Stock Illiquidity and Option Returns

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Abstract

We provide evidence of a strong effect of the underlying stock's illiquidity on option returns. By conditioning on end user demand, we find that the corresponding illiquidity premiums are negative and decrease in stock illiquidity if there is net buying pressure, while premiums are positive and tend to increase otherwise. Our results cannot be explained by common risk factors and cross-sectional differences in stock volatility or option spreads and are robust to different illiquidity measures and data periods. We explain the observed pattern through an intermediary hedging cost channel. The magnitudes of our illiquidity premiums are in line with reasonable transaction cost assumptions.

JEL Classification: G12; G13

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I. Introduction

There is growing evidence that intermediaries play an important role in determining asset prices, particularly so in option markets, where trading is dominated by specialized intermediaries, the market makers (He and Krishnamurthy 2013, He, Kelly, and Manela 2017). Because market makers hedge their risky options positions (Engle and Neri 2010), cross-sectional differences in hedging costs and risks should be mirrored in corresponding premiums and thus the cross-section of expected option returns (Christoffersen et al. 2018). A better understanding of these premiums is pivotal for our understanding of the functioning of options markets and their capacity to serve risk allocation.

Stock illiquidity crucially affects the hedging costs and risks of market makers and should therefore lead to premiums in option returns. In this paper, we investigate the detailed pattern of these premiums. Surprisingly, very little is known about the connection between stock illiquidity and option returns and the scarce empirical literature shows conflicting evidence. Results in Cao and Han (2013), Karakaya (2014), and Cao et. al (2017) suggest that delta-hedged option returns decrease with stock illiquidity, however, Christoffersen et al. (2018) report a positive relation. We offer a potential explanation for this conflicting evidence. By now, it is broadly accepted that the signs of premiums in option markets depend on the sign of the net demand the market maker faces: net selling pressure in a specific option series leads to price discounts and higher expected option returns as a compensation for costs and risks to be taken and vice versa.[1] We therefore conjecture that, once we condition on end-user demand, expected option returns increase in stock illiquidity for option series in which end users are net sellers, while for series characterized by net buying pressure there is a negative relation between stock illiquidity and expected returns. We empirically investigate this hypothesis by analyzing the cross-section of option returns. Consistent with the above predictions we find that delta-hedged option returns increase with stock illiquidity if proxies indicate end-user net selling pressure in options. If there is an indication for end-user net buying pressure, option returns decrease with stock illiquidity. To our knowledge, we are the first to uncover this relation between stock illiquidity and option returns

[1] Demand-based option pricing theory and empirical evidence by Bollen and Whaley (2004), Gârleanu, Pedersen, and Poteshman (2009), Muravyev (2016), and Fournier and Jacobs (2020) shows that demand pressure indeed influences index and equity option prices and returns in this way. See also Deuskar, Gupta, and Subrahmanyam (2011) for an empirical analysis of OTC interest rate options.

by conditioning on end-user net demand, highlighting both the importance of stock illiquidity for the price setting of options and the crucial role of conditioning on end-user net demand for a better identification of the determinants of the cross-section of expected option returns.

Naturally, conditioning would be superfluous if equity option markets were exclusively characterized by net selling (or buying) pressure. However, empirical evidence on net demand by Ni, Pan, and Poteshman (2008), Goyenko (2015), Muravyev (2016), and Christoffersen et al. (2018) suggests that we find both net long and net short positions of market makers, depending on the particular option series. This property of options markets makes conditioning necessary to effectively disclose the actual relation between stock illiquidity and returns. Indeed, it is this approach that allows us to identify a strong effect of the underlying stock's illiquidity on option returns.

Our empirical investigation proceeds in three steps. First, we investigate whether there is a compensation for stock illiquidity—conditional on end-user demand—in option excess returns. We use trading strategies with delta-hedged call options, put options, straddles, and delta-hedged synthetic futures constructed from options to obtain option excess returns. Second, we investigate different explanations for the observed patterns of option returns and stock illiquidity. A first test investigates whether option returns can be explained by standard risk factors suggested in the literature, and a second test checks to what extent cross-sectional differences in stock volatility or bid–ask spreads of options can explain our results. A final test uses a simulation study to assess 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 third and final step of our analysis, we perform different robustness checks with respect to the chosen illiquidity measure and the data period.

Our work contributes to the literature investigating how stock illiquidity affects option markets. A first important question is whether stock illiquidity has just an impact on options' illiquidity or also affects their mid prices. As we document a strong relation between stock illiquidity and option returns, we provide empirical evidence that hedging costs influence not only options' bid and ask prices (and therefore the bid–ask spread as shown by Engle and Neri (2010), Goyenko, Ornthanalai, and Tang (2015), and Christoffersen et al. (2018)) but also the mid prices of options. A basic economic rationale for the latter point is the following: If stock illiquidity is the only market friction and a (representative) market maker for stock options already has a long position in options, an end user's sell order leads to additional hedging costs, affecting the option's bid price. If it were a buy order, however, the market maker could hedge the new demand without additional costs just by reducing inventory, and the ask price would be the reference price in a frictionless market. If the market maker has a short position initially, the situation is reversed. The ask price would be affected by the additional hedging costs but the bid price would be the reference price in a frictionless market. Therefore, hedging costs due to stock illiquidity lead to different mid prices, depending on whether the market maker is initially long or short in options.[2]

A second important question is how stock illiquidity affects the cross-section of expected option returns. To our knowledge, only very few other papers provide empirical evidence on this question. Cao and Han (2013) study the impact of systematic and idiosyncratic volatility on the cross-section of option returns and show that options on high idiosyncratic volatility stocks have lower returns than options on low idiosyncratic volatility 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. In one of their robustness tests, Cao and Han (2013) also provide evidence on the relation between stock illiquidity and option returns.[3] In multivariate Fama-MacBeth regressions[4] they find a significant negative coefficient for stock illiquidity and conclude that "delta-hedged option returns are more negative when the underlying stock is less liquid …". Karakaya (2014) provides an extensive study on the relation between option returns and a variety of different stock and options characteristics. In an analysis based on single sorting and decile portfolios formed with respect to stock illiquidity, he finds a negative relation between stock illiquidity and the returns of long positions in options,[5] which is consistent with the results by Cao and Han (2013). However, Karakaya (2014) finds no clear evidence whether this relation is explained by common risk factors. Christoffersen et al. (2018) investigate how option illiquidity affects delta-hedged

[2] A formal analysis of the effects of a market makers' inventory on the mid price of a financial asset is provided by Hendershott and Menkveld (2014). In a dynamic model of inventory control they show that the mid price can be above or below the unobserved efficient price, depending on whether the market maker's equilibrium inventories are negative or positive. In their setting, inventory risk cannot be hedged at all, whereas in the options market hedging is possible but costly.
[3] See Cao and Han (2013), Table 6, and the discussion of the results on pages 241 and 242.
[4] Cao et al. (2017) report similar results.
[5] See Karakaya (2014), Table 9, Panel H. Note that Karakaya's actual analysis uses sold options.

option returns and document highly significant positive premiums for buying illiquid options. In some of their analyses, they also provide evidence on the relation between stock illiquidity and option returns. Based on single sorting, they find a positive relation between stock illiquidity and option returns.[6] This positive relation is confirmed in multivariate Fama-MacBeth regressions.[7] A potential reason for the conflicting evidence in previous research—and the starting point of our paper—is that the relation between stock illiquidity and option returns depends on the sign of the net demand of end users. If this net demand varies a lot both over time and in the cross section between different option series, then looking at average effects might lead to different results, depending on the specific data period and the specific coverage of options in the cross section that a particular study uses.

