.357	0.603	0.623	0.817	11.350	–0.795	–0.38
log(option volume)	0.211	0.146	0.392	0.640	1.484	1.278	14.340	–0.027	–0.07
log(stock volume)	–0.127	0.093	0.264	0.464	0.869	0.997	9.500	–0.521	–0.31
PIN	0.325	0.309	0.288	0.311	0.259	–0.069	–1.140	–0.139	–0.14
Vega*ES^S	0.034	0.147	0.336	0.400	0.660	0.626	8.460	–0.590	–0.09
Gamma*σ	0.239	0.363	0.385	0.320	0.267	0.028	0.340	–0.239	–0.20
Positive imbalances	0.555	0.147	–0.137	–0.845	–1.090	–1.645	–13.660	0.239	0.07
Negative imbalances	1.235	1.170	1.279	1.160	0.757	–0.478	–5.180	0.912	0.54
Imbalances	1.224	1.261	0.861	0.317	–0.777	–2.001	–26.750	0.755	0.73

The table reports portfolio results for daily delta-hedged risk adjusted with Fama-French-Carhart factors call and put returns on day t+1. We sort stocks into quintiles based on each of the variables on day t. The variables are described in the text. For each quintile, we report in percentage the mean return. The sample includes the S&P 500 constituents with valid traded options data from January 2004 to December 2012, except for the last three rows, which use data from January 2005 to December 2012.

For our purpose, it is important that Table 7 indicates that there are large differences in statistical significance between the variables. Imbalances, $Vega * ES^S$, the volume variables, the absolute delta and of course ES^O are highly statistically significant. Interestingly, $Vega * ES^S$ is not statistically significant in the effective spread regressions in Table 6. This suggests that this inventory rebalancing cost is primarily incorporated in expected returns but not in spreads. On the other hand, the PIN variable is not significant in Table 7 but it is highly statistically significant in the effective spread regressions in Table 6. This suggests that market makers primarily react to asymmetric information by adjusting the spreads like in Copeland and Galai (1983) and Glosten and Milgrom (1985), rather than requiring higher returns.

We now turn to a multivariate regression analysis. This allows us to determine if ES^O remains significant when controlling for these other determinants of returns, or if the effect of ES^O is instead due to other previously identified measures of hedging and inventory costs. Another question we address with the multivariate regressions is how the statistical significance of the variables in Table 7 changes in a multivariate setup.

4.2 Multivariate return regressions

To test $H_0(4)$, we now investigate if ES^O remains an important determinant of returns after controlling for the proxies of ES^O studied in Section 3. Recall that the existing theory suggests many determinants of ES^O that can presumably be rather precisely measured, such as the option Greeks, for instance. On the other hand, other theoretical determinants of ES^O, such as investors' liquidity needs or the expected arrival rate of counterparties are much more difficult or almost impossible to measure. By regressing returns on ES^O as well as observable determinants of ES^O, we directly address the question if ES^O contains information on the costs of market making that is not captured by other variables used in the literature. This also allows us to investigate if these two sources of market makers' compensation are determined by the same proxies for the risks and costs of market making, or alternatively if some costs are primarily reflected in spreads and others in returns.

Table 8 reports the results for the multivariate return regressions. Panel A reports on call options and panel B on put options. In each panel, we report on two regressions. Here we discuss the rightmost two columns, where we include all variables from Tables 6 and 7 including imbalances as a single, signed variable. We discuss the leftmost two columns, where we account for a potential differential impact of negative and positive imbalances, in Section 4.3 below.

Table 8
Multivariate Fama-MacBeth regressions for delta-hedged ATM option returns

	A. Daily ATM call option returns at t+1				*B. Daily ATM put option returns at t+1*			
	Coeff	***t*-stat**	**Coeff**	***t*-stat**	**Coeff**	***t*-stat**	**Coeff**	***t*-stat**

