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Abstract

We provide evidence of a strong effect of the underlying stock's illiquidity on option prices by showing that the average absolute difference between historical and implied volatility increases with stock illiquidity. This pattern translates into significant excess returns of option trading strategies that are not explained by common risk factors. Simulation results show, however, that our results can be explained by the hedging costs of market makers who are net long in options on some underlyings and net short in options on other underlyings. Our empirical findings are robust with respect to the chosen illiquidity measure, the measure of option expensiveness, and the return period.

JEL Classification: G12; G13

Keywords: Illiquidity, equity options, option returns, option strategies

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In a Black–Scholes (1973) economy, intermediaries can perfectly hedge their options positions via dynamic trading strategies in the underlying and a risk-free bond. In reality, perfect hedging is infeasible or too costly due to market incompleteness and market frictions. Demand-based option pricing theory addresses this issue by showing how market makers account for unhedgeable risks depending on the sign and magnitude of the net demand they face. If there is higher end user demand to buy a specific option series than to sell it, market makers will charge a higher option price as compensation for risks to be taken. Conversely, if market makers face end user selling pressure, they will lower the option price. Empirical evidence by Bollen and Whaley (2004), Gârleanu, Pedersen, and Poteshman (2009), and Muravyev (2016) shows that demand pressure indeed influences option prices in this way.

Taken together, the demand-based option pricing literature recognizes that option prices are influenced by the sign and magnitude of market makers net option position and the unhedgeable risk inherent to market makers' option inventories. Unhedgeable risks include the inability to continuously rebalance hedging positions (Gârleanu, Pedersen, and Poteshman, 2009). Naturally, the liquidity of the underlying affects hedging costs and could also decrease rebalancing frequencies and thus increase inventory risk. Stock illiquidity should therefore affect the way market makers' inventories impact option prices, depending on whether these inventories are positive or negative. Surprisingly, however, very little is known about the connection between stock illiquidity and option prices and the scarce empirical evidence (Karakaya, 2014; Christoffersen et al., 2015; Choy and Wei, 2016) is mixed. Our paper documents a strong relation between stock illiquidity and option prices. In our cross-sectional analysis, we find that the *absolute* deviations of implied from historical volatility increase with stock illiquidity. Such a relation naturally arises if market makers are net long in options on some stocks and net short in others, which is a realistic scenario. Although there is evidence that market makers are, on average, net long in options written on individual stocks (Lakonishok et al., 2007; Ni, Pan, and Poteshman, 2008; Gârleanu, Pedersen, and Poteshman, 2009; Muravyev, 2016), the standard deviation is very large (Ni, Pan, and Poteshman, 2008; Muravyev, 2016), which implies that we find both net long and net short positions of market makers, depending on the particular option series.

The idea that stock illiquidity is an important driver of option prices is further tested by looking at option trading strategies that build on information on the underlying stock's illiquidity. These strategies deliver significant excess returns that cannot be explained by standard risk factors. Our results also show that a large part of the returns of option trading strategies based on the difference between historical and implied volatility (Goyal and Saretto, 2009) can be captured by stock illiquidity.

Our empirical investigation proceeds in four steps. First, we study the relation between option expensiveness and stock illiquidity. In our base case, we measure option expensiveness as the difference between option implied volatility and realized historical volatility and relate this difference to the underlying stock's Amihud (2002) illiquidity measure. Second, we investigate how greater differences between historical and implied volatility translate into higher option excess returns. If higher volatility differences are not due to the market's superior volatility forecasting abilities but are the result of market imperfections, they should predict higher option excess returns. We use trading strategies with straddles and delta-hedged options throughout the paper to obtain option excess returns. Third, we investigate different explanations for the observed patterns of option prices, option returns, and stock illiquidity. A first test investigates whether option returns can be explained by standard risk factors suggested in the literature. A second test uses a simulation study to see if the magnitude of our empirical findings is consistent with market makers accounting for transaction costs in the underlying stocks and being net long in options on some underlyings and net short in options on other underlyings. In the fourth and final step of our analysis, we perform different robustness checks with respect to the chosen illiquidity measure, the measure of option expensiveness, and the return period.

Our paper adds to a small but growing literature that attempts to relate market frictions and option returns. Christoffersen et al. (2015) investigate how option illiquidity and stock illiquidity affect delta-hedged option returns. They document significant premiums for illiquid options but do not find clear evidence for the role of stock illiquidity. Choy and Wei (2016) find premiums for options' illiquidity risk, however, option returns do not significantly load on a stock market liquidity factor. Although market makers are, on average, long in individual equity options, they could be short, especially in options with highly illiquid underlyings, which is likely to conceal a direct connection between stock illiquidity and option returns. Cao and Han (2013) study the effects of systematic and idiosyncratic volatility on option returns and show that options on high idiosyncratic volatility stocks have lower returns than options on low idiosyncratic risk stocks. They have in mind a setting where speculative investors buy options on stocks with high idiosyncratic volatility. These speculative investors, demanding liquidity in the option market, are willing to pay a premium, while the market makers who are net short find it costly to provide these options and charge a higher price. Frazzini and Pedersen (2012) advocate the role of embedded leverage in alleviating investors' leverage constraints. They provide evidence that intermediaries who meet investors' demand for equity options with higher embedded leverage are compensated for their higher risk. Goyal and Saretto (2009) find that long–short option portfolios based on the deviation between historical and implied volatility produce excess returns that cannot be explained by standard risk factors.[1] Karakaya (2014) suggests that market frictions could help explain the returns of Goyal and Saretto's (2009) portfolios and shows that the premium earned by the strategy depends on overall market and funding liquidity. Our study can be seen as a cross-sectional version of this test, because we show that the trading profits from Goyal and Saretto's (2009) strategy are much higher for options on less liquid stocks.

Finally, our findings complement the literature on the impact of stock illiquidity on option illiquidity. Two recent examples are the studies of Engle and Neri (2010) and Goyenko, Ornthanalai, and Tang (2015), who show empirically that both the transaction costs of the initial option hedge as well as the costs of rebalancing the hedge position widen an option's bid–ask spread. We provide empirical evidence that hedging costs influence not only bid and ask prices (and therefore the bid–ask spread) but also the mid price of options.

The remainder of the paper is organized as follows. Section I provides background on the data used in our empirical study. Section II presents our main results on the relations between option prices (returns) and the underlying stock's illiquidity. Section III investigates different explanations for the observed patterns. Section IV presents a robustness analysis and Section V concludes the paper.

[1] Goyal and Saretto (2009) advocate a behavioral explanation based on overreaction. Karakaya's (2014) findings on put portfolios and the results of An et al. (2014) on the effects of earnings dispersion, however, raise doubts that overreaction is the only reason.

I. Data Set and Data Processing

A. Data Sources and Filters

Our primary data source is the OptionMetrics Ivy DB database. This database contains information on all U.S. exchange-listed individual equity options, including daily closing bid and ask quotes, trading volumes, open interest, and options' Greeks (delta, gamma, vega) and implied volatility. The delta and implied volatility we use are calculated by OptionMetrics' proprietary algorithms that account for discrete dividend payments and the early exercise of American options.[2] The database also contains the closing prices, trading volumes, and information on dividend payments, stock splits, and total return calculations for the options' underlying stocks. Our Ivy DB database sample period is from January 1996 to August 2015.

We use similar filters as in previous studies (Goyal and Saretto, 2009; Cao and Han, 2013; Karakaya, 2014) to minimize the impact of recording errors. We drop all observations where the option bid price is zero and the bid price is higher than the ask price. In addition, we eliminate options with a bid–ask spread smaller than the minimum tick size ($0.05 for options trading below $3 and $0.1 for all other options). We remove observations with zero open interest and require a non-missing delta and implied volatility to keep the observation in the sample. Options with an ex dividend date during the holding period are excluded. We also eliminate option observations that violate obvious no arbitrage conditions such as $S \geq C \geq \max(S - Ke^{-rT}, 0)$ for call price C, underlying stock price S, strike K, risk-free rate r, and time to maturity T.

B. Return Calculations

Our portfolio formation follows that of Goyal and Saretto (2009). To reduce the impact of stock price risk on an option's return, we use two kinds of portfolios. The first contains delta-hedged call options and the second consists of straddles. The portfolios of options and their underlying stocks are based on information available on the first trading day (usually a Monday) after the expiration day of the month.[3] We consider only options that mature the next month and restrict our sample to at-the-money (ATM) options with moneyness (defined as the ratio of the strike price to the stock price) between 0.975 and 1.025 on the day of portfolio formation (usually a

[2] We refer the reader to the Ivy DB reference manual for further details.

[3] Before February 2015, all options expire on the Saturday following the third Friday of the month. Thereafter, they expire at the close of business of the expiration month's third Friday.

Monday). Throughout the sample period, we have 156,849 straddle pairs of calls and puts and 197,374 delta-hedged call observations. To avoid microstructure biases, we follow Goyal and Saretto (2009) and start trading the trading day (usually a Tuesday) after the day on which we obtain the trading signal (usually a Monday) and hold the option until maturity. This implies that the option payoffs and the returns of stock positions used for delta hedging are based on the last closing stock prices prior to expiration.

B.1. Delta-Hedged Option Returns

We calculate the returns of delta-hedged call options portfolios that buy one option contract and sell delta shares of the underlying stock, with the net investment earning the risk-free rate (obtained from Kenneth French's data library). The return is calculated as

$$\Pi_{t,t+\tau} = \frac{\max(S_{t+\tau} - \mathrm{K}, 0) - \Delta_{C,t}\, S_{t+\tau} - \left(C_t - \Delta_{C,t}\, S_t\right)e^{r\tau}}{Abs\left(C_t - \Delta_{C,t}\, S_t\right)}, \tag{1}$$

where *K* is the option's strike price, $\Delta_{C,t}$ is the option's delta, and *C* and *S* are the mid prices of the call and the underlying stock, respectively, at *t,* the trading initiation date, and $t + \tau$, the last trading day prior to expiration. We scale the dollar return by the absolute value of the option bought and the delta shares $\left(\Delta_{C,t}\, S_t\right)$ sold at trading initiation.