More broadly, our study belongs to the group of studies that provide evidence for a strong connection between market frictions and the cross-section of expected option returns, complementing previous results on such a connection. Choy and Wei (2020) find premiums for options' illiquidity risk. 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. Similarly, Byun and Kim (2016) show that options providing exposure to lottery-like stocks trade at a premium. Hitzemann et al. (2018) find empirical evidence for a margin premium in the cross-section of option returns. They explain their findings by a model of funding-constrained derivatives dealers that require compensation for satisfying end users' option demand.

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

[6] See Christoffersen et al. (2018), Table 7.
[7] See Christoffersen et al. (2018), Table 8.

II. Empirical Design, Data Set, and Data Processing

A. Motivation for Empirical Design

End-user option demand is a crucial moderating variable for the relation between stock illiquidity and option returns. Unfortunately, demand is not observable. Theory, however, can shed light on the linkages between demand and option prices and guide the empirical design to investigate our research questions. Following Gârleanu, Pedersen, and Poteshman (2009), Hitzemann et al. (2018) develop a stylized model of a representative market maker who is facing unhedgeable risks, margin requirements both for the option and the underlying, and funding restrictions. A modified version of their model allows us to characterize the equilibrium relation between hedging costs arising from stock illiquidity, end-user demand, and option prices. In particular, assume that instead of margin requirements and funding restrictions the market maker has to bear hedging costs when hedging her options. Then the time t equilibrium option price F_t equals

$$F_t = F_t^0 + d\,\gamma[\sigma_F^2 - \Delta\sigma_{SF}]\,/R_f + sign(d)\,|\Delta|\,HC/R_f\ , \tag{1}$$

where F_t^0 is the reference price in a frictionless market, d the end-user net demand, $\gamma > 0$ the market maker's risk aversion, σ_F^2 the variance of the option price at time t+1, σ_{SF} the corresponding covariance between stock price and option price, and Δ the option's delta. HC are the hedging costs per unit and R_f denotes the gross return of a risk-free asset.

Eq. (1) shows that the sign of the difference between the equilibrium option price F_t and the reference price F_t^0 in a frictionless market is identical to the sign of end-user net demand d. Therefore, the sign of d can be inferred from the sign of the option's expensiveness $F_t - F_t^0$, suggesting that proxies for option expensiveness are tied to the conditioning information we need in our investigation. Moreover, it can be shown that expected option returns increase with stock illiquidity (HC) for option series in which end users are net sellers and option expensiveness is negative, while for series characterized by net buying pressure and positive expensiveness expected option returns decrease with stock illiquidity.

Similar conclusions can be drawn in other settings. In his classical model of option hedging with transaction costs, Leland (1985) introduces a discrete-time hedging strategy which considers expected transaction costs in the underlying stock. He derives the following modification (σ_m^2) of the Black-Scholes variance (σ^2) for hedging and pricing, where k represents the hedging costs due to stock illiquidity and δt is the length of the discrete time interval:[8]

$$\sigma_m^2 = \sigma^2 \left(1 + \frac{k}{\sigma} \sqrt{\frac{2}{\pi \delta t}} \ sign(V_{SS}) \right). \tag{2}$$

In Eq. (2), V_{ss} denotes the gamma of the end-users options positions. The sign of gamma equals the sign of the end-user net demand that the market maker (hedger) is facing. Therefore, hedging costs raise the variance σ_m^2 when end-used net demand is positive and lower the variance otherwise. If we interpret $\sigma_m^2 - \sigma^2$ as a measure of option expensiveness, the sign of this expensiveness measure is again tied to the sign of demand, i.e., the conditioning information we need in our empirical analysis.

In summary, these considerations show that regardless of the specific design, above-discussed models predict a direct link between end-user demand and option expensiveness. Our empirical design exploits this relation and uses a price-based measure that infers the sign of end-user demand from the relative expensiveness of an option on a particular date.

B. 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, 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.[9] 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

[8] See Leland (1985), p. 1289. In the original paper, Leland considers the replication of one call option, i.e., end-user net demand is positive and the market maker has a short position. For a generalization with general option positions leading to Eq. (2) see Hoggard, Whalley, and Wilmott (1994).
[9] We refer the reader to the Ivy DB reference manual for further details.

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. 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.

C. Return Calculations

Our analysis builds on the formation of portfolios, following Goyal and Saretto (2009). To concentrate on option-specific effects and reduce (or eliminate) the impact of stock price risk on options' returns, we use three kinds of portfolios. The first kind contains either delta-hedged call or put options. The second, that does not rely on model-dependent deltas, consists of straddles. The third uses a long position in a call and a short position in a put with the same strike, delta hedged with the underlying stock. These delta-hedged synthetic futures share the advantage of straddles of not requiring model-dependent deltas. Moreover, because synthetic futures are linear in the stock price, a static hedge is sufficient. Thus, the strategy is not prone to hedging errors, and portfolio returns do not depend on stock price changes. The formation of portfolios of delta-hedged options, straddles, and delta-hedged synthetic futures is based on information available on the first trading day (usually a Monday) after the expiration day of the month.[10] 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. Throughout the sample period, we have 153,381 delta-hedged call observations, 142,267 delta-hedged put observations, 135,149 straddle pairs of calls and puts, and 134,525 pairs of calls and puts building synthetic futures. The number of synthetic futures is slightly lower than the number of straddles because for this portfolio we exclude all call and put combinations for one underlying where the strike prices do not exactly match.[11] 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 select the portfolios and hold the option until

[10] 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.

[11] The reason why we demand an exact match of strike prices in this case is to eliminate the effects of hedging errors on our results.

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.