ES^O	0.762	29.69	0.755	29.50	0.656	21.27	0.650	21.10
Positive imbalances	–0.039	–23.08			–0.027	–19.44		
Negative imbalances	–0.011	–8.69			–0.004	–3.23		
Imbalances			–0.024	–29.47			–0.015	–24.52
ES^S	4.273	3.93	4.603	4.35	9.868	9.42	9.989	9.53
PIN	–0.013	–2.11	–0.013	–2.00	–0.013	–2.10	–0.014	–2.22
Gamma*σ	–0.558	–13.24	–0.556	–13.21	–0.483	–12.17	–0.483	–12.16
Vega*ES^S	–0.207	–3.43	–0.214	–3.67	–0.381	–6.47	–0.369	–6.30
log(O/S)	0.005	24.74	0.005	26.93	0.002	13.38	0.003	15.01
Controls								
σ	0.069	11.76	0.072	12.16	0.053	12.04	0.055	12.55
b	0.009	3.67	0.009	3.61	0.009	4.08	0.009	3.91
log(size)	0.005	12.70	0.005	13.99	0.001	4.07	0.002	5.43
Leverage	–0.006	–5.37	–0.007	–5.50	–0.003	–2.36	–0.003	–2.39
|Delta|	0.159	23.09	0.152	22.25	0.139	23.26	0.131	22.57
Adjusted R^2	0.090		0.090		0.079		0.078	
# CS regressions	2011		2011		2011		2011	
# Obs in CS (avg)	302		302		228		228	

We report the results of cross-sectional Fama-Macbeth regressions for daily delta-hedged call option (panel A) and put option (panel B) returns. The regressors are described in the text. Reported are coefficients and Fama-MacBeth t-statistics with Newey-West correction for serial correlation using eight lags. We also provide the adjusted R^2, the number of cross-sectional (CS) regressions, and the average number of observations in each cross-sectional regression. The sample starts in January 2005 and ends in December 2012, following the availability of the imbalance variable.

The most important conclusion from Table 8 is that in the presence of a large number of control variables, many of which are determinants of ES^O, ES^O remains a highly significant predictor of future returns, with the expected positive sign. Several findings in Table 8 are consistent with those of Table 7. Imbalances, volume, the absolute delta and ES^O are highly significant.

There are a number of interesting differences between the univariate results in Table 7 and the multivariate results. Most notably, the signs on $Gamma * \sigma$ and $Vega * ES^S$ are negative in Table 8. Moreover, in Table 8 the $Gamma * \sigma$ variable is strongly significant, as opposed to the results in Table 7. Consistent with Table 7, the statistical significance of systematic risk and PIN is rather low.

Recall that the R-squares in the linear ES^O regressions in Table 6 are around 50%. About half of the variation in ES^O is explained by known factors while about half remains unexplained. The multivariate return regressions in Table 8 confirm that ES^O contains a substantial amount of additional information about the liquidity needs of investors and the costs and risks of market making in option markets, that is not captured by the regressors in Table 6. There are several potential explanations for this finding. It is possible that certain costs and risks of market making are primarily reflected in spreads, while others are primarily reflected in expected returns. Perhaps a more plausible explanation is that several of the ES^O determinants are very difficult or impossible to measure or even observe directly, but they are reflected in spreads.

In summary, we find an extremely robust relation between ES^O and future returns even after controlling for other variables, confirming H_0 (4). We conclude that ES^O is a very informative summary statistic for illiquidity and the risks and costs of market making.

4.3 Imbalances and returns

Existing studies have highlighted the impact of imbalances on option prices (Bollen and Whaley 2004; Gârleanu et al. 2009; Muravyev 2016). We now discuss our results for imbalances in more detail. Imbalances are negative (end users are net sellers) on average over the sample period, but Figure 4 indicates that their cross-sectional average is positive in many weeks. Figure 7 provides additional perspective by plotting the percentage of stocks with positive (dashed lines) and negative (solid lines) option order imbalances for each week for ATM calls (top panel) and ATM puts (bottom panel). For calls, we have negative imbalances for a large majority of stocks for virtually every week of our sample. For puts the pattern is somewhat less evident.