B.2. Straddle Returns

Straddles are formed as a combination of one call and one put on the same underlying with identical strike prices and maturity. Although we restrict our sample to options with moneyness between 0.975 and 1.025 and then choose the call and put closest to being ATM for each month and each underlying, there could be a difference between the call and put strikes. The straddle returns are therefore calculated as

$$\Pi_{t,t+\tau} = \frac{\max(S_{t+\tau} - K_{Call}, 0) + \max(K_{Put} - S_{t+\tau}, 0) - (C_t + P_t)e^{r\tau}}{C_t + P_t}, \tag{2}$$

where K_{Call} and K_{Put} could be slightly different.

C. Measures of Option Expensiveness

HV–IV: Our main measure of option expensiveness is the difference between a benchmark estimate of volatility from historical stock return data (HV) and the option's implied volatility (IV). The lower the measure, the more expensive the option. HV–IV is a standard measure for investigating the impact of frictions on option prices and, for example, the empirical work by Bollen and Whaley (2004) and Gârleanu, Pedersen, and Poteshman (2009) concentrates on the impact of demand pressure on this form of expensiveness. As the implied volatility for one stock on the portfolio formation date (t - 1), we use the average of the implied volatilities of the respective put and call options on the stock. For the delta-hedge call strategy, this volatility is replaced by the implied volatility of the call option. The historical volatility is, following Goyal and Saretto (2009), the standard deviation of daily stock returns using the 12 months preceding portfolio formation, unless stated otherwise.

PVOL–CVOL: HV–IV is a measure of the average expensiveness of put and call options because IV uses the average implied volatility of puts and calls. However, stock illiquidity and demand pressure could also have an impact on the relative pricing of puts and calls. In accordance with this idea of order imbalances in put and call options, Bali and Hovakimian (2009) have shown that the difference between put and call implied volatility can predict future stock returns. Therefore, we use the difference between the implied volatilities of ATM put options (PVOL) and ATM call options (CVOL) as a measure of the relative expensiveness of put options compared to calls.

D. Measures of Stock Illiquidity

Our main measure of underlying stock illiquidity is the average of the daily Amihud (2002) measure over the month preceding the portfolio formation date. Goyenko, Holden, and Trzcinka (2009) show that the Amihud measure is the best low-frequency market impact measure and also a good proxy for effective and realized bid–ask spreads. We also use Roll's (1984) and Corwin and Schultz's (2012) stock spread estimates as well as the stock's trading volume and market capitalization in our robustness checks. Details on the liquidity measure calculations can be found in Appendix A.

II. Main Results

A. Stock Illiquidity and Option Expensiveness

Our first analysis examines the relation between option expensiveness and stock illiquidity. Every month, on the portfolio formation date, we first sort stocks into quintiles based on their Amihud measure; then the stocks in each Amihud quintile are sorted into quintiles based on HV–IV. For every month throughout the observation period, we calculate the mean HV–IV for each combination of Amihud quintiles and the HV–IV quintiles. Table I reports the time-series averages and t-statistics of these monthly means. In addition, the last two columns show the time-series average of the mean and standard deviation of HV–IV within the Amihud quintiles.

If stock illiquidity affects option prices, we expect the distribution of HV–IV to change with illiquidity. If market makers were only buyers of individual equity options, the mean HV–IV should increase with illiquidity and, if market makers were only sellers, the mean HV–IV should decrease. The last two columns in Table I show that the mean HV–IV differs only insignificantly between the Amihud quintiles, while the standard deviation doubles from the lowest to the highest quintile, with a t-statistic above 10 for the difference between the lowest and highest quintiles. In principle, an increase of the HV–IV standard deviation is in line with market makers being net long in options on some stocks and net short in options on others. Moreover, the double-sorted portfolios show smooth monotonic increases and decreases of the average HV–IV values with illiquidity. The relatively "expensive" options located in the first and second HV–IV quintile columns show a monotonic decrease of HV–IV with higher illiquidity, while the "cheap" ones in the two highest HV–IV quintile columns show a monotonic increase. The difference between the highest and lowest Amihud quintiles for the center HV–IV quintile column is the only one that is not highly significant.

[Insert Table I about here]

These observations suggest that higher illiquidity leads to broader dispersion of implied volatility around historical volatility, with cheap options becoming cheaper and expensive options becoming more expensive with increasing stock illiquidity.[4] The results in Table I are consistent with market makers pricing options in a way that takes hedging costs due to stock illiquidity into account while being net long in options on some stocks and net short in options on others. To check whether observed end user net demand is in line with this argument, we use a publicly available net option demand data sample of all closing short and long open interests on all equity options for public customers and firm proprietary traders traded at the Chicago Board Options Exchange (CBOE).[5] The sample covers 29,037 different option series on 1,620 underlyings, with the number of open buy, close buy, open sell, and close sell positions summarized for July 7, 2006. To calculate the net demand on this day per underlying, we calculate the net amount of options bought (open buys plus close buys) and subtract the net amount sold (open sells plus close sells) for every underlying. This measure is the amount of options sold (if positive) or bought (if negative) by the market makers for one underlying on the observation date.

[Insert Figure 1 about here]

Figure 1 shows the distribution of these net demand measures for different stocks. The median is -2 (mean 19) and is close to zero compared to the huge standard deviation (862) of the net demand. Although our sample is small compared to the sample of Ni, Pan, and Poteshman (2008) and Muravyev (2016), our results show the same pattern of average net demand being close to zero, with a very large standard deviation.[6]

As an alternative to the double sorting, we now look at the relation between stock illiquidity and option expensiveness in a regression framework. Every month, we run a cross-sectional regression of HV–IV on different variants of the Amihud measure. Table II shows the time-series averages of the regression coefficients, with their t-statistics in parentheses. If we just use the Amihud measure, as in model (1), the coefficient is negative, which is in line with the decreasing mean values in the second to last column of Table I. In contrast, the Amihud measure multiplied by the sign function of HV–IV, as in model (2), has a positive and highly statistically significant

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[4] Since the absolute measurement error for volatility increases with the volatility level and average stock volatility increases with illiquidity, some of the increased dispersion of HV–IV could be caused by increasing measurement error divergence. Such an effect could be alleviated by using the logarithms of the historical and implied volatility. However, our results are qualitatively unchanged when using log(HV/IV).

[5] The sample was available on the website of Market Data Express, LLC (November 1, 2014), at http://www.marketdataexpress.com/User_Data/Files/openclose_20060707.zip.

[6] The results of Carr and Wu (2009) on variance risk premiums provide complementary evidence, because premiums on individual stocks show large cross-sectional variation.

impact on HV–IV. If we include the Amihud measure multiplied by the sign function in addition to the raw Amihud measure, as in model (3), the latter becomes insignificant. Finally, model (4) uses the Amihud measure multiplied by a dummy variable that is equal to one if HV–IV is positive and by a dummy variable that is equal to one if it is negative. The model confirms our observation from Table I that increasing illiquidity leads to higher HV–IV on the condition that HV–IV is positive and to a lower HV–IV on the condition that HV–IV is negative.

[Insert Table II about here]

In summary, the regression results also show a strong relation between stock illiquidity and option expensiveness. However, it is crucial to distinguish between cheap options and expensive options. For cheap options, higher stock illiquidity is associated with options being even cheaper. For expensive options, higher illiquidity is associated with options being more expensive.

B. Stock Illiquidity and Option Returns

We next look at the relation between stock illiquidity and option returns. If the observed pattern of stock illiquidity and option expensiveness is indeed due to the higher hedging costs for illiquid underlyings, we should see a similar pattern for stock illiquidity and option returns. However, historical volatility could just be a noisier estimator of the desired future volatility for less liquid stocks, resulting in higher mean absolute estimation errors. If these higher estimation errors were not reflected in the option's market price, that is, the market's volatility forecast does not contain this noise, the pattern could disappear if we move from option expensiveness to option returns.

The results for stock illiquidity and option returns in Table III are based on the same sorting procedure as used for Table I. They show the time-series averages of the mean (equally weighted) monthly option portfolio returns in the different Amihud and HV–IV quintiles and their corresponding t-statistics. The straddle returns in Panel A and the delta-hedged call returns in Panel B are calculated as described in Section I.B.

For the straddles, we find increasing option returns for the highest HV–IV quintile column and decreasing option returns for the column with the lowest HV–IV values. The delta-hedged call returns show a similar structure.[7] Both patterns mirror the increasing and decreasing HV–IV values of Table I for the corresponding columns. The average returns of the 5–1 columns and

[7] Delta-hedged put returns also show a similar structure in unreported results.

rows are calculated from a portfolio that is $1 long in the fifth portfolio and $1 short in the first portfolio. As shown in the 5–1 column, the returns are monotonically increasing along the Amihud quintiles.

The return difference of being long in the 5–1 strategy in the highest illiquidity quintile and short in the 5–1 strategy in the lowest illiquidity quintile, that is, high Amihud(5–1) minus low Amihud(5–1), is 8.1% for the straddles and 1.4% for the delta-hedged calls. This strategy combines the impact of illiquidity into a single number, which is highly significant for both straddles and delta-hedged calls.[8]

The last two columns in Table III show that the mean option returns only significantly decline along the Amihud quintiles for the delta-hedged calls, while they do not change significantly for the straddle portfolios. The standard deviation smoothly increases for straddles and delta-hedged calls with high significance.

[Insert Table III about here]

To obtain a deeper understanding of the liquidity effect on option returns, we refine the sorting on our liquidity measure. For Figure 2, we repeat our analysis from Table III but sort the options every month into deciles instead of quintiles on the Amihud measure. The lower plots in Figure 2 show the average delta-hedged call or straddle returns of the Amihud deciles. The overall negative relation between option returns and illiquidity mirrors the findings of Christoffersen et al. (2015) and Karakaya (2014), who reports that returns to selling delta-hedged options increase with higher underlying stock illiquidity. However, this negative relation is almost completely driven by the highest illiquidity decile, while there is no clear pattern along the remaining deciles. In contrast, a clear pattern emerges once we sort option observations within the Amihud deciles into HV–IV quantiles. To retain a sufficiently large number of options within our double-sorted portfolios, we limit our analysis to HV–IV terciles and display the returns on the 3–1 portfolios. The upper plots in Figure 2 reveal a clear positive trend with stock illiquidity. Even for the lowest illiquidity decile, however, the returns of the 3–1 portfolios are still positive, with a return of

[8] From a theoretical perspective, other developments of option returns and HV–IV are also plausible. Assume, for example, a situation in which market makers are always net short on all options. In such a market, all options would be, with our theoretical argument, more expensive when the underlying is more costly to trade. We should then find decreasing returns along the Amihud quintiles, not only for the lowest but also for the highest HV–IV quintiles, and the returns of the 5–1 strategy should not be liquidity driven. In contrast, our empirical evidence that large positive and negative HV–IV values can be found in all liquidity quintiles prompts us to focus on the development of the 5–1 strategy along the illiquidity quintiles.