C.1. Delta-Hedged Option Returns

We calculate returns of initially delta-hedged call and put 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). Following Cao and Han (2013), we calculate the return of the delta-hedged call as the excess dollar return of the delta-hedged option scaled by the absolute value of the securities involved, i.e., the return of a delta-hedged call is calculated as

$$\Pi_{t,t+\tau}^{c} = \frac{C_{t+\tau} - \Delta_{C,t}\, S_{t+\tau} - \left(C_t - \Delta_{C,t}\, S_t\right)e^{r\tau}}{Abs\left(C_t - \Delta_{C,t}\, S_t\right)}, \tag{3}$$

where $\mathrm{C}_{t+\tau}$ and $S_{t+\tau}$ are the mid prices of the call and the underlying stock, respectively, at time $t + \tau$, $\Delta_{C,t}$ is the option's delta, and C_t and S_t are the mid prices of the call and the underlying stock, respectively, at *t*, the trading initiation date (the trading day after the portfolio formation date). The return calculation for delta-hedged puts is the same as in Eq. (3), except that the call option price and call delta are replaced by the price and delta of the put.

C.2. Straddle Returns

Straddles are formed as a combination of one call and one put on the same underlying with closest strike prices and identical 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 slight difference between the call and put strikes. The straddle returns are calculated as

$$\Pi_{t,t+\tau}^{str} = \frac{C_{\ t+\tau} + P_{t+\tau} - (C_t + P_t)e^{r\tau}}{C_t + P_t}. \tag{4}$$

C.3. Delta-hedged Synthetic Futures Returns

To construct synthetic futures we use an ATM call long and an ATM put short. This position is then delta hedged with a short position in the stock. The return of this portfolio is

$$\Pi^{sf}_{t,t+\tau} = \frac{C_{t+\tau} - P_{t+\tau} - S_{t+\tau} - (C_t - P_t - S_t)e^{r\tau}}{Abs(C_t - P_t - S_t)}. \tag{5}$$

Since our strikes are equal ($K_{Call} = K_{Put} = K$), if the portfolio is held until the options' expiration, the portfolio return simplifies to

$$\Pi^{sf}_{t,t+\tau} = \frac{(S_t - C_t + P_t)e^{r\tau} - K}{Abs(C_t - P_t - S_t)}, \tag{6}$$

showing that no hedging error exists and the return can be deduced from information available at time *t*. End-user demand pressure can affect calls and puts differently such that the put-call-parity needs not to hold and market frictions directly translate into non-zero returns in Eq. (6). In contrast to the delta-hedged call, put, and straddle returns, which are inherently non-linear, the return pattern of a synthetic future is that of a linear instrument. Thus, it is not affected by variance risk. All this renders delta-hedged synthetic futures returns particularly suitable for our purpose.[12]

D. Measuring 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 illiquidity measure calculations can be found in Appendix A.

E. Measuring End-User Demand Pressure

Our main proxy for end-user option demand pressure is option expensiveness, measured as the difference between the option's implied volatility (IV) and a benchmark estimate of volatility from historical stock return data (HV). Based on theoretical considerations, as discussed in Section II.A., and shown empirically by Bollen and Whaley (2004), Gârleanu, Pedersen, and Poteshman (2009), and Fournier and Jacobs (2020) there is a strong relation between demand pressure and expensiveness. The more expensive an option, the higher the net end-user options

[12] Bali and Murray (2013) also use portfolios of calls, puts, and stocks that eliminate the impact of both stock price risk and variance risk. However, because their objective is the study of skewness premiums, their portfolios are sensitive to skewness risk.

demand (for long positions in options). When implementing our expensiveness measure for the delta-hedged call and put strategies, the implied volatility estimate is the implied volatility of the call and put options, respectively, on the portfolio formation date (t - 1). 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. For the straddles (call long and put long), we use the sum of the implied volatilities of the respective put and call options on the stock as our IV measure and two times the historical volatility as our benchmark volatility HV. The delta-hedged synthetic futures strategy (call long and put short) uses the difference between the implied volatilities of the call and the put (CVOL–PVOL) as the implied measure, which is a measure of relative expensiveness of calls as compared to puts. A historical volatility benchmark is not required for this strategy because the historical volatilities would just cancel out. Thus, the delta-hedged synthetic futures strategy uses CVOL–PVOL as a proxy for the relative end-user demand for calls as compared to puts.[13]

III. Main Results

Our analysis examines the relation between option returns and stock illiquidity, conditional on end-user net demand. Every month, on the portfolio formation date, we first sort stocks into quintiles based on their Amihud illiquidity measure; then the stocks in each illiquidity quintile are sorted into quintiles based on the demand proxy (IV–HV or CVOL–PVOL). For every month throughout the observation period, we calculate the mean (equally weighted) monthly option portfolio returns for each combination of stock illiquidity quintiles and demand quintiles, with options being held until the last trading day prior to expiration. Table I reports the time-series averages of these monthly means. For each demand quintile, we also calculate returns of long–short portfolios that buy options on the most illiquid stocks (5-high quintile) and sell options on the least illiquid stocks (1-low quintile). The average returns of these portfolios are shown in the 5–1 row. In addition, for each illiquidity quintile, we consider long–short portfolios that buy options with the lowest end-used demand pressure (5-low quintile) and sell options with the highest demand pressure (1-high quintile). The corresponding average returns are presented in the 5–1 column. The last two columns of Table I finally show the time-series averages of the mean

[13] In accordance with this idea of relative order imbalances in call and put options, Bali and Hovakimian (2009) have shown that the difference between call and put implied volatility can predict future stock returns.

and standard deviation of option returns within the illiquidity quintiles. The delta-hedged call and put returns in Panels A and B as well as the straddle returns in Panel C and the delta-hedged synthetic futures returns in Panel D are calculated as described in Section II.C.

[Insert Table I about here]

If stock illiquidity affects option returns, we expect the return distribution to change with illiquidity. If market makers were only buyers of individual equity options, the mean option return should increase with illiquidity and, if market makers were only sellers, the mean return should decrease. For both delta-hedged calls and puts, we indeed find decreasing option returns for the quintile with the highest end-user demand and at least a tendency of increasing option returns for the quintile with the lowest end-user demand. For straddles, the pattern is also similar, while the magnitudes of returns are substantially higher. Delta-hedged synthetic futures show the strongest results in terms of statistical significance, again with decreasing returns for the highest (relative) end-user demand quintile and increasing returns for the lowest one. Note that the synthetic futures returns do not exhibit a hedging error. So these more distinctive results do not come as a surprise. The strong results for delta-hedged synthetic futures are also interesting for another reason. They provide evidence that the observed regularity is indeed due to market frictions and not just a compensation for variance risk. Overall, the results of Table I give a first indication that stock illiquidity influences option returns negatively for high (positive) end-user demand and positively for low (negative) end-user demand.

For comparison, we also present the usual procedure in the literature, a simple univariate sort (last but one column in all four panels of Table I), which does not account for different signs of end-user demand. Here, it turns out that the mean option returns in the stock illiquidity quintiles have a tendency to decline with stock illiquidity for calls, puts, and straddles and to rise for synthetic futures. However the relation is generally not monotonous and essentially results from the relatively low (high) returns of the highest illiquidity quintile. In contrast, the standard deviation (last column in all four panels of Table I) smoothly increases for all four options strategies, which is in line with the idea of stock illiquidity being important for option returns but working into opposite directions depending on whether demand is positive or negative.