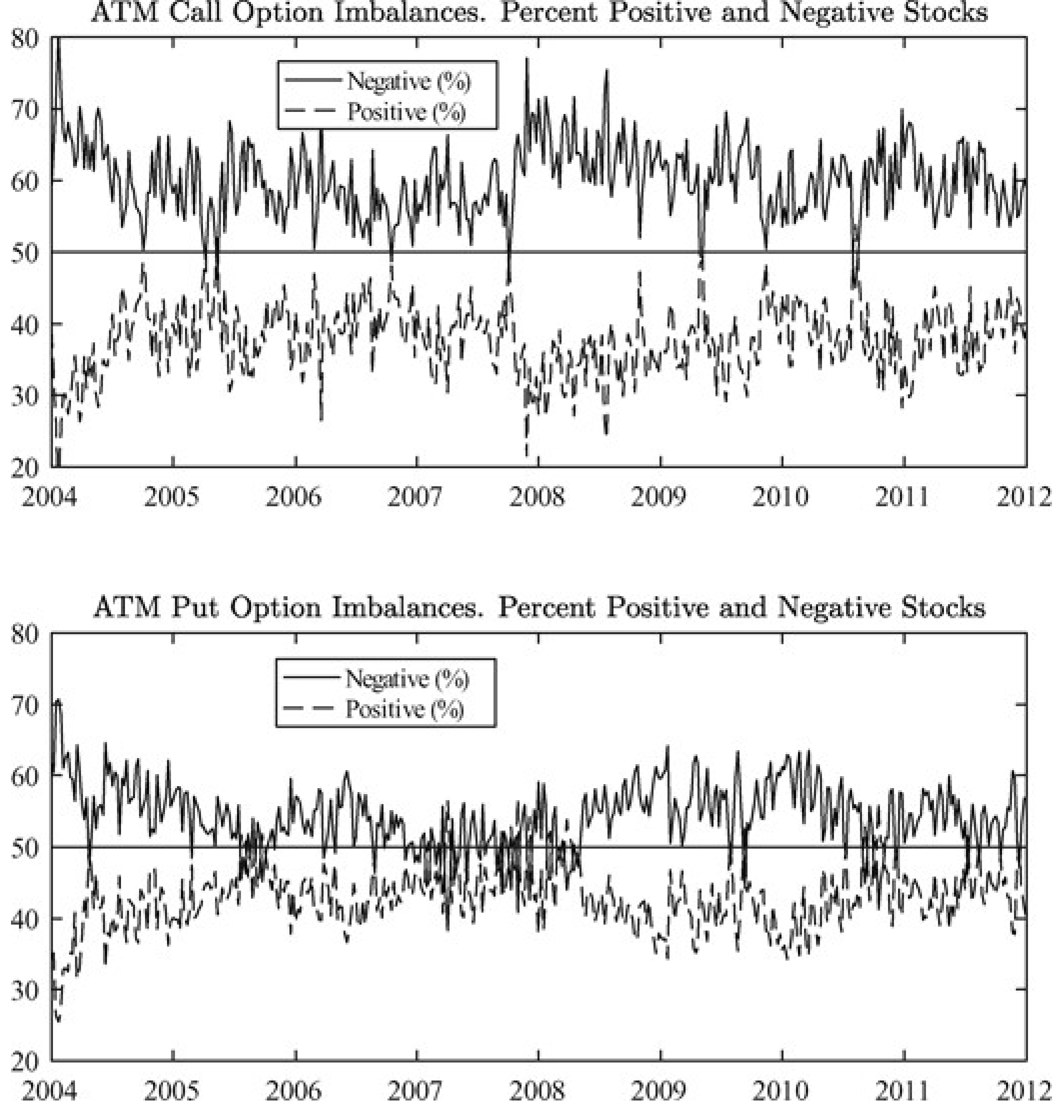

Figure 7 **Percentage of stocks with positive and negative ATM option order imbalances**

The plot shows the percentage of stocks for which the total weekly ATM option order imbalance is positive (dashed lines) or negative (solid lines), where negative indicates that end users are net sellers. The top panel reports on call options and the bottom panel on put options.

The last row of Table 7 indicates that the long-short return is negative and highly statistically significant for both calls and puts. To provide intuition for this sign, Table 7 also provides sorts based on negative and positive imbalances separately. The market maker is buying at time t when imbalances are negative at time t, and selling at time t when imbalances are positive. For negative imbalances the first quintile contains the options with the most imbalanced net demand; for positive imbalances the fifth quintile is the most unbalanced. If the market maker sets prices and prices revert at $t+1$, we expect positive returns for the negative imbalances, because the market maker is now selling some of her inventory. For the case of positive imbalances, the market maker is presumably trying to correct some of her earlier net selling at $t+1$, and we expect returns at $t+1$ to be negative as a result. We expect maximum price impact in the first quintile for negative imbalances and in the fifth quintile for positive imbalances, which should result in negative long-short returns at $t+1$ in both cases.[25]

Table 7 confirms these theoretically expected patterns consistent with price reversal.[26] The cross-sectional effect of imbalances on returns is economically large and negative and statistically significant, as expected. The effect is economically and statistically stronger for positive imbalances. In the multivariate return regressions in Table 8, the results for negative and positive imbalances are consistent with the univariate results in Table 7. Table 7 also indicates that returns are monotonic as a function of imbalances regardless of sign. The last two columns of each panel in Table 8 therefore repeat the regression with the single, signed imbalance variable, which is estimated with a statistically very significant negative sign. The Online Appendix further investigates the relation between imbalances and option returns spreads. We find that the strength of the cross-sectional relation between option effective spreads and option returns on day $t+1$ depends on the option order imbalance on day t.