0.55% and a t-statistic of 2.58 for the delta-hedged calls and a straddle return of 3.65% with a t-statistic of 2.08. Such a positive return is unlikely to be explained by hedging costs due to stock illiquidity alone, because we would then expect the return of the 3–1 portfolio to vanish for very liquid underlyings. However, other market frictions and market incompleteness, for example, caused by jumps or stochastic volatility, could still prevent perfect hedging. In summary, Figure 2 illustrates the main contribution of the paper. By looking at the dispersion of HV–IV and the returns of HV–IV long–short trading strategies, we have uncovered a clear connection between stock illiquidity and option returns and are able to capture a large proportion of the mean returns of long–short strategies based on HV–IV.

[Insert Figure 2 about here]

III. Potential Explanations for the Main Results

A. Option Returns and Risk Factors

So far, we have established an empirical pattern that relates option prices and option returns to the underlying's illiquidity. We now look at different potential explanations. A first idea is that the returns of options portfolios are exposed to common risk factors besides stock illiquidity. After controlling for these risks, illiquidity effects could no longer exist. We therefore check whether the increasing excess returns of the 5–1 HV–IV strategies with greater illiquidity of the underlyings can be explained by common risk factors. We run a time-series regression of the returns from the 5–1 HV–IV portfolios within the liquidity quintiles on several risk control variables.

Especially due to the imperfections in our delta hedge and the monthly holding period of the straddle portfolio, the returns could be related to known patterns in the cross section of stock returns. We control for this potential explanation by including the three factors of Fama and French (1993) and Carhart's (1997) momentum factor in a time-series regression.[9] In addition, we control for aggregate volatility and correlation risk premiums following Cao and Han (2013). For market volatility risk, we include the excess returns of the Coval and Shumway (2001) zero-beta

[9] Goyal and Saretto (2009), Schürhoff and Ziegler (2011), Frazzini and Pedersen (2012), Cao and Han (2013), Buraschi, Trojani, and Vedolin (2014), and Christoffersen et al. (2015) also include these four factors as control variables for option returns.

Standard & Poor's (S&P) 500 straddle. We also include the value-weighted average return of (available) zero-beta straddles on the S&P 500 component stocks minus the risk-free rate. Driessen, Maenhout, and Vilkov (2009) show that the returns of an index straddle can be decomposed into the returns of index component straddles and a correlation risk trading strategy. Thus, inclusion of the index straddle and the average of its component straddles can be interpreted as a control for correlation risk. Schürhoff and Ziegler (2011) use the component straddle factor as a proxy for the common idiosyncratic volatility risk premium in their empirical work. Details on our risk factor calculations can be found in Appendix B.

The regression results are presented in Table IV. They show that the loadings on the Fama–French (1993) and momentum factors are insignificant in most cases. The HML and the momentum factor is significant for the delta-hedged call 5–1 strategy in the low liquidity quintile. The loading on the zero-beta S&P 500 straddle is positive and significant for straddles in the low liquidity quintiles. For comparison, Goyal and Saretto (2009) also report for their HV–IV trading strategy a significant positive coefficient for the zero-beta S&P 500 straddle and insignificant coefficients for the Fama–French (1993) and momentum factors. The coefficient of the zero-beta S&P 500 component straddle, which is not included in the analysis of Goyal and Saretto (2009), is insignificant for our sample. Overall, the alphas of the portfolios are all significant and very close to the average raw returns reported in Table III.

[Insert Table IV about here]

The regression alphas of the 5–1 HV–IV strategies within the high liquidity quintile are significantly lower than the alphas of the 5–1 strategies within the low liquidity quintile. The differences for the alphas of the high and low liquidity straddle and delta-hedged call portfolios are 8.0% and 1.2%, respectively. We conclude that the higher absolute option returns we find for the portfolios with more illiquid underlyings cannot be explained by common risk factors.

Other authors have attributed the returns of volatility trading strategies to uncertainty risk, informed trading, and behavioral biases. Buraschi, Trojani, and Vedolin (2014) suggest an explanation for the returns of volatility strategies that is based on the role of priced disagreement risk, but the returns from disagreement risk strategies are very small compared to the option returns we find. Similarly, stocks with higher illiquidity are more likely to be stocks with more private information being available. Since Easley, O'Hara, and Srinivas (1998) and Pan and

Poteshman (2006) show evidence of informed trading in the options market too, one could argue that our option returns stem from asymmetric information. Theoretical models with competitive risk-neutral market makers consider asymmetric information to be a determinant of bid–ask spreads (Copeland and Galai, 1983; Glosten and Milgrom, 1985; Easley and O'Hara, 1987). However, in such a setting, private information does not lead to excess returns of market makers unless market makers charge an information risk premium in the sense of Easley, Hvidkjaer, and O'Hara (2002). In addition, Christoffersen et al. (2015) have empirically shown that private information is a strong determinant of option bid–ask spreads but not of average option returns. Given this evidence and the results of Buraschi, Trojani, and Vedolin (2014), we do not control for disagreement risk and private information. Goyal and Saretto (2009) hypothesize that the returns to their HV–IV strategies could be caused by investors becoming excessively optimistic (pessimistic) about the future riskiness of a stock after large positive (negative) returns. Similarly, An et al. (2014) show that realized excess stock returns help to predict changes in implied volatility. Their findings are consistent with investors' speculative demand for options and intermediaries hedging constraints. Therefore, the findings are complementary to our main result, that higher stock illiquidity is associated with wider fluctuations of option prices around reference prices expected in perfect market environments.

B. Impact of Transaction Costs on Option Prices and Returns

In principle, the relation between stock illiquidity and option prices observed in the data is consistent with a demand-based option pricing theory and demand pressure coming from end users, with varying signs across individual equity options. However, the question remains as to whether stock illiquidity can be a viable explanation for the empirical patterns. This would require that realistic illiquidity costs of market makers be compatible with the observed magnitudes of price and return effects. We investigate this issue by conducting a simulation study.

Our analysis is based on Leland's (1985) option pricing approach with discrete-time replication and transaction costs that provides estimates of the maximum potential price impact of the illiquidity of the underlying.[10] We first briefly describe Leland's approach. We then explain how we simulate option prices using this approach under realistic assumptions for transaction costs,

[10] Alternative pricing models are presented by Boyle and Vorst (1992) and Cetin et al. (2006). The latter model also considers market impact costs that depend on the trade size, which would likely lead to even greater effects.

hedging frequency, market maker positions, and underlying dynamics. Finally, we compare the resulting simulated HV–IV values, option prices, and option returns with our empirical findings.

B.1. Options Replication for Illiquid Underlyings

Leland (1985) uses a Black–Scholes setting with proportional transaction costs for the underlying and derives the following modification of the variance used in the Black–Scholes model:

$$\sigma_m^2 = \sigma^2 \left(1 - \frac{k}{\sigma} \sqrt{\frac{2}{\pi \delta t}}\, sgn(V_{SS}) \right),$$

where $k = (S_{bid} - S_{ask})/S_{mid}$ denotes the round-trip transaction costs for trading in the underlying, σ is the Black–Scholes volatility, and δt is the time interval between two hedging revisions. The sign function on the option gamma ($sgn(V_{SS})$) leads to higher volatility (price) when the market maker has to hedge a short option position and decreases the volatility (price) when the market maker has a long position. The higher (lower) option prices for short (long) positions can be thought of as compensation for the market maker to cover the additional hedging costs due to transaction costs. Leland shows that this modified variance results in an upper (lower) bound of the option price from a discrete-time replication strategy with proportional transaction costs.

Leland's (1985) approach has the interesting feature that the standard deviation of the hedging profit and loss (P&L) is close to the standard error of a discrete-time Black–Scholes hedging strategy without transaction costs. If the market maker adjusts the volatility and therefore the price of the option with Leland's adjustment and uses Leland's delta for hedging, the resulting P&L distribution is, ceteris paribus, close to the P&L distribution in a frictionless market with the usual Black–Scholes pricing and hedging at the same frequency. Using Leland's adjustment for pricing and hedging accounts for transaction costs but does not change the resulting risks of the hedged option position. This enables us to interpret the effect of transaction costs independently of the effects described by Gârleanu, Pedersen, and Poteshman (2009). While their work concentrates on the price effects of unhedgeable risks, the Leland adjustment can be seen as the incremental price change due to transaction costs.

B.2. Simulation Design

In our simulation, we consider a market maker who manages options on several underlyings and accounts for transaction costs by using Leland's (1985) adjustment. We simulate 10,000 underlyings following uncorrelated geometric Brownian motions with a volatility σ of 40% and a stock price drift μ of 10%. For every underlying, there is one ATM call option with a strike of 100 and a time to maturity of one month. The risk-free rate r is 5%. The market maker is either long or short in the call option on one underlying with a 50% chance. When the market maker is trading the underlying, there are transaction costs $k/2$ that are proportional to the stock price (relative half-spread). The transaction costs are either 0.1%, 0.2%, 0.3%, 0.4%, or 0.5%, all with equal probability across stocks.[11] Market makers adjust the hedge of their short or long positions with the risk-free asset and stocks every day until maturity and account for the hedging costs by using Leland's (1985) adjustment, considering their long or short position in options.

We concentrate on a trading strategy using delta-hedged calls as defined in Section I.B. The expected return for the delta-hedged call according to Eq. (1) is calculated as[12]

$$E\left(\Pi_{t,t+\tau}\right) = \frac{E[\max(S_{t+\tau} - \mathrm{K}, 0)] - \Delta_{C,t}\, S_t e^{\mu\tau} - \left(C_t - \Delta_{C,t}\, S_t\right)e^{r\tau}}{Abs\left(C_t - \Delta_{C,t}\, S_t\right)}. \tag{3}$$

To obtain our results, we first sort options on their underlying liquidity costs into five groups, each consisting of 2,000 option observations, where we assume that the market maker is long on one half and short on the other. Within these groups, we sort the options again into quintiles based on their HV–IV values, where the historical volatilities are estimates based on one year of simulated daily return data with a true return volatility of 40%.