If the return-illiquidity relation indeed depends on the sign of end-user demand, there is a straightforward strategy to disclose the relationship between option returns and stock illiquidity:

if end-users are on the long side of the market (high demand, expensive options), option returns should decrease with stock illiquidity, while they are supposed to increase otherwise. Thus, buying cheap options (lowest demand quintile) and shorting the corresponding expensive ones (highest demand quintile) should lead to positive long-short returns that monotonously increase in illiquidity (5–1 columns).

For all four return measures (delta-hedged calls, delta-hedged puts, straddles, delta-hedged futures), we can clearly confirm this prediction. Moreover, the return differences between the options in the highest and the lowest illiquidity quintile are highly significant in all cases. For the cases of straddles, e.g., the average monthly return difference is 9.6%.[14]

To obtain a deeper understanding of the illiquidity effect on option returns, we refine the sorting on our illiquidity measure. For Figure 1, we repeat our analysis from Table I but sort the options every month into deciles instead of quintiles on the stock illiquidity measure.[15] Again, according to our hypothesis, the long-short returns of our demand-sorted portfolios should monotonously increase in illiquidity. For comparison, we also consider the simple average returns along the illiquidity deciles which do not account for differences in expensiveness. The lower plots in Figure 1 show these values for calls and straddles. The overall negative relation between option returns and illiquidity mirrors some findings of Cao and Han (2013) and Karakaya (2014), who report that returns to buying delta-hedged options decrease 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 take the demand dimension into account. Consistent with our hypothesis, the upper plots reveal a clear positive trend with stock illiquidity for the 3–1 portfolios. In summary, Figure 1 illustrates the main contribution of the paper: By long–short trading strategies that

[14] Two equivalent strategies lead to such a return: conditional on high demand, one can take a long position in options referring to the least illiquid stocks and a short position in options referring to the most illiquid ones. Additionally, conditional on low demand, the strategy is reversed, i.e., one buys options referring to the most illiquid stocks and sells those referring to the least illiquid ones. For straddles, the high-demand part of the strategy yields an average monthly return of 5.9%, while the low-demand part amounts to 3.7%. Taken together, the average monthly return is thus 9.6%. This conditional strategy corresponds exactly to a long–short strategy that takes a long position in the 5–1 demand-sorted options portfolio referring to the most illiquid stocks and a short position in the 5–1 demand-sorted options portfolio referring to the most liquid stocks (with average monthly return of 16.5% on the long position and -6.9% on the short position, thus overall 9.6%).

[15] To retain a sufficiently large number of options within our double-sorted portfolios, we limit our analysis to demand tertiles and display the returns on the 3–1 portfolios.

condition on end-user demand, we have uncovered a clear connection between stock illiquidity and option returns.

[Insert Figure 1 about here]

Note that even for the lowest illiquidity decile the returns of the 3–1 portfolios are still positive, with a return of 0.56% per month and a t-statistic of 2.87 for the delta-hedged calls and a straddle return of 3.72% with a t-statistic of 1.91. 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.

So far, we have used a monthly holding period for the options portfolios and start trading one day after the end-user demand proxies are observed (portfolio formation date). While this approach is interesting from an investment perspective, it may cause undesirable noise for two reasons. First, during the one-month holding period, option moneyness could change drastically and the returns of delta-hedged calls, puts, and straddles could be exposed to substantial underlying stock price risk. Second, from the portfolio formation date until trading initiation, market makers' inventories could change signs and we would not correctly classify end-user demand any more after such a change had taken place. We therefore repeat our analysis from Table I for a one-day holding period starting at the portfolio formation date. This procedure leaves the number of observations unchanged as compared to Table I. The corresponding results for the one-day holding period are presented in Table II.

[Insert Table II about here]

Again, in the high demand columns, returns decrease in stock illiquidity while they increase in the low demand columns. This pattern holds for all four strategies and is indeed more pronounced than before. So overall, the results point to a highly significant, robust relation between option returns and stock illiquidity once we condition on the expensiveness of options.

IV. Potential Explanations for the Main Results

A. Option Returns and Risk Factors

So far, we have established an empirical pattern that relates 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 might no longer exist. We therefore check whether the pattern of increasing excess returns of 5–1 demand-sorted portfolios (low end-user demand minus high end-user demand) 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 demand-sorted portfolios within the lowest and highest illiquidity quintiles and the difference between these portfolios (5–1 high illiquidity minus 5–1 low illiquidity) on several risk control variables.

Especially due to imperfections in our delta hedge for the monthly holding period, 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.[16] We also check whether the observed illiquidity effects are related to different variance risk premiums of individual stocks. The returns of our options portfolios should then be correlated with the market variance risk premium.[17] Therefore, we control for variance risk premiums following Cao and Han (2013). For market variance risk, we include the excess returns of the Coval and Shumway (2001) zero-beta 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 a correlation risk premium. 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.

[16] 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. (2018) also include these four factors as control variables for option returns.
[17] Bollerslev, Tauchen, and Zhou (2009) present a general equilibrium model of the market variance risk premium.

The regression results are presented in Table III. They show that the loadings on the Fama–French (1993) and momentum factors are insignificant in almost all cases and the few exceptions show no clear pattern in terms of options strategies or specific factors. The coefficients of the zero-beta S&P 500 straddle and the zero-beta S&P 500 component straddles are all insignificant for our sample, i.e., we find no evidence that variance or correlation risk premiums can explain the portfolio returns. Overall, the alphas of the portfolios are all significant and very close to the average raw returns reported in Table I.

[Insert Table III about here]

In particular, the regression alphas of the 5–1 demand strategies within the low illiquidity quintile are significantly lower than the alphas of the 5–1 strategies within the high illiquidity quintile. The differences for the alphas of the high and low illiquidity delta-hedged call, delta-hedged put, straddle, and delta-hedged synthetic futures portfolios are 1.4%, 1.8%, 9.3%, and 0.6%, 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.

B. Option Returns, Individual Volatility, and Option Spreads

Another explanation for our observed pattern could be that more illiquid stocks tend to be more volatile. This positive correlation between stock illiquidity and stock volatility might be reflected in our option returns.[18] To check this possibility, we repeat our main analysis but control for historical volatilities. Table IV shows the results from a controlled portfolio sort. Each month, we sort all options into conditional quintile portfolios according to historical volatility, the Amihud illiquidity measure, and the end-user demand proxy. The resulting 125 portfolios are then averaged along the historical volatility quintiles, such that we obtain 25 illiquidity/end-user demand portfolios with similar historical volatility. The resulting option return patterns in Table IV are qualitatively the same as in Table I. The returns of delta-hedged calls, delta-hedged puts, straddles, and delta-hedged synthetic futures tend to increase with illiquidity if end-user demand is low and clearly decrease with illiquidity if end-user demand is high. The conditional long–short returns are highly significant in all four cases. So, we conclude that cross-sectional differences in stock volatility cannot explain the effect of stock illiquidity on option returns.