Overall, the results in Tables 7 and 8 highlight the differences between our findings and those of Gârleanu et al. (2009) and Bollen and Whaley (2004): these papers study the effect of imbalances on option prices, while our findings in Tables 3 and 4 establish an illiquidity premium using option effective spreads. Effective spreads reflect the illiquidity characteristics of options including inventory carrying and holding costs, volatility risks, the inability to perfectly hedge accumulated inventory, information asymmetries (Goyenko, Ornthanalai, and Tang 2015), as well as market makers deviations from their preferred inventory position (Amihud and Mendelson 1980). Some of these risks and costs of market making are difficult to measure precisely, but are transmitted into the illiquidity premium and captured by the more precisely measured effective spreads. Because effective spreads encompass these different risks, their effect on expected option returns is distinct from the relation between net option imbalances and returns, as evidenced by the multivariate regressions in Table 8.

4.4 Robustness checks on return regressions

In this section we investigate if the impact of ES^O on option returns documented in the cross-sectional regressions in Table 8 is robust to various permutations of the empirical setup. To address the possibility that misspecified delta hedges generate the return premia we document, we add various variables to the return regressions that can capture shortcomings in the Black-Scholes delta-hedging formula.

In Table 9 we report Fama–MacBeth coefficients on the ES^O variable from multivariate regressions using daily ATM option returns. We also report the corresponding t-statistics and regression R^2s. For reference, the first column for each panel reports the base case results from the leftmost columns in Table 8. Panel A contains daily ATM call option regressions, and panel B contains daily ATM put option regressions.

Table 9

Option effective spread coefficients from Fama-Macbeth regressions: Various robustness checks

A. Daily call option return regressions. ES^O coefficients and statistics

		Base case from Table 8	**Nonfinancial stocks only**	**Trim 1 % of returns in each tail**	**Add $R^S(t+1)$**	**Add S(t+1), O(t+1)**	**Add $R^O(t)$, $\lvert R^S(t)\rvert$**	**Add al variab**
ATM	Coeff	0.762	0.752	0.493	0.749	0.747	0.587	0.601
Calls	t-stat	29.690	28.390	44.090	29.840	29.670	28.070	28.94(
	Adj R^2	0.090	0.090	0.077	0.171	0.097	0.288	0.324

B. Daily put option return regressions. ES^O coefficients and statistics

		Base case from Table 8	Nonfinancial stocks only	Trim 1 % of returns in each tail	Add $R^S(t+1)$	Add S(t+1), O(t+1)	Add $R^O(t)$, $\lvert R^S(t)\rvert$	Add al variab
ATM	Coeff	0.656	0.655	0.429	0.659	0.655	0.511	0.526
Puts	t-stat	21.270	21.200	29.880	21.470	21.300	18.330	19.38(
	Adj R^2	0.079	0.078	0.067	0.158	0.084	0.217	0.303

We report the coefficients on option effective spreads from Fama-Macbeth regressions using daily ATM option returns. Except for the penultimate column, the regressors from Table 8 Column 1 are always included in the regressions but are not reported here. t-statistics are computed with Newey-West correction for serial correlation using eight lags. Adjusted R^2 are reported as well. The sample includes the S&P 500 constituents with valid traded options data from January 2005 to December 2012. Each column corresponds to a different robustness check described in the text. “All variables” refers to the current stock price, the current stock return, the current volume-weighted option price, the lagged absolute stock return, and the lagged return on the option delta hedge.

We report on the eight robustness tests from Table 9. In the second column, we remove corporations with SIC codes between 6200 and 6299 as well as between 6700 and 6799, corresponding to financials, insurance and real estate companies. In the third column, we trim the largest 1% and smallest 1% option returns from the sample to assess if our results are driven by outliers. In the fourth column, we add the contemporaneous stock return, $R^S_{i,t+1}$, to pick up any error in the delta-hedging procedure. In the fifth column, we instead add the current stock price, S_{t+1} and option price, O_{t+1}, to pick up any biases from omitted regressors. In the sixth column, we instead add the lagged option return, R^O_t and the lagged absolute stock return $\left|R^S_t\right|$ to pick up biases from omitted regressors. In the seventh column, we add all the variables from columns 4 to 6.