B.3. Simulation Results

Table V shows the results for the simulated data, which correspond to the results of Tables I and III. Panel A reports the average HV–IV values and Panel B the average returns. The results are very similar to those obtained for the market data. The average absolute HV–IV values of the low and high HV–IV quintiles increase with higher transaction costs, while the mean HV–IV values of all options along the transaction cost quintiles are comparably small. The results for the returns

[11] Bessembinder (2003) reports large, medium, and small New York Stock Exchange stocks' average quoted half bid–ask spreads, which are equal to 0.2%, 0.5%, and 0.8%, respectively.

[12] We calculate the expected option payoff under the P-measure based on a geometric Brownian motion for the stock price process with 40% volatility and a drift rate of 10% per year.

of delta-hedged calls show a similar picture. As for our market data, the returns on the long–short (5–1) strategy are much higher in the high transaction cost category than in the low transaction cost category. Remarkably, the magnitudes of the average HV–IV differences and delta-hedged return differences between the quintiles are similar to those observed in the empirical data.

The penultimate column of Table V shows the mean HV–IV and mean returns of all options within one transaction cost group. The differences between these means are relatively small across the transaction cost groups. Thus, in our scenario, when market makers are equally likely net long or net short, the effect of transaction costs cannot be seen from the interaction of underlying transaction costs with average HV–IV expensiveness or option returns alone. The last column of Table V reports the standard deviation of HV–IV and option returns within the transaction cost groups. Our simulation shows a positive correlation of the standard deviations with transaction costs, as in Section II. Only the magnitude of the standard deviations is smaller, since we do not account for variation in true volatility, which we fixed at 40%, and use fixed expected option returns according to Eq. (3).

[Insert Table V about here]

For Figure 2, we used extended sorting on the liquidity measure. Every month, option observations were sorted into deciles based on their underlying Amihud measure. Within these deciles, the options were again sorted by HV–IV into terciles. We now follow the same procedure with the simulated data. Figure 3 shows the results by depicting both the empirical average monthly delta-hedged returns of the 3–1 long–short strategy and the corresponding ones from the simulation. We see that the pattern is very similar and the magnitude of the simulated delta-hedged call returns also comes close to the average empirical returns.

[Insert Figure 3 about here]

We conclude that our empirical results for option expensiveness and option returns under the double sorting with respect to the Amihud measure and HV–IV can be reproduced by a simple simulation with realistic transaction cost assumptions, a market maker being equally likely long or short in options on one underlying and accounting for transaction costs in a simple way with Leland’s (1985) adjustment.

IV. Robustness Checks

The previous analysis raises different questions about the robustness of our main results. A first issue is the measurement of option expensiveness, particularly the estimation of historical volatility, and the measurement of illiquidity. We deal with this problem in Section IV.A. A second robustness issue refers to the time periods considered. This issue has two aspects: the chosen return period and the chosen sample period. Sections IV.B and IV.C, respectively, deal with these points. A third robustness issue refers to the underlying rationale for our results. If it is really demand pressure and the fact that market makers are long in some and short in other specific option series that drives our findings, we should not only find effects related to general expensiveness, as measured by HV-IV, but also similar illiquidity effects for the relative expensiveness of puts and calls, given that market makers could be on different sides of the market in both types of options. This issue is investigated in Section IV.D.

A. Alternative Volatility and Illiquidity Measures

The analysis in Section 3 can be criticized due to measurement problems. First, the specific historical volatility used could be an inadequate benchmark for measuring option expensiveness. Second, because illiquidity is a multidimensional phenomenon, our results could depend on the specific illiquidity measure used. We investigate these issues in different robustness analyses.

As alternative volatility measures, we use a GARCH(1,1) estimate for the option's lifetime volatility and the standard deviation of daily stock returns using the six and 24 most recent months.[13] The results are presented in Table VI. There is no clear pattern in the mean expensiveness resulting from these alternative measures: the change of the average HV–IV with illiquidity is significantly positive for the GARCH(1,1) estimate, whereas it is significantly negative for the six-month estimate and insignificant for the 24-month estimate. In contrast, the increase of the standard deviation is highly significant for all volatility measures. Overall, these findings are in line with the results and conclusions from Table I.

[Insert Table VI about here]

Another doubt about the previous results is that they could be tied to our illiquidity measure. For Table VII, we repeat our analysis of Table I but replace the Amihud illiquidity measure with

[13] Details on the GARCH(1,1) estimation process can be found in Appendix C.

alternative measures: the log market capitalization of the underlying stock, the dollar trading volume of the underlying, and Roll's (1984) and Corwin and Schultz's (2012) bid–ask spread estimates. The picture of an increasing standard deviation of HV–IV with increasing illiquidity remains unchanged for all alternative measures, while the mean HV–IV is either positively or negatively correlated with illiquidity, depending on the measure.

[Insert Table VII about here]

In Table VIII, we check if the increasing absolute HV–IV values with the alternative historical volatility and illiquidity measures translate into higher excess returns. We repeat the analysis from Table IV, but with the alternative measures. The differences of the alphas from the 5–1 strategy in the lowest liquidity quintile compared to the 5–1 strategy in the highest liquidity quintile are significant with all alternative liquidity and volatility measures.

[Insert Table VIII about here]

B. Daily Returns

So far, we have used monthly option returns, as described in Section I.B. During the one-month holding period, option moneyness could change drastically and the returns of the delta-hedged calls could be exposed to substantial underlying stock price risk. We therefore repeat our analysis from Table III with daily delta-hedged call and straddle returns. The delta-hedged call return calculation is similar to that presented in Eq. (1). Instead of holding the option until maturity and calculating the option payoff, we use the option mid price of the day following the trading initiation date t. Similarly, we modify the straddle return calculation from Eq. (2) by replacing the option payoffs with the next day's option mid prices and adjust the funding costs for a one-day holding period.

The resulting option returns in Table IX are qualitatively the same as in Table III. Again, the returns in the low and high HV–IV columns smoothly decrease and increase, respectively, across the Amihud quintiles. In addition, the increasing profitability of the 5–1 HV–IV strategy with higher stock illiquidity is highly significant, especially for the delta-hedged call returns; the significance increases and now has a t-statistic above 10. Interestingly, the option return of the first day seems to capture a large fraction of the monthly option returns reported in Table III.

[Insert Table IX about here]

C. Alternative Sample Periods

Until 1999, options were often listed only on one exchange, which governed all interactions between market participants. In October 1999, the U.S. Securities and Exchange Commission (SEC) ordered the option exchanges to develop a plan to electronically link the various market centers. Battalio, Hatch, and Jennings (2004) have shown that option market efficiency improved during this period, in which the equity option market evolved toward a national market system. The final implementation of the SEC's options exchange linkage plan and more stringent quoting and disclosure rules became effective in April 2003. We therefore check if our results are driven by market inefficiencies before these structural changes took place and exclude the period before May 2003 from our analysis. In a next step, we also exclude the period during the financial crisis to ensure that the market turmoil in this period does not drive our results.

The portfolio construction and return calculation for Table X are the same as for Table III. The first column returns correspond to the 5–1 column returns in Table III. The second and third columns exclude observations before the option market structure changes up to May 2003 and the third column additionally excludes the financial crises from June 2007 to December 2009.

The difference of the portfolio returns between the highest and lowest illiquidity quantiles for the period May 2003 to August 2015 is very similar to the difference for the complete sample period. Interestingly, the overall performance of the HV-IV trading strategy decreases in all illiquidity quantiles if we exclude the period before the market reforms. The market seems to have become more efficient, while the link between stock illiquidity and option returns has remained stable.

[Insert Table X about here]

D. Relative Expensiveness of Puts and Calls

So far, we have looked at average expensiveness and have not considered possible distortions in the relative pricing of calls and puts due to stock illiquidity. However, stock illiquidity could well drive a wedge between put and call prices. A natural measure for this discrepancy is the difference between put and call implied volatility. If calls are cheap compared to corresponding puts, this could reflect a situation with a relatively low or, let us say, negative net demand for calls and a relatively high demand for puts. In such a situation, the difference between put and call implied volatilities (PVOL–CVOL) is positive and higher stock illiquidity is expected to decrease call prices even further relative to their corresponding put prices. Conversely, if call prices are relatively expensive, the negative PVOL–CVOL measure should decrease even further with higher stock illiquidity. We therefore repeat our analysis from Table I but use the difference between put and call implied volatilities (PVOL–CVOL) as a measure of (relative) expensiveness. For the new analysis, we exclude all put and call combinations for one underlying where the moneyness does not exactly match. The sample size is therefore slightly smaller, with 156,125 observations, compared to the original straddle sample with 156,849 observations.

[Insert Table XI about here]

Table XI shows our results. The absolute deviations between the two implied volatility measures indeed increase with stock illiquidity. Consistent with the above arguments, we also find higher negative and positive differences within the higher illiquidity quantile. The column with the mean PVOL–CVOL values of all observations within the Amihud quantiles shows a significant tendency toward more expensive puts with higher illiquidity.

To analyze the return implications, we next consider a portfolio consisting of an ATM call long and an ATM put short (synthetic future) delta hedged with a short position in the stock. The return of this portfolio is

$$\Pi_{t,t+\tau} = \frac{\max(S_{t+\tau} - K_C, 0) - \max(K_P - S_{t+\tau}, 0) - S_{t+\tau} - (C_t - P_t - S_t)e^{r\tau}}{Abs(C_t - P_t - S_t)}.$$

Since our strikes are equal ($K_C = K_P$), this simplifies to

$$\Pi_{t,t+\tau} = \frac{(S_t - C_t + P_t)e^{r\tau} - K}{Abs(C_t - P_t - S_t)}.$$

The returns then do not depend on the stock's return until maturity. Table XII shows the resulting returns of an equal-weighted investment in the illiquidity and PVOL–CVOL categories. The structure of the returns is as we would expect from the structure in Table XI. The differences between the highest and lowest illiquidity quantiles are highly significant, showing that stock illiquidity has an impact on the relative pricing of puts and calls, which is in accordance with the idea of order imbalances in put and call options.