[18] Hu and Jacobs (2020) investigate the relation between option returns and the volatility level of the underlying. With static delta-hedges, similar to the ones deployed in this study, the volatility level is an important determinant of option returns.

[Insert Table IV about here]

An alternative explanation for our findings might be the higher bid–ask spreads of options associated with less liquid stocks (Christoffersen et al. 2018). Table V presents the results from another controlled portfolio sort, but now we control for the options' illiquidity, i.e. we form 125 portfolios sorted on the (average) relative option spread, the Amihud illiquidity measure, and the end-user demand proxy. Again, the corresponding long–short returns exhibit a similar pattern as in our main analysis. Thus, when holding option spreads constant, we still find a clear relation between stock illiquidity and option returns. This evidence implies that options' bid–ask spreads do not already reflect the role of stock illiquidity as a determinant of option returns.

[Insert Table V about here]

From our controlled portfolio sorts we conclude that neither cross-sectional differences in stock volatility nor option's illiquidity can explain the documented effect of stock illiquidity on option returns. Still, our empirical evidence on the relation between stock illiquidity and option returns is consistent with an intermediary hedging cost channel.

Further alternative explanations for the option return patterns are uncertainty risk, informed trading, and behavioral biases. Buraschi, Trojani, and Vedolin (2014) suggest an argument 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. (2018) 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 IV–HV 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, their findings are complementary to our main result, that higher stock illiquidity is associated with wider fluctuations of option returns around reference values expected in perfect market environments.

C. Option returns, option demand, and the impact of transaction costs

In principle, the relation between stock illiquidity and option returns 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. It would require that realistic illiquidity costs of market makers be compatible with the observed magnitudes of the return effects. Moreover, we would also like to rule out that the observed return effects just reflect potential illiquidity premiums in the underlying stocks, affecting our options portfolios via hedging errors.

We investigate these issues 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 upper bound for the price impact of the illiquidity of the underlying.[19] We simulate prices of call options according to this model under realistic assumptions for transaction costs, hedging frequency, market maker positions, and underlying dynamics. The details of these simulations are described in Appendix C. We finally calculate delta-hedged option returns and perform the same sorting procedure that led to Table I, this time using the simulated data.

Table VI shows the results for the simulated data, which correspond to the results in Panel A of Table I. We observe that the results are very similar to those obtained for the 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 and the magnitudes of the average delta-hedged return differences between the quintiles are similar to those observed in the empirical data. The

[19] 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.

penultimate column shows that the differences between mean returns are relatively small across the transaction cost groups, thus the effect of transaction costs cannot be seen from the unconditional interaction of underlying transaction costs and option returns. In contrast, the standard deviation of option returns, as shows in the last column, clearly grows with transaction costs. This is the same pattern as for the market data in Section III.[20]

[Insert Table VI about here]

We now use our simulated data to check whether they lead to a similar pattern than the market data in Figure 1. Figure 2 shows the results. It depicts both the empirical average monthly delta-hedged returns of the 3–1 long–short strategies and the corresponding ones resulting from the simulation. We see that the patterns are indeed very similar and even the magnitudes of the simulated delta-hedged call returns come close to the average empirical returns.

[Insert Figure 2 about here]

We conclude that our empirical results for option returns under the double sorting with respect to the stock illiquidity measure and IV–HV can be reproduced by a simple simulation with realistic transaction cost assumptions.

V. Robustness Checks

Finally, we address some additional robustness issues. A first issue is the measurement of end-user demand pressure. We start by asking whether the results depend on the specific method to estimate historical volatility when calculating our demand proxy IV–HV. A second issue is the measurement of illiquidity, asking for robustness with respect to alternative illiquidity measures. We deal with these problems in Section V.A. A third robustness issue refers to the sample period considered. Section V.B. investigates this point.

A. Alternative Volatility and Illiquidity Measures

As alternative historical volatility measures to calculate IV–HV, we use a GARCH(1,1) estimate for the option's lifetime volatility and the standard deviation of daily stock returns using the six

[20] Only the magnitude of the standard deviations is smaller, since our simulation does not account for the cross-sectional variation in true volatility.

and 24 most recent months.[21] With respect to the measurement of illiquidity we replace the Amihud illiquidity measure with alternative measures: the log market capitalization of the underlying stock, the dollar trading volume of the underlying, and Roll's (1984) and Corwin's and Schultz's (2012) bid–ask spread estimates. In Table VII, we repeat the analysis from Table III, but with the alternative measures. The differences of the alphas from the 5–1 strategy in the highest illiquidity quintile compared to the 5–1 strategy in the lowest illiquidity quintile are positive across all alternative illiquidity and volatility measures and significant at the 5% level in 27 out of 28 cases. Therefore, these findings are in line with the results and conclusions from Table III.

[Insert Table VII about here]

B. 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 VIII are the same as for Table I. The first column returns correspond to the 5–1 column returns in Table I. The second column excludes 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 similar to the difference for the complete sample period and generally statistically significant. Interestingly, the overall performance of the trading strategy

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

that conditions on end-user demand is worse 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 VIII about here]

VI. Conclusions

This paper is the first to present empirical evidence that underlying stock illiquidity is strongly related to option returns. We show in a cross-sectional analysis that the returns of delta-hedged calls, delta-hedged puts, straddles, and delta-hedged synthetic futures increase with illiquidity if end-user demand is low and decrease with illiquidity if end-user demand is high.

Our findings are in line with intermediaries considering different option hedging costs depending on stock illiquidity and being net long in options on some stocks and short in options on others. 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 option returns are strikingly similar to those observed in our empirical data.

We find no evidence that the returns of the analyzed option strategies can be explained by common risk factors. In particular, we find no explanatory power for proxies of the market variance risk premium and a correlation risk premium. Moreover, the results for synthetic futures constructed from call and put option show a similar pattern than the results for the other strategies, which cannot be due to variance risk. Cross-sectional differences in stock volatility and option spread are also unable to explain the observed patterns of option returns. However, our results still leave room for alternative explanations based on market frictions or market incompleteness for two reasons. First, parts of the excess option returns (alpha) are unexplained by illiquidity. Second, stock illiquidity may well be correlated with other characteristics, like embedded options leverage or stock price jumps, and may therefore partly capture the corresponding effects on option returns.