Our last two robustness checks are slightly different in that they do not build directly on the base case regressions from Table 8. In the eighth column, we run simple univariate regressions of option returns on ES^O without any control variables. In the ninth column, we use R^O_{t+2} instead of R^O_{t+1} on the left-hand side of the regressions. This matches panels A and B in Table 3. We use the same regressors used in the base case in Table 8.

The results for ATM call options in panel A of Table 9 are quite striking. The coefficient on ES^O is positive and highly significant in all cases. In panel B of Table 9, the coefficient on ES^O for ATM puts is always positive and significant as well. Not surprisingly the ES^O coefficients are smaller when using R^O_{t+2} on the left-hand side. This matches the return spread results in Table 3. We conclude that the illiquidity premium is robust to variations in the empirical design.

4.5 The economic magnitude of the illiquidity premium

Our results suggest that ignoring option illiquidity is tantamount to overestimating option prices, and this effect is large and significant. For example, for ATM call options, the average coefficient on ES^O in the R^O_{t+1} regressions in panel A of Table 9 is 0.637. Table 2 shows that the standard deviation for ATM call option illiquidity is 4.02%. Therefore, a one-standard-deviation positive shock to ATM call option illiquidity on day t would result in a 2.56% increase in the day $t+1$ return on the call option. This is a large magnitude for daily returns. For ATM put options the corresponding effect is $0.563 * 3.62 = 2.04\%$ per day, which is also large.

As a consistency check, we can compare the 3.92% 5–1 return spread for ATM calls in panel C of Table 3 with the univariate regression coefficient of 0.407 in Table 9. Multiplying 0.407 by the difference between the average ES^O for quintile 5 (11.44) and quintile 1 (1.77) yields 3.93%. For ATM puts, the 5–1 spread of 3.33% in Table 3 can be compared with the univariate regression coefficient of 0.416 in Table 9 multiplied by ES^O quintile means of 8.68 less 1.33, which yields 3.06%. Note that we do not report the ES^O quintile means in the tables, but they can be gleaned from Figure 6.

5 Conclusion

We present evidence on illiquidity premia in equity option markets. Using portfolio sorts, we find a large and significantly positive impact of effective spreads on expected option returns. This result is not altered in a variety of robustness checks.

The economic mechanism underlying these findings is that illiquidity premia reflect market makers' compensation for the risks and costs of market making. Lakonishok et al. (2007) and Gârleanu et al. (2009) document that end users have net short positions in the equity options market, requiring market makers to hold net long positions. Market makers respond by adjusting spreads and requiring positive returns on long positions. In the cross-section, more imbalanced demand and higher costs leads to larger spreads as well as higher expected returns.

Regression results confirm that option effective spreads increase with stock illiquidity, asymmetric information, more extreme imbalances, and hedging costs. When we regress returns on effective spreads and proxies for the risks of market making, effective spreads remain an economically and statistically important determinant of expected returns. This confirms that besides readily measurable costs of market making, effective spreads reflect inventory holding costs and risks that are difficult to observe and quantify separately.

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Footnotes

1 Other studies of illiquidity premia in the equity market include Amihud and Mendelson (1989), Eleswarapu and Reinganum (1993), Brennan and Subrahmanyam (1996), Amihud (2002), Jones (2002), Pastor and Stambaugh (2003), Acharya and Pedersen (2005), and Lee (2011). Bond market studies include Warga (1992), Warga (1992), Boudoukh and Whitelaw (1993), Kamara (1994), Krishnamurthy (2002), Longstaff (2004), Goldreich, Hanke, and Nath (2005), Bao, Pan, and Wang (2011), and Beber, Brandt, and Kavajecz (2009).

2 See also Duffie, Gârleanu, and Pedersen (2007) and Weill (2008), among others.

3 See also Engle and Neri (2010), Wei and Zheng (2010), and Huh, Lin, and Mello (2015), among others.

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

5 Madhavan and Smidt (1993), Hendershott and Seasholes (2007), Comerton-Forde et al. (2010), and Hendershott and Menkveld (2014), among others, have investigated the importance of inventory for market makers in the stock market.