[Insert Table XII about here]

V. Conclusions

This paper is the first to present empirical evidence that underlying stock illiquidity is strongly related to option expensiveness and option returns. We show in a cross-sectional analysis that the standard deviation of our option expensiveness measure HV–IV increases with stock illiquidity, while the mean HV–IV does not change with illiquidity. The documented pattern also translates into economically and statistically significant delta-hedged call and straddle excess returns, showing that stock illiquidity can capture a large part of the option returns determined by Goyal and Saretto (2009). The results are qualitatively unchanged for different measures of option expensiveness and stock illiquidity. Moreover, similar illiquidity effects hold for the relative expensiveness of put and call options.

Our findings are in line with intermediaries considering different option hedging costs depending on stock liquidity and being net long in options on some stocks and short in options on others, a setting supported by an empirical sample of end user net demand data. A simulation study shows that if an intermediary is equally likely to be long or short in options on one underlying and accounts for realistic hedging costs when setting options prices, the resulting deviations of historical and implied volatility as well as the resulting option returns are strikingly similar to those observed in our empirical data.

Our results suggest that stock illiquidity plays an important role in the explanation of the difference between historical and implied volatility. Theoretically, the effect depends on the sign of the end users' net demand, which intermediaries have to supply. Therefore, our analysis provides a rationale for using the sign of HV–IV as a proxy for the sign of end users' net demand, which offers new ways to study the impact of demand on option prices.

Table I

Historical minus implied volatility (HV–IV) of two-way sorted portfolios.

The sample between January 1996 and August 2015 includes 156,849 pairs of call and put options. Each month option observations are first sorted into quintiles based on the Amihud illiquidity measure. Within these quintiles, options are sorted into quintiles based on the difference between the historical and implied volatility. This table shows the average difference between historical volatility and implied volatility for the different categories. The historical volatility is the standard deviation of daily stock returns using the 12 most recent months. The implied volatility is the average of the call and put implied volatilities. Associated t-statistics are corrected for autocorrelation following Newey and West (1987).

		Average HV–IV								
		Historical - implied volatility (HV–IV)							*mean*	*sd*
		1-low	2	3	4	5-high	5–1	t-stat.	all	
Amihud	1-low	-7.0%	-1.5%	1.2%	4.2%	12.4%	19.4%	17.52	1.8%	7.7%
	2	-9.0%	-2.3%	0.8%	4.1%	13.4%	22.5%	18.66	1.4%	9.0%
	3	-10.9%	-2.9%	0.9%	4.8%	15.5%	26.3%	22.13	1.5%	10.6%
	4	-12.8%	-3.3%	0.9%	5.5%	17.5%	30.2%	25.69	1.6%	12.4%
	5-high	-16.2%	-4.4%	0.8%	6.2%	20.3%	36.4%	30.44	1.3%	15.0%
	5–1	-9.2%	-2.9%	-0.4%	2.0%	7.9%	17.1%		-0.5%	7.3%
	t-stat.	-17.55	-7.30	-1.18	5.31	12.06	23.88		-1.27	14.48

Table II

Regressions of HV–IV on different variations of the Amihud illiquidity measure.

The sample between January 1996 and August 2015 includes 156,849 pairs of call and put options. This table reports the average coefficients from monthly Fama-MacBeth regressions of HV–IV on a constant and the Amihud illiquidity measure multiplied by the sign function of HV–IV, a dummy if HV–IV is positive or negative, or the identity function 1. HV-IV is calculated for the pairs of call and put options as in Table 1. Newey and West (1987) t-statistics are given in parentheses.

		Amihud x			
	const.	sign (HV–IV)	(HV–IV) > 0	(HV–IV) < 0	1
(1)	0.016				-0.180
	(1.64)				(-2.30)
(2)	0.016	2.551			
	(1.65)	(12.61)			
(3)	0.015	5.153			-0.560
	(1.48)	(7.22)			(-0.67)
(4)	0.015		4.593	-5.713	
	(1.48)		(11.43)	(-3.82)	

Table III

Average monthly post-formation returns of two-way sorted portfolios.

The sample between January 1996 and August 2015 includes 156,849 pairs of call and put options for the straddle returns. For the delta-hedged call returns, the sample includes 197,374 calls. Each month, option observations are first sorted into quintiles based on the Amihud liquidity measure. Within these quintiles, options are sorted into quintiles based on the difference between the historical and implied volatility. This table shows the average monthly returns of the portfolios for the different categories. The portfolio returns use an equal weighting of the returns of all straddles (delta-hedged calls) falling in the category. For the return calculation, the average of the closing bid and ask quotes is the reference beginning price. The terminal payoff of the options depends on the stock price and the strike price of the option. The hedge ratio for the delta-hedged calls is determined from the implied volatility at trading initiation. Associated t-statistics are corrected for autocorrelation following Newey and West (1987).

Panel A

Straddle returns

		Historical - implied volatility (HV–IV)							*mean*	*sd*
		1-low	2	3	4	5-high	5–1	t-stat.	all	
Amihud	1-low	-4.5%	-1.3%	0.6%	-0.3%	2.9%	7.4%	3.66	-0.5%	74.9%
	2	-4.5%	-2.9%	1.4%	-0.7%	4.4%	8.9%	4.99	-0.4%	75.6%
	3	-6.1%	-0.3%	0.2%	1.9%	4.5%	10.5%	5.49	0.0%	77.0%
	4	-6.7%	-1.0%	0.6%	3.4%	7.7%	14.4%	6.50	0.8%	80.7%
	5-high	-9.7%	-3.4%	-3.8%	-0.2%	5.8%	15.5%	8.07	-2.2%	81.6%
	5–1	-5.1%	-2.1%	-4.4%	0.1%	3.0%	8.1%		-1.7%	6.7%
	t-stat.	-3.18	-1.09	-2.16	0.06	1.56	3.68		-1.40	4.91

Panel B

Delta-hedged call returns

		Historical - implied volatility (HV–IV)							*mean*	*sd*
		1-low	2	3	4	5-high	5–1	t-stat.	all	
Amihud	1-low	-0.4%	-0.1%	0.0%	0.0%	0.4%	0.7%	2.97	0.0%	6.3%
	2	-0.4%	-0.2%	0.0%	0.1%	0.5%	1.0%	4.54	0.0%	7.1%
	3	-0.7%	-0.1%	0.0%	0.4%	0.6%	1.3%	5.34	0.0%	8.3%
	4	-1.1%	-0.2%	0.1%	0.3%	0.9%	2.0%	6.19	0.0%	9.2%
	5-high	-1.5%	-0.6%	-0.4%	-0.2%	0.6%	2.1%	8.48	-0.4%	10.6%
	5–1	-1.1%	-0.5%	-0.3%	-0.2%	0.3%	1.4%		-0.4%	4.3%
	t-stat.	-4.28	-2.46	-2.05	-1.14	1.05	4.75		-2.51	21.75

Table IV

Risk-adjusted straddle and delta-hedged call returns.

This table presents the coefficients and t-statistics of a time-series regression of the portfolio returns on the Fama and French (1993) factors (MKT-Rf, SMB, HML), the Carhart (1997) momentum factor (MOM), the Coval and Shumway (2001) excess zero-beta S&P 500 straddle factor (ZB-STR–Index), and the value-weighted average of the zero-beta straddles of the S&P 500 components (ZB-STR–Stocks). The 5-1 portfolios from the highest and lowest liquidity quintiles are constructed as in Table III. The t-statistics for the coefficients in brackets are calculated with Newey and West (1987) standard errors.

	Straddles			Delta-hedged calls		
	5–1 high liq.	5–1 low liq.	5–1 low liq. - 5–1 high liq.	5–1 high liq.	5–1 low liq.	5–1 low liq. - 5–1 high liq.
Alpha	0.077	0.159	0.081	0.009	0.021	0.012
	(3.89)	(8.47)	(3.68)	(3.33)	(8.78)	(4.29)
MKT–Rf	-0.495	0.035	0.530	-0.086	0.059	0.145
	(-0.56)	(0.07)	(0.74)	(-0.89)	(0.82)	(1.85)
SMB	-0.373	1.032	1.404	-0.132	-0.048	0.083
	(-0.35)	(1.61)	(1.44)	(-0.86)	(-0.50)	(0.47)
HML	1.054	0.743	-0.311	0.029	0.206	0.177
	(1.48)	(1.34)	(-0.48)	(0.24)	(2.02)	(1.23)
MOM	0.794	0.805	0.010	0.009	0.200	0.192
	(1.32)	(1.61)	(0.02)	(0.09)	(3.22)	(1.84)
ZB-STR-Index	0.008	0.082	0.074	0.005	0.008	0.002
	(0.14)	(2.17)	(1.21)	(0.93)	(1.58)	(0.33)
ZB-STR-Stocks	0.092	0.027	-0.065	-0.005	-0.004	0.001
	(0.67)	(0.31)	(-0.43)	(-0.38)	(-0.35)	(0.08)

Table V

Average HV–IV and average expected delta-hedged call returns of two-way sorted portfolios, historical volatility estimated from simulated data, and implied volatility from Leland's adjustment.

For the simulation, we use 1,000 options for every combination of transaction costs (k/2 = 0.1%, 0.2%, 0.3%, 0.4%, or 0.5%) and market maker position (long or short). Within the transaction cost groups k, every option is assigned to a quintile based on the difference between historical and implied volatility (HV–IV). The historical volatility is measured from one year of simulated daily returns (with σ = 40%) for every option.The implied volatility is the one resulting from Leland's adjustment. Panel A shows the average HV–IV values for all combinations of transaction costs and HV–IV quintiles. Panel B shows the average expected delta-hedged returns of the options for all combinations of transaction costs and HV–IV quintiles.