Table I

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

The sample between January 1996 and August 2015 includes 153,381 delta-hedged call returns, 142,267 delta-hedged put returns, 135,149 pairs of call and put options for the straddle returns, and 134,525 pairs of call and put options with the same ATM moneyness for the synthetic futures returns. 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 implied and historical volatility (Panel A-C). For Panel D the options in the Amihud quintiles are sorted into quintiles based on the difference between the call and put implied volatility (CVOL–PVOL). This table shows the average monthly returns of the portfolios for the different categories. The portfolio returns use an equal weighting of the option returns in a 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 options is determined from the implied volatility at trading initiation. Associated t-statistics are corrected for autocorrelation following Newey and West (1987).

Panel A

Delta-hedged call returns

		End-user demand proxy (IV–HV)							*mean*	*sd*
		1-high	2	3	4	5-low	5–1	t-stat.	all	
Stock illiquidity	1-low	-0.4%	-0.2%	-0.1%	0.1%	0.3%	0.7%	2.87	-0.1%	6.3%
	2	-0.5%	-0.3%	-0.1%	0.0%	0.6%	1.1%	4.29	-0.1%	7.1%
	3	-0.8%	-0.1%	0.0%	0.3%	0.6%	1.4%	5.50	0.0%	8.3%
	4	-1.1%	-0.2%	0.0%	0.2%	0.8%	1.9%	6.17	-0.1%	9.3%
	5-high	-1.7%	-0.7%	-0.5%	-0.3%	0.6%	2.3%	7.56	-0.5%	10.4%
	5–1	-1.3%	-0.5%	-0.4%	-0.4%	0.3%	1.6%		-0.4%	4.1%
	t-stat.	-4.28	-2.72	-2.12	-1.60	1.16	4.32		-3.08	20.97

Panel B

Delta-hedged put returns

		End-user demand proxy (IV–HV)							*mean*	*sd*
		1-high	2	3	4	5-low	5–1	t-stat.	all	
Stock illiquidity	1-low	-0.6%	-0.3%	-0.1%	-0.1%	0.1%	0.7%	3.75	-0.2%	5.7%
	2	-0.5%	-0.4%	-0.2%	0.0%	0.2%	0.7%	3.41	-0.2%	6.4%
	3	-0.7%	-0.3%	-0.2%	-0.1%	0.3%	1.0%	4.96	-0.2%	7.3%
	4	-1.4%	-0.4%	-0.2%	0.0%	0.5%	1.9%	6.65	-0.3%	8.2%
	5-high	-2.1%	-0.9%	-0.8%	-0.4%	0.3%	2.4%	9.22	-0.8%	9.3%
	5–1	-1.5%	-0.6%	-0.7%	-0.3%	0.2%	1.7%		-0.6%	3.6%
	t-stat.	-7.57	-3.39	-4.03	-1.68	0.80	6.46		-5.12	19.85

Table I (Continued…)

Panel C

Straddle returns

		End-user demand proxy (IV–HV)							*mean*	*sd*
		1-high	2	3	4	5-low	5–1	t-stat.	all	
Stock illiquidity	1-low	-4.1%	-1.0%	0.5%	-0.7%	2.8%	6.9%	3.22	-0.5%	74.5%
	2	-4.5%	-4.4%	1.0%	0.6%	2.6%	7.1%	3.72	-0.9%	74.7%
	3	-5.8%	0.5%	-1.6%	0.6%	4.7%	10.5%	5.05	-0.3%	76.3%
	4	-7.4%	-1.3%	-0.4%	1.9%	7.4%	14.8%	6.73	0.0%	79.2%
	5-high	-10.0%	-4.4%	-5.2%	-1.3%	6.5%	16.5%	8.03	-2.9%	80.5%
	5–1	-5.9%	-3.4%	-5.7%	-0.6%	3.7%	9.6%		-2.4%	6.0%
	t-stat.	-3.27	-1.66	-2.81	-0.25	1.75	3.55		-1.87	4.12

Panel D

Synthetic future returns

		End-user demand proxy (Call implied VOL – Put implied VOL)							*mean*	*sd*
		1-high	2	3	4	5-low	5–1	t-stat.	all	
Stock illiquidity	1-low	-0.01%	0.00%	0.02%	0.03%	0.09%	0.10%	7.14	0.0%	0.2%
	2	-0.02%	0.02%	0.04%	0.07%	0.18%	0.20%	7.38	0.1%	0.3%
	3	-0.04%	0.02%	0.06%	0.10%	0.27%	0.31%	8.62	0.1%	0.4%
	4	-0.03%	0.02%	0.07%	0.13%	0.39%	0.42%	11.75	0.1%	0.5%
	5-high	-0.09%	0.01%	0.08%	0.18%	0.59%	0.68%	13.21	0.2%	0.8%
	5–1	-0.08%	0.01%	0.06%	0.15%	0.50%	0.58%		0.2%	0.6%
	t-stat.	-2.85	0.71	6.59	11.20	17.23	13.88		12.29	23.84

Table II

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

The sample between January 1996 and August 2015 includes 153,381 delta-hedged call returns, 142,267 delta-hedged put returns, 135,149 pairs of call and put options for the straddle returns, and 134,525 pairs of call and put options with the same ATM moneyness for the synthetic futures returns. 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 implied and historical volatility (Panel A-C). For Panel D the options in the Amihud quintiles are sorted into quintiles based on the difference between the call and put implied volatility (CVOL–PVOL). 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 delta-hedged calls, delta-hedged puts, straddles, and synthetic futures 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 bid and ask quotes on the following trading day. The hedge ratio for the delta-hedged calls and puts is determined from the implied volatility upon trading initiation. Associated t-statistics are corrected for autocorrelation following Newey and West (1987).

Panel A

Delta-hedged call returns

		End-user demand proxy (IV–HV)							*mean*	*sd*
		1-high	2	3	4	5-low	5–1	t-stat.	all	
Stock illiquidity	1-low	-0.05%	-0.05%	0.00%	0.03%	0.04%	0.09%	1.97	0.0%	1.0%
	2	-0.16%	-0.02%	-0.01%	0.01%	0.06%	0.22%	6.14	0.0%	0.9%
	3	-0.26%	-0.05%	0.00%	0.06%	0.08%	0.34%	8.75	0.0%	1.1%
	4	-0.35%	-0.06%	-0.02%	0.06%	0.11%	0.46%	12.64	-0.1%	1.1%
	5-high	-0.76%	-0.16%	-0.02%	0.13%	0.32%	1.08%	15.20	-0.1%	1.7%
	5–1	-0.71%	-0.11%	-0.02%	0.10%	0.28%	0.99%		-0.1%	0.7%
	t-stat.	-11.75	-3.28	-0.46	2.96	7.43	13.71		-3.93	6.11