6 Equity options are exchange traded (see Battalio, Shkilko, and Van Ness 2016 for details on market structure), and, so strictly speaking, there is no search in these markets. However, the characteristics of the search process in Duffie, Gârleanu, and Pedersen (2005) can be thought of as determining the ability of market makers in equity options markets to provide liquidity, while managing holding costs and inventory risk. See Duffie, Gârleanu, and Pedersen (2005) and Amihud, Mendelson, and Pedersen (2005) for a discussion.

7 When computing returns, we use the adjustment factor for splits and other distribution events provided by CRSP.

8 Battalio, Hatch, and Jennings (2004) document structural changes in option markets until 2002, after which the market has come to closely resemble a national market.

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

10 Jensen and Pedersen (2016) show that transaction costs and other frictions can overturn Merton's rule that one should never exercise a call on a nondividend paying stock early. Because we focus on ATM and OTM options, this result is not likely to significantly affect our sample, and we therefore do not filter out options for which early exercise might be optimal.

11 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.

12 Note that our choice of illiquidity measure requires that the option series is traded. Also, it effectively assumes that the midpoint is equal to the fundamental value. This assumption may be tenuous for options on stocks with high borrowing costs, but for our sample of S&P 500 stocks it is relatively innocuous.

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

14 Although we rely on relative effective spreads throughout this paper, the Online Appendix reports on how the distribution of dollar spreads varies with the bid size of the option.

15 This trend partly reflects the move to quoting in pennies and nickels, and the introduction of the make-or-take pricing model, both of which started in 2007. We are grateful to the referee for pointing this out.

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

17 Additional risk factors could be considered, in particular liquidity risk factors. However, because we study daily returns, it is not obvious that standard equity liquidity factors, such as those in Pastor and Stambaugh (2003), are applicable.

18 See, for example, the recent evidence in Goncalves-Pinto et al. (2016) and the literature review therein on the implications of this discrepancy for predicting the underlying stock return. Note that Muravyev, Pearson, and Broussard (2013) find that options markets do not facilitate stock price discovery.

19 Note, however, that Muravyev and Pearson (2014) argue that because option prices tend to move slower than the underlying stock price, investors can dramatically reduce the effective dollar spreads (from 6.2 to 1.3 cents in their sample) by timing their option trades.

20 The Online Appendix also presents option return spreads computed from OptionMetrics and discusses the differences.

21 On asymmetric information, see Copeland and Galai (1983), Glosten and Milgrom (1985), Kyle (1985), and Easley and O'Hara (1987). On inventory costs, see Amihud and Mendelson (1980) and Ho and Stoll (1983).

22 We include b_t as a firm-specific effect, which is the square root of the R-square from the regression of stock returns on the Carhart (1997) factors. Following Duan and Wei (2009), we obtain daily estimates of b_t by using one-year rolling windows to run daily

OLS regressions of excess stock returns on the market, size, book-to-market, and momentum factors.

23 We are grateful to our discussant, Nick Bollen, for suggesting this interpretation.

24 Recall that our main results in Tables 3 through 5 are obtained by skipping one day between the computation of illiquidity measures and the computation of returns to alleviate potential asynchronicity biases. Panels C and D of Table 3 indicate that the effect of ES^O on the return at $t+1$ is qualitatively similar but larger than the effect on the return at $t+2$. When using returns at $t+2$ instead we get similar results, with the exception of the imbalance variable, which we discuss in more detail in Section 4.3 below.

25 As mentioned above, we use returns at $t+1$ throughout Section 4 to highlight the results for imbalances. The Online Appendix presents the results for returns at $t+2$, which are qualitatively similar but quantitatively less strong, presumably due to reversal. See also Chordia, Roll, and Subrahmanyam (2002) and Hendershott and Menkveld (2014) for evidence on price reversal. The evidence in Comerton-Forde et al. (2010) suggests that skipping a day is likely to obscure important interactions between demand pressures, spreads, and prices.

26 When imbalances are negative, all returns at $t+1$ are positive. When imbalances are positive on the other hand, some returns are positive, but they are economically small. Also note that they are delta-hedged and not raw returns.

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JEL: G12 - Asset Pricing; Trading volume; Bond Interest Rates

Issue Section: Articles

- Supplementary data

Supplementary data

Online Appendix - pdf file