Panel A

Average HV-IV

		Historical - implied volatility (HV-IV)						*mean*	*sd*
		1-low	2	3	4	5-high	5-1	all	
Transaction costs	1-low	-3.1%	-1.2%	0.0%	1.3%	3.0%	6.1%	0.0%	2.2%
	2	-4.4%	-2.1%	0.0%	1.9%	4.1%	8.5%	-0.1%	3.1%
	3	-5.8%	-3.5%	-0.3%	3.1%	5.3%	11.1%	-0.2%	4.2%
	4	-7.3%	-4.9%	-0.3%	4.4%	6.6%	13.9%	-0.3%	5.5%
	5-high	-8.7%	-6.5%	-0.6%	5.5%	7.7%	16.4%	-0.5%	6.7%
	5-1	-5.6%	-5.3%	-0.6%	4.3%	4.6%	10.3%	-0.5%	4.5%

Panel B

Average delta-hedged call returns

		Historical - implied volatility (HV-IV)						*mean*	*sd*
		1-low	2	3	4	5-high	5-1	all	
Transaction costs	1-low	-0.2%	-0.1%	0.0%	0.1%	0.2%	0.5%	0.0%	0.3%
	2	-0.6%	-0.5%	0.0%	0.6%	0.6%	1.2%	0.0%	0.6%
	3	-0.9%	-0.9%	0.1%	0.9%	0.9%	1.8%	0.0%	0.9%
	4	-1.1%	-1.1%	0.1%	1.3%	1.3%	2.4%	0.1%	1.2%
	5-high	-1.4%	-1.4%	0.1%	1.6%	1.6%	3.0%	0.1%	1.5%
	5-1	-1.2%	-1.3%	0.1%	1.5%	1.4%	2.5%	0.1%	1.2%

Table VI

Average HV–IV with alternative volatility measures.

The sample between January 1996 and August 2015 includes 156,849 pairs of call and put options. Each month, option observations are sorted into quintiles based on the Amihud measure. The table shows the time-series average mean and standard deviation of the difference between historical volatility and implied volatility for the different illiquidity quintiles. The implied volatility is the average of the call and put implied volatilities. The historical volatility in HV–IV is defined with alternative volatility estimates. The first two columns utilize a GARCH(1,1) model using at least one month and a maximum of five years of daily return data. The remaining columns use the standard deviation of the most recent six months and two years of daily returns. Associated t-statistics are corrected for autocorrelation following Newey and West (1987).

		GARCH (1,1)		*6-month*		*2-year*	
		mean	*sd*	*mean*	*sd*	*mean*	*sd*
Amihud	1-low	-1.3%	10.3%	1.1%	7.6%	2.9%	8.4%
	2	-0.9%	13.0%	0.7%	9.0%	2.5%	9.7%
	3	0.1%	15.9%	0.6%	10.7%	2.7%	11.3%
	4	1.3%	18.0%	0.6%	12.4%	3.0%	13.1%
	5-high	2.5%	21.2%	-0.2%	15.1%	3.0%	15.9%
	5–1	3.7%	10.9%	-1.3%	7.5%	0.1%	7.4%
	t-stat.	6.73	16.10	-3.31	16.92	0.30	17.80

Table VII

Average HV–IV with alternative stock illiquidity measures.

The sample between January 1996 and August 2015 includes 156,849 pairs of call and put options. Each month, option observations are sorted into quintiles based on different illiquidity measures. The table shows the time-series mean and standard deviation of the difference between historical volatility and implied volatility for the different illiquidity quintiles. The implied volatility is the average of the call and put implied volatilities. The historical volatility in HV–IV is the standard deviation of the most recent 12 months of daily returns. The logarithm of the stock's market capitalization [ln(Size)] and the stock's dollar trading volume [Dollar Volume] are measured on the portfolio formation date. The Roll (1984) [Roll] and Corwin and Schultz (2012) [Corwin-Schultz] measures are estimated from daily stock price data of the month preceding the portfolio formation date. Associated t-statistics are corrected for autocorrelation following Newey and West (1987).

	ln(Size)		*Dollar Volume*		*Roll*		*Corwin-Schultz*	
	mean	*sd*	*mean*	*sd*	*mean*	*sd*	*mean*	*sd*
1-low	1.9%	16.1%	1.2%	13.7%	1.0%	8.7%	0.7%	7.5%
2	1.6%	11.9%	1.5%	11.8%	1.1%	8.6%	0.6%	7.8%
3	1.4%	10.6%	1.5%	11.1%	1.4%	9.5%	1.1%	9.5%
4	1.3%	8.5%	1.6%	9.9%	2.0%	10.9%	2.1%	11.9%
5-high	1.5%	7.1%	2.0%	9.2%	3.4%	14.9%	3.3%	16.1%
5–1	-0.5%	-9.0%	0.8%	-4.5%	2.4%	6.2%	2.6%	8.7%
t-stat.	-1.16	-25.39	2.08	-8.60	4.19	13.08	4.08	21.94

Table VIII

Risk-adjusted straddle and delta-hedged call returns with alternative volatility measures and stock illiquidity definitions.

This table presents the alphas (t-statistics) of a time-series regression of the portfolio returns on the Fama and French (1993) factors, the Carhart (1997) momentum factor, the Coval and Shumway (2001) excess zero-beta S&P 500 straddle factor, and the value-weighted average of the zero-beta straddles of the S&P 500 components. The 5–1 portfolios from the highest and lowest liquidity quintiles are constructed as in Table IV but in Panel A the HV measure is replaced with alternative volatility estimates and in Panel B alternative illiquidity measures are used instead of the Amihud measure. Panel B uses the same HV measure as in Table IV. The t-statistics for the coefficients in brackets are calculated with Newey and West (1987) standard errors.

	Straddles			Delta-hedged calls		
	5–1 high liq.	5–1 low liq.	5–1 low liq. - 5–1 high liq.	5–1 high liq.	5–1 low liq.	5–1 low liq. - 5–1 high liq.
Panel A: Alternative volatility estimates						
GARCH(1,1)	0.018	0.097	0.079	0.004	0.012	0.008
	(0.88)	(4.65)	(3.07)	(1.54)	(4.46)	(2.33)
6-month	0.071	0.144	0.073	0.007	0.020	0.012
	(3.16)	(7.27)	(2.71)	(2.93)	(8.19)	(3.79)
2-year	0.070	0.127	0.056	0.007	0.017	0.010
	(3.74)	(6.64)	(2.42)	(3.18)	(7.12)	(3.75)
Panel B: Alternative illiquidity measures						
	big	small	small–big	big	small	small–big
ln(Size)	0.103	0.171	0.068	0.011	0.022	0.011
	(5.81)	(8.81)	(3.02)	(5.32)	(7.66)	(3.47)
	high	low	low–high	high	low	low–high
Dollar Volume	0.078	0.160	0.082	0.011	0.021	0.010
	(4.13)	(8.78)	(3.73)	(3.66)	(9.19)	(3.12)
	low	high	high–low	low	high	high–low
Roll	0.095	0.166	0.071	0.009	0.026	0.017
	(4.73)	(7.70)	(2.65)	(3.95)	(6.49)	(4.23)
	low	high	high–low	low	high	high–low
Corwin–Schultz	0.116	0.165	0.049	0.010	0.028	0.018
	(4.98)	(10.32)	(1.83)	(4.87)	(8.07)	(5.13)

Table IX

Average daily post-formation returns of two-way sorted portfolios.

The sample between January 1996 and August 2015 includes 156,849 pairs of call and put options for the straddle returns. For the delta-hedged call returns, the sample includes 197,374 calls. Each month, option observations are first sorted into quintiles based on the Amihud liquidity measure. Within these quintiles, options are sorted into quintiles based on the difference between the historical and implied volatility. This table shows the average daily returns of the portfolio for the different categories. The portfolio returns use an equal weighting of the returns of all straddles (delta-hedged calls) falling in the category. For the return calculation, the average of the closing bid and ask quotes is the reference beginning price. The option positions are closed at the average of the closing bid and ask quotes on the following trading day. The hedge ratio for the delta-hedged calls is determined from the implied volatility upon trading initiation. Associated t-statistics are corrected for autocorrelation following Newey and West (1987).

Straddle returns

		Historical - implied volatility (HV–IV)							*mean*	*sd*
		1-low	2	3	4	5-high	5–1	t-stat.	all	
Amihud	1-low	-1.26%	-0.72%	-0.55%	-0.08%	-0.23%	1.03%	5.28	-0.6%	7.3%
	2	-1.45%	-0.68%	-0.59%	-0.10%	-0.14%	1.31%	7.57	-0.6%	7.1%
	3	-1.49%	-0.63%	-0.35%	0.08%	-0.15%	1.34%	8.25	-0.5%	7.5%
	4	-1.58%	-0.54%	-0.20%	0.04%	0.04%	1.62%	9.63	-0.4%	7.6%
	5-high	-1.99%	-0.82%	-0.32%	0.00%	0.26%	2.25%	12.01	-0.6%	8.2%
	5–1	-0.73%	-0.10%	0.22%	0.08%	0.49%	1.22%		0.0%	1.0%
	t-stat.	-3.64	-0.61	1.09	0.40	2.28	4.65		-0.07	4.89

Delta-hedged call returns

		Historical - implied volatility (HV–IV)							*mean*	*sd*
		1-low	2	3	4	5-high	5–1	t-stat.	all	
Amihud	1-low	0.04%	-0.05%	0.01%	0.02%	0.02%	-0.02%	-0.28	0.0%	1.1%
	2	-0.19%	-0.02%	-0.01%	0.01%	0.06%	0.24%	8.16	0.0%	0.9%
	3	-0.23%	-0.05%	-0.02%	0.07%	0.09%	0.32%	9.27	0.0%	1.1%
	4	-0.33%	-0.06%	-0.03%	0.05%	0.11%	0.44%	13.56	-0.1%	1.1%
	5-high	-0.72%	-0.17%	-0.01%	0.14%	0.29%	1.01%	16.35	-0.1%	1.6%
	5–1	-0.76%	-0.12%	-0.02%	0.11%	0.28%	1.04%		-0.1%	0.6%
	t-stat.	-9.92	-3.93	-0.73	3.95	8.55	12.25		-4.46	4.47

Table X

Post-formation option returns for alternative sample periods.