Panel B

Delta-hedged put returns

		End-user demand proxy (IV–HV)							*mean*	*sd*
		1-high	2	3	4	5-low	5–1	t-stat.	all	
Stock illiquidity	1-low	-0.20%	-0.10%	-0.06%	-0.04%	-0.02%	0.18%	4.58	-0.1%	0.9%
	2	-0.22%	-0.10%	-0.04%	-0.05%	-0.01%	0.21%	6.70	-0.1%	0.8%
	3	-0.26%	-0.08%	-0.06%	0.01%	0.04%	0.30%	7.54	-0.1%	0.9%
	4	-0.32%	-0.08%	-0.02%	0.03%	0.08%	0.40%	9.70	-0.1%	1.0%
	5-high	-0.49%	-0.13%	-0.01%	0.09%	0.18%	0.67%	13.48	-0.1%	1.4%
	5–1	-0.29%	-0.03%	0.05%	0.13%	0.20%	0.49%		0.0%	0.5%
	t-stat.	-6.37	-0.95	1.67	5.73	5.02	8.16		0.75	3.73

Table II (Continued…)

Panel C

Straddle returns

		End-user demand proxy (IV–HV)							*mean*	*sd*
		1-high	2	3	4	5-low	5–1	t-stat.	all	
Stock illiquidity	1-low	-1.25%	-0.80%	-0.63%	-0.21%	-0.12%	1.13%	5.80	-0.6%	7.1%
	2	-1.50%	-0.70%	-0.48%	-0.14%	-0.10%	1.40%	6.87	-0.6%	7.0%
	3	-1.55%	-0.78%	-0.23%	-0.01%	-0.22%	1.33%	6.72	-0.6%	7.3%
	4	-1.66%	-0.58%	-0.15%	-0.14%	0.05%	1.71%	9.44	-0.5%	7.4%
	5-high	-2.08%	-0.95%	-0.24%	0.03%	0.24%	2.32%	11.39	-0.6%	8.1%
	5–1	-0.83%	-0.15%	0.39%	0.24%	0.36%	1.19%		0.0%	1.0%
	t-stat.	-4.15	-0.87	1.78	1.16	1.42	4.21		0.01	5.34

Panel D

Synthetic future returns

		End-user demand proxy (Call implied VOL – Put implied VOL)							*mean*	*sd*
		1-high	2	3	4	5-low	5–1	t-stat.	all	
Stock illiquidity	1-low	-0.09%	0.02%	0.04%	0.07%	0.20%	0.29%	7.15	0.0%	0.6%
	2	-0.14%	-0.03%	0.01%	0.10%	0.23%	0.37%	10.30	0.0%	0.5%
	3	-0.26%	-0.08%	0.00%	0.10%	0.31%	0.57%	14.34	0.0%	0.5%
	4	-0.42%	-0.08%	0.02%	0.12%	0.40%	0.82%	17.48	0.0%	0.6%
	5-high	-0.70%	-0.17%	0.02%	0.20%	0.65%	1.35%	23.46	0.0%	0.9%
	5–1	-0.61%	-0.19%	-0.02%	0.13%	0.45%	1.06%		0.0%	0.3%
	t-stat.	-15.58	-5.27	-0.90	7.02	14.61	20.17		-2.87	2.43

Table III

Risk-adjusted post-formation 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 illiquidity quintiles are constructed as in Table I. The t-statistics for the coefficients in brackets are calculated with Newey and West (1987) standard errors.

	Delta-hedged calls			Delta-hedged puts		
	5–1 low ill.	5–1 high ill.	5–1 high ill. - 5–1 low ill.	5–1 low ill.	5–1 high ill.	5–1 high ill. - 5–1 low ill.
Alpha	0.8%	2.3%	1.4%	0.7%	2.5%	1.8%
	(3.18)	(7.79)	(4.15)	(3.69)	(9.64)	(6.83)
MKT–Rf	-0.107	0.038	0.145	-0.013	0.013	0.026
	(-1.25)	(0.43)	(1.64)	(-0.15)	(0.14)	(0.33)
SMB	-0.116	0.118	0.234	-0.209	-0.009	0.199
	(-0.91)	(1.09)	(1.47)	(-1.53)	(-0.07)	(1.67)
HML	0.099	0.202	0.103	0.162	-0.113	-0.275
	(1.02)	(1.62)	(0.70)	(1.80)	(-1.02)	(-2.42)
MOM	-0.012	0.161	0.173	0.016	0.002	-0.014
	(-0.13)	(2.26)	(1.66)	(0.22)	(0.03)	(-0.17)
ZB-STR-Index	0.000	0.008	0.007	0.003	0.008	0.005
	(0.02)	(1.28)	(0.97)	(0.55)	(1.38)	(0.99)
ZB-STR-Stocks	0.005	0.000	-0.005	-0.008	0.011	0.019
	(0.33)	(-0.02)	(-0.25)	(-0.63)	(0.91)	(1.06)

Table III (Continued…)

	Straddles			Synthetic futures		
	5–1 low ill.	5–1 high ill.	5–1 high ill. - 5–1 low ill.	5–1 low ill.	5–1 high ill.	5–1 high ill. - 5–1 low ill.
Alpha	7.4%	16.7%	9.3%	0.1%	0.7%	0.6%
	(3.51)	(8.64)	(3.64)	(7.19)	(13.21)	(13.87)
MKT–Rf	-0.488	0.180	0.667	0.001	0.002	0.000
	(-0.55)	(0.38)	(0.87)	(0.51)	(0.17)	(0.05)
SMB	-0.699	1.568	2.266	-0.001	-0.005	-0.004
	(-0.57)	(2.81)	(1.97)	(-0.14)	(-0.37)	(-0.39)
HML	1.271	0.231	-1.040	0.004	-0.019	-0.023
	(1.69)	(0.38)	(-1.35)	(1.11)	(-1.29)	(-1.85)
MOM	0.650	0.826	0.176	0.004	0.011	0.007
	(1.07)	(1.65)	(0.29)	(1.83)	(1.41)	(1.06)
ZB-STR-Index	0.013	0.056	0.043	0.000	-0.001	-0.001
	(0.21)	(1.45)	(0.71)	(-0.29)	(-1.14)	(-1.27)
ZB-STR-Stocks	0.094	0.128	0.034	0.000	0.001	0.001
	(0.65)	(1.38)	(0.22)	(0.60)	(0.72)	(0.68)

Table IV

Average monthly post-formation returns of three-way sorted portfolios (volatility).

The sample between January 1996 and August 2015 includes 153,381 delta-hedged call returns, 142,267 delta-hedged put returns, 135,149 pairs of call and put options for the straddle returns, and 134,525 pairs of call and put options with the same ATM moneyness for the synthetic future returns. Each month, option observations are first sorted into quintiles based on the historical volatility (HV). Within these quintiles, option observations are sorted into quintiles based on the Amihud illiquidity measure. Within the first and second sort quintiles, options are sorted into quintiles based on the difference between the implied and historical volatility (Panel A-C). For Panel D the options in the first and second sort quintiles are sorted into quintiles based on the difference between the call and put implied volatility. This table reports the average of the 25 second and third sort portfolios along the 5 volatility categories. The portfolio returns use an equal weighting of the option returns in a 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 options is determined from the implied volatility at trading initiation. Associated t-statistics are corrected for autocorrelation following Newey and West (1987).