The sample between January 1996 and August 2015 includes 156,849 pairs of call and put options for the straddle returns. For the delta-hedged call returns, the sample includes 197,374 calls. The sample between May 2003 and August 2015 excludes the period before the SEC's options exchange linkage plan became effective. In addition, the last column excludes the financial crisis between June 2007 and December 2009. Each month, option observations are first sorted into quintiles based on the Amihud liquidity measure. Within these quintiles, options are sorted into quintiles based on the difference between the historical and implied volatility. This table shows the averages of the monthly differences between the returns of the high HV-IV portfolios and the low HV-IV portfolios (5-1) within the Amihud quantiles. The portfolio returns use an equal weighting of the returns of all straddles (Panel A) and delta-hedged calls (Panel B) falling in the category. For the return calculation, the average of the closing bid and ask quotes is the reference beginning price. The terminal payoff of the options depends on the stock price and the strike price of the option. Associated t-statistics are corrected for autocorrelation following Newey and West (1987).

		Jan. 1996 - Aug. 2015	May 2003 - Aug. 2015	May 2003 - Aug. 2015 excl. Jun. 2007 - Dec. 2009
Panel A: Straddle returns (5-1)				
Amihud	1-low	7.4%	3.4%	3.8%
	2	8.9%	5.4%	4.4%
	3	10.5%	5.6%	5.2%
	4	14.4%	9.4%	7.5%
	5-high	15.5%	11.8%	11.2%
	5–1	8.1%	8.4%	7.4%
	t-stat.	3.68	3.13	2.38
Panel B: Delta-hedged call returns (5-1)				
Amihud	1-low	0.7%	0.2%	0.9%
	2	1.0%	0.5%	1.1%
	3	1.3%	0.5%	1.5%
	4	2.0%	1.0%	2.1%
	5-high	2.1%	1.4%	2.3%
	5–1	1.4%	1.2%	1.5%
	t-stat.	4.75	4.56	4.45

Table XI

Average PVOL-CVOL of two-way sorted portfolios.

The sample between January 1996 and August 2015 includes 156,125 pairs of call and put options with the same ATM moneyness. Each month option observations are first sorted into quintiles based on the Amihud illiquidity measure. Within these quintiles, options are sorted into quintiles based on the difference between the call and put implied volatility. This table shows the average difference between call and put implied volatility for the different categories. Associated t-statistics are corrected for autocorrelation following Newey and West (1987).

		Put implied VOL - Call implied VOL							*mean*	*sd*
		1-low	2	3	4	5-high	5–1	t-stat.	all	
Amihud	1-low	-1.7%	-0.3%	0.3%	1.0%	2.8%	4.5%	14.38	0.4%	1.9%
	2	-2.2%	-0.3%	0.5%	1.4%	4.0%	6.1%	14.43	0.7%	2.6%
	3	-3.2%	-0.5%	0.6%	1.9%	5.5%	8.7%	16.04	0.9%	3.6%
	4	-4.3%	-0.7%	0.8%	2.4%	7.6%	11.9%	18.31	1.1%	4.9%
	5-high	-7.3%	-1.4%	1.0%	3.7%	11.9%	19.2%	21.81	1.6%	7.9%
	5–1	-5.6%	-1.1%	0.7%	2.7%	9.2%	14.7%		1.2%	6.0%
	t-stat.	-14.70	-7.08	9.40	22.38	27.17	23.50		10.46	23.64

Table XII

Average monthly synthetic future returns.

The sample between January 1996 and August 2015 includes 156,125 pairs of call and put options with the same ATM moneyness. Each month, option observations are first sorted into quintiles based on the Amihud liquidity measure. Within these quintiles, options are sorted into quintiles based on the difference between the call and put implied volatility. This table shows the average monthly returns of the portfolios for the different categories. The portfolio returns use an equal weighting of the returns of the long call, short put and short stock portfolios falling in the category. For the return calculation, the average of the closing bid and ask quotes is the reference beginning price. Associated t-statistics are corrected for autocorrelation following Newey and West (1987).

		Put implied VOL - Call implied VOL							*mean*	*sd*
		1-low	2	3	4	5-high	5–1	t-stat.	all	
Amihud	1-low	0.00%	0.01%	0.03%	0.05%	0.13%	0.12%	9.07	0.0%	0.2%
	2	-0.01%	0.03%	0.05%	0.08%	0.22%	0.23%	8.80	0.1%	0.3%
	3	-0.02%	0.03%	0.06%	0.12%	0.31%	0.33%	9.66	0.1%	0.4%
	4	-0.03%	0.03%	0.08%	0.14%	0.43%	0.46%	12.57	0.1%	0.5%
	5-high	-0.10%	0.03%	0.08%	0.18%	0.62%	0.71%	13.30	0.2%	0.8%
	5–1	-0.10%	0.02%	0.06%	0.13%	0.49%	0.59%		0.1%	0.6%
	t-stat.	-3.10	1.32	6.54	13.20	18.52	13.77		11.15	24.13

Figure 1. Distribution of end user net demand across underlyings.
This figure plots the number of underlyings in net demand intervals. Net demand is defined as the difference between end user-initiated buys and sells per underlying. The sample comprises option trading data for 1,620 underlyings, traded on July 7, 2006, at the CBOE.

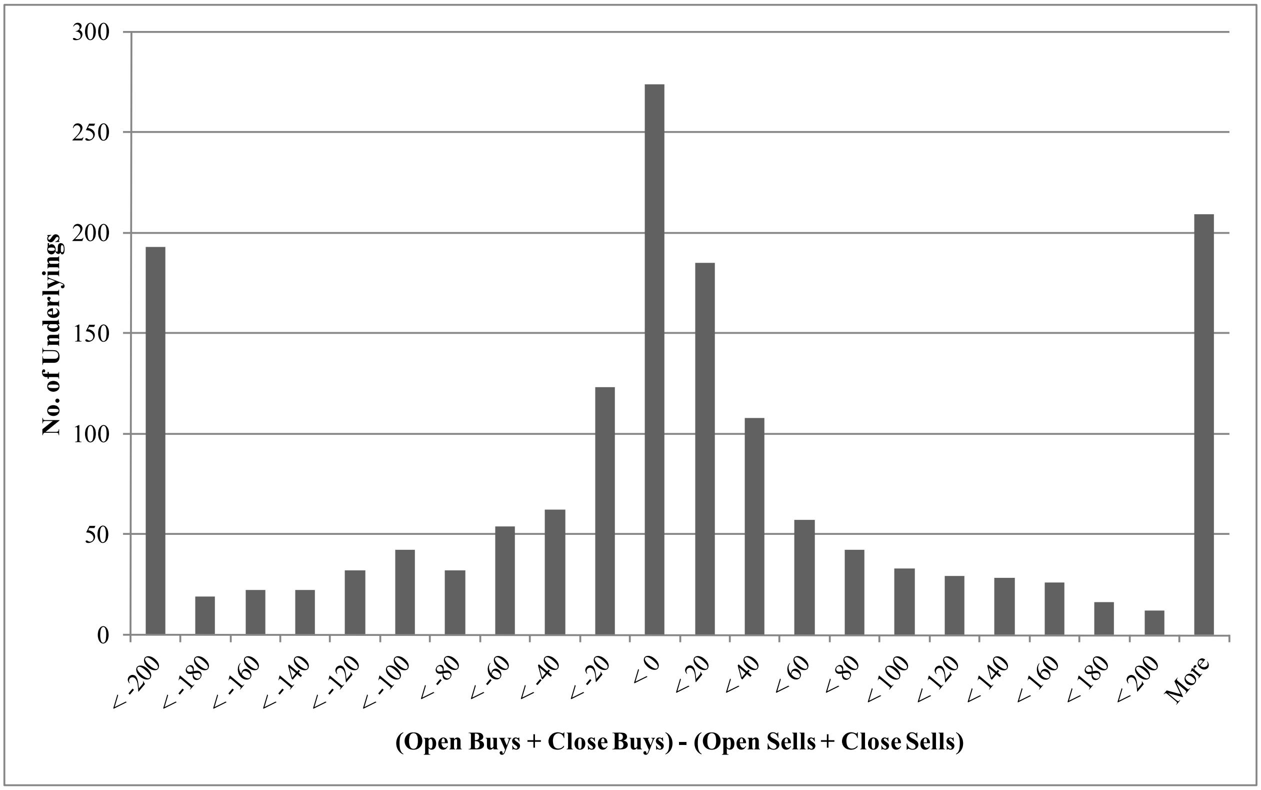


Figure 2. Average option returns for Amihud deciles.
The 3–1 return is calculated as in Table III, but with a decile sorting on the Amihud measure and a second sorting on HV–IV into three portfolios. The average return for the Amihud decile is the equally weighted return of all delta-hedged calls or straddles in the decile.

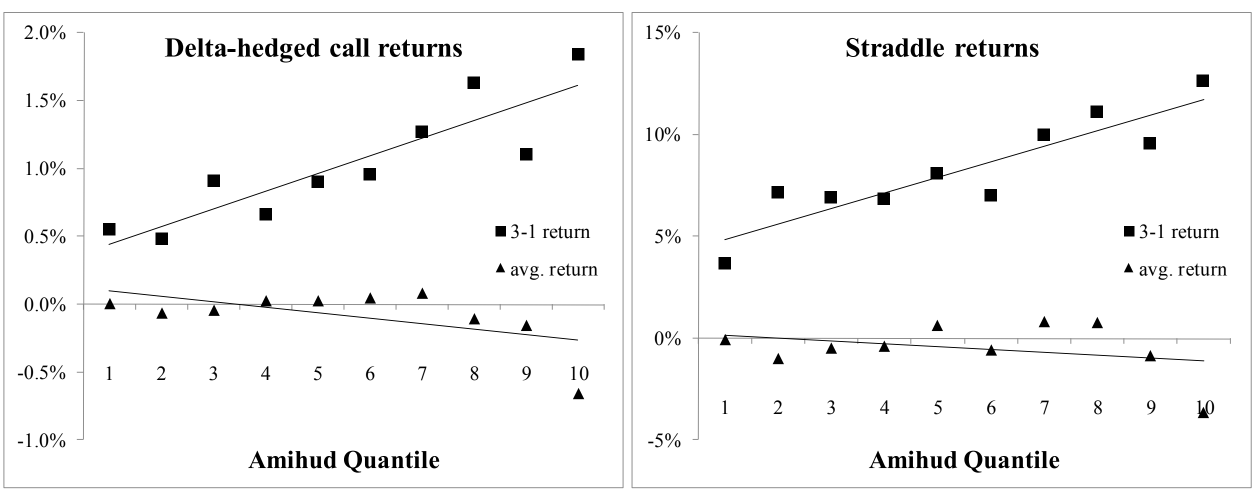
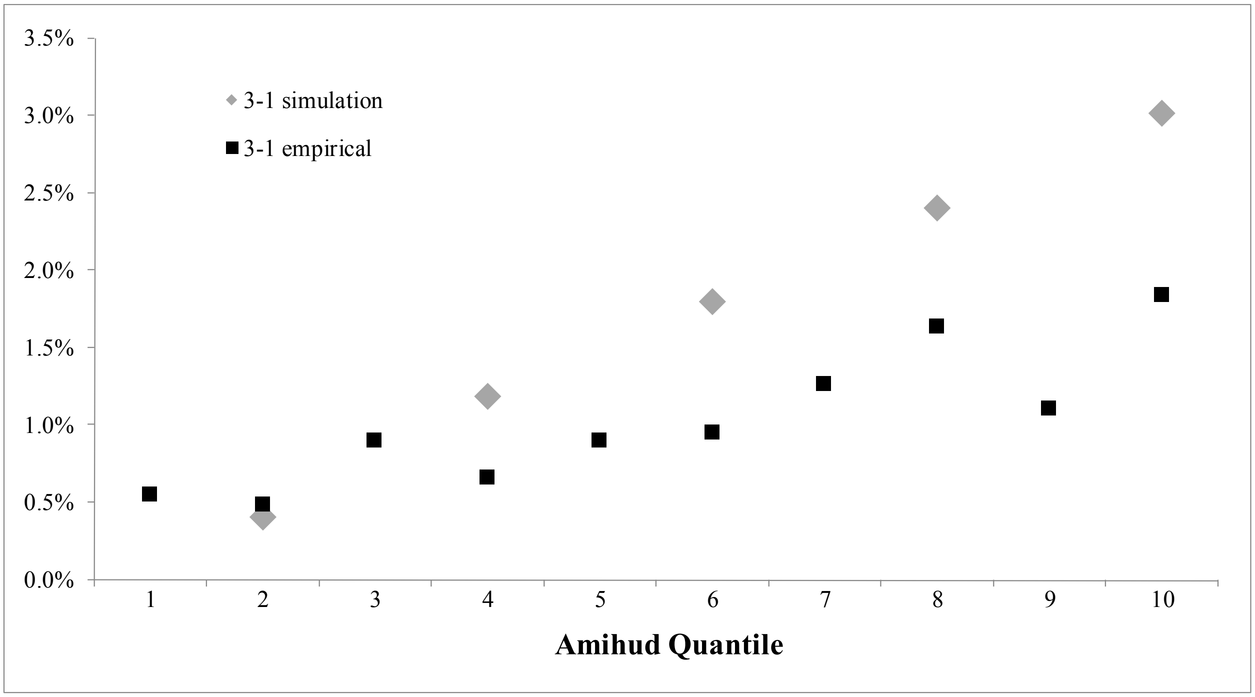


Figure 3. Average empirical and simulated delta-hedged call returns.
The 3–1 empirical returns are calculated as in Table III, but with a decile sorting on the Amihud measure and a three-quantile second sort on HV–IV. The 3–1 simulated returns are calculated as in Table V, but with a tercile sorting on HV–IV. Proportional transaction cost assumptions are $k/2$ = 0.05%, 0.1%, 0.15%, 0.2%, 0.25%, 0.3%, 0.35%, 0.4%, 0.45%, and 0.5%.



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Appendix A: Liquidity Measure Calculations

Amihud measure: Following Cao and Han (2013), we calculate the Amihud (2002) illiquidity measure for the month preceding the trading initiation date t as

$$ILLIQ_{i,t} = {}^{1}/_{m_{i,t}} \sum_{d=t-m_{i,t}}^{t-1} \frac{|R_{i,d}|}{VOLD_{i,d}},$$

where $m_{i,t}$ is the number of trading days from last month's trading initiation date until t - 1 with available return and volume data for stock i. The absolute daily total return $|R_{i,d}|$ for stock i on day d is divided by the dollar trading volume $VOLD_{i,d}$, which we calculate by multiplying the closing price for stock i on day d with the trading volume on that date.

Roll measure: Roll (1984) introduced an estimator of bid–ask spreads based on the serial covariance of price changes. While changes of the fundamental stock value are assumed to be serially uncorrelated, closing prices are either bid or ask prices, which introduces negative serial correlation. We calculate the Roll spreads $sp_{i,t}^{R}$ as

$$sp_{i,t}^{R} = 2\sqrt{-Cov_{i,t}},$$

where $Cov_{i,t}$ is the covariance of the daily returns of the close prices for stock i in the month preceding the trading initiation date t. This is an estimate of the relative bid–ask spread. We drop observations with positive covariance values.

Corwin–Schultz measure: Corwin and Schultz (2012) show that bid–ask spreads can be estimated from daily high and low prices. Since daily high (low) prices are almost always buy (sell) trades, the ratio of these prices reflects the fundamental stock volatility and its bid–ask spread. The suggested bid–ask spread estimator uses the fact that the fundamental volatility increases proportionally with the length of the observation interval while the bid–ask spread does not. For every overlapping two-day period $d, d+1$ within the month preceding the trading initiation date t, we calculate

$$\beta = \left[\ln\left(\frac{H_d^{i,t}}{L_d^{i,t}}\right)\right]^2 + \left[\ln\left(\frac{H_{d+1}^{i,t}}{L_{d+1}^{i,t}}\right)\right]^2, \qquad \gamma = \left[\ln\left(\frac{H_{d,d+1}^{i,t}}{L_{d,d+1}^{i,t}}\right)\right]^2,$$

where $H_d^{i,t}$ and $L_d^{i,t}$ are the high and low prices, respectively, for stock *i* on day *d* and $H_{d,d+1}^{i,t}$ and $L_{d,d+1}^{i,t}$ are, respectively, the high and low prices in the two-day period. The bid–ask spread estimate for the two-day period can then be calculated as

$$sp_{i,t,d}^{CS} = \frac{2(e^{\alpha} - 1)}{1 + e^{\alpha}},$$

where

$$\alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}}.$$

The estimate of the relative spread for stock *i* on the trading initiation date *t* is the average of the two-day spread estimates for the preceding month.

Size and trading volume: We also use the underlying's market capitalization and trading volume as illiquidity measures. We calculate the log of market capitalization (size), where market capitalization is the number of shares outstanding times the underlying closing price the day preceding the trading initiation date. A stock's dollar trading volume is the number of shares traded on all U.S. exchanges the day preceding the trading initiation date multiplied by the closing prices. Shares outstanding, trading volumes, and the closing prices are from the OptionMetrics database.

Appendix B: Risk Factor Calculations

Fama–French and Carhart factors: Since the returns of delta-hedged calls and straddles could still be exposed to stock price risk, we consider the Fama–French (1993) and Carhart (1997) factors as potential explanatory variables. These factors are calculated from the daily factor returns from Kenneth French's website. Since our monthly holding period starts at the beginning of the fourth week of the month and ends at the end of the third week, we do not use standard monthly returns. Instead, we compound the factor returns over the holding period from the trading initiation date until the trading day prior to expiration, at which point we also calculate the option payoffs. We calculate the factor return for one month as

$$\mathrm{F}_{t,t+\tau} = \prod_{d=1}^{N}(1 + f_d),$$

where N is the number of trading days between t and $t + \tau$ and f_d is the daily factor return of the $MKT - Rf$, SMB, HML, and MOM portfolios.

Zero-beta straddles: We use index and index component straddle returns to control for market volatility risk and common individual stock variance risk. We form zero-beta straddles similar to those of Coval and Shumway (2001). The zero-beta straddles are constructed the same day we initiate our trading strategy with one ATM call and one ATM put on the underlying. Call returns $r_{C,i,t}$ and put returns $r_{P,i,t}$, referring to the underlying stock or index i, are calculated with the option payoffs at $t + \tau$ and the option mid prices at t as the reference beginning price. These returns are then weighted so that the portfolio beta equals zero, leading to the zero-beta straddle return $r_{zb,i,t}$.

Appendix C: GARCH Calculations

If available, we use five years of daily return data for the estimation of the GARCH(1,1) parameters. We drop a stock from the GARCH estimation if less than one month of return data are available, if five consecutive trading days have no return data, or if more than 10% of the returns are zero. We employ a maximum likelihood estimation for the GARCH(1,1) equation on the portfolio formation date t - 1:

$$\sigma_{i,t-1,d}^2 = \omega_{i,t-1} + \alpha_{i,t-1} u_{i,t-1,d-1}^2 + \beta_{i,t-1} \sigma_{i,t-1,d-1}^2,$$

where $\omega_{i,t-1}$ is the product of the parameter $\gamma_{i,t-1}$ and the long-term variance $V_{i,t-1}$ for stock i, $\sigma_{i,t-1,d-1}^2$ is the estimated variance for stock i on day d within the estimation period, and $u_{i,t-1,d-1}^2$ is the squared stock return of the previous trading day. The weights $\gamma_{i,t-1}$, $\alpha_{i,t-1}$, and $\beta_{i,t-1}$ have to satisfy $\gamma_{i,t-1} + \alpha_{i,t-1} + \beta_{i,t-1}$ = 1. Once $\omega_{i,t-1}$, $\alpha_{i,t-1}$, and $\beta_{i,t-1}$ are estimated, the long-term variance $V_{i,t-1}$ can be deduced from this condition. Hull and White (1987) have suggested using the average variance rate during the life of the option when volatility is stochastic but uncorrelated with the asset price. We use the GARCH(1,1) model to forecast the volatility on the days between trading initiation t until maturity $t + \tau$. The average of these forecasts can be calculated with

$$\sigma(t+\tau)_i^2 = 252\left(V_{i,t-1} + \frac{1-e^{\tau \cdot \ln\left(\alpha_{i,t-1}+\beta_{i,t-1}\right)}}{-\ln\left(\alpha_{i,t-1}+\beta_{i,t-1}\right) \cdot \tau}\left[\sigma_{i,t-1,t-1}^2 - V_{i,t-1}\right]\right),$$

assuming 252 trading days per year.

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