Panel A

Delta-hedged call returns

		End-user demand proxy (IV–HV)							*mean*	*sd*
		1-high	2	3	4	5-low	5–1	t-stat.	all	
Stock illiquidity	1-low	-0.2%	-0.2%	0.0%	0.4%	0.3%	0.5%	2.83	0.1%	7.6%
	2	-0.6%	-0.1%	0.1%	0.3%	0.1%	0.7%	3.64	0.0%	8.2%
	3	-0.7%	-0.3%	0.2%	0.4%	0.4%	1.1%	5.15	0.0%	8.5%
	4	-0.9%	-0.5%	-0.2%	0.1%	0.5%	1.4%	4.96	-0.2%	8.6%
	5-high	-1.6%	-0.9%	-0.5%	-0.3%	0.5%	2.1%	8.37	-0.6%	9.1%
	5–1	-1.4%	-0.7%	-0.5%	-0.7%	0.2%	1.6%		-0.7%	1.5%
	t-stat.	-5.63	-4.06	-2.45	-3.15	0.92	5.03		-4.64	6.64

Panel B

Delta-hedged put returns

		End-user demand proxy (IV–HV)							*mean*	*sd*
		1-high	2	3	4	5-low	5–1	t-stat.	all	
Stock illiquidity	1-low	-0.4%	-0.2%	0.0%	0.0%	0.1%	0.5%	3.02	-0.1%	6.8%
	2	-0.8%	-0.1%	-0.1%	0.0%	0.1%	0.9%	4.91	-0.2%	7.2%
	3	-1.0%	-0.2%	-0.1%	0.0%	0.2%	1.2%	7.35	-0.2%	7.4%
	4	-1.3%	-0.5%	-0.4%	-0.1%	0.3%	1.6%	6.90	-0.4%	7.7%
	5-high	-1.8%	-0.9%	-0.6%	-0.4%	0.0%	1.8%	7.85	-0.7%	8.1%
	5–1	-1.4%	-0.7%	-0.6%	-0.4%	-0.1%	1.3%		-0.6%	1.3%
	t-stat.	-6.11	-3.81	-3.45	-2.04	-0.87	4.47		-5.27	6.75

Table IV (Continued…)

Panel C

Straddle returns

Stock illiquidity	End-user demand proxy (IV–HV) 1-high	2	3	4	5-low	5–1	t-stat.	*mean* all	*sd* all
1-low	-2.8%	-1.1%	1.7%	3.7%	2.2%	5.0%	2.59	0.7%	74.6%
2	-4.9%	-1.5%	3.2%	1.9%	0.4%	5.3%	2.70	-0.2%	76.0%
3	-5.3%	-1.9%	1.2%	0.8%	3.3%	8.6%	4.20	-0.4%	76.6%
4	-8.5%	-2.6%	-0.4%	1.0%	5.0%	13.5%	6.44	-1.1%	78.1%
5-high	-9.6%	-4.4%	-4.8%	-1.9%	4.1%	13.7%	6.26	-3.3%	80.1%
5–1	-6.8%	-3.3%	-6.5%	-5.6%	1.9%	8.7%		-4.0%	5.5%
t-stat.	-4.39	-1.81	-3.58	-3.01	1.03	3.73		-3.59	5.01

Panel D

Synthetic future returns

Stock illiquidity	End-user demand proxy (Call implied VOL – Put implied VOL) 1-high	2	3	4	5-low	5–1	t-stat.	*mean* all	*sd* all
1-low	-0.01%	0.01%	0.03%	0.05%	0.12%	0.13%	9.37	0.0%	0.2%
2	-0.01%	0.02%	0.05%	0.08%	0.21%	0.22%	9.62	0.1%	0.3%
3	-0.02%	0.02%	0.06%	0.11%	0.28%	0.30%	9.98	0.1%	0.4%
4	-0.03%	0.03%	0.08%	0.12%	0.34%	0.37%	10.63	0.1%	0.5%
5-high	-0.09%	0.02%	0.08%	0.16%	0.45%	0.54%	11.42	0.1%	0.7%
5–1	-0.08%	0.01%	0.05%	0.11%	0.33%	0.41%		0.1%	0.5%
t-stat.	-3.41	0.39	5.00	10.10	15.63	10.73		9.86	19.75

Table V

Average monthly post-formation returns of three-way sorted portfolios (option spread).

The sample between January 1996 and August 2015 includes 153,381 delta-hedged call returns, 142,267 delta-hedged put returns, 135,149 pairs of call and put options for the straddle returns, and 134,525 pairs of call and put options with the same ATM moneyness for the synthetic future returns. Each month, option observations are first sorted into quintiles based on the (average) relative option spread. Within these quintiles, option observations are sorted into quintiles based on the Amihud illiquidity measure. Within the first and second sort quintiles, options are sorted into quintiles based on the difference between the implied and historical volatility (Panel A-C). For Panel D the options in the first and second sort quintiles are sorted into quintiles based on the difference between the call and put implied volatility. This table reports the average of the 25 second and third sort portfolios along the 5 option spread categories. The portfolio returns use an equal weighting of the option returns in a 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 options is determined from the implied volatility at trading initiation. Associated t-statistics are corrected for autocorrelation following Newey and West (1987).

Panel A

Delta-hedged call returns

		End-user demand proxy (IV–HV)							*mean*	*sd*
		1-high	2	3	4	5-low	5–1	t-stat.	all	
Stock illiquidity	1-low	-0.4%	-0.2%	0.0%	-0.1%	0.4%	0.8%	4.58	-0.1%	5.9%
	2	-0.5%	-0.2%	-0.1%	-0.2%	0.4%	0.9%	4.65	-0.1%	7.0%
	3	-0.7%	-0.3%	-0.1%	0.1%	0.9%	1.6%	5.37	0.0%	8.0%
	4	-0.9%	-0.4%	0.3%	0.2%	0.7%	1.6%	5.52	0.0%	9.4%
	5-high	-1.6%	-0.6%	-0.3%	-0.5%	0.4%	2.0%	7.91	-0.5%	11.0%
	5–1	-1.2%	-0.4%	-0.3%	-0.4%	0.0%	1.2%		-0.4%	5.1%
	t-stat.	-4.42	-2.15	-1.48	-2.23	0.14	4.21		-2.86	21.60

Panel B

Delta-hedged put returns

		End-user demand proxy (IV–HV)							*mean*	*sd*
		1-high	2	3	4	5-low	5–1	t-stat.	all	
Stock illiquidity	1-low	-0.7%	-0.3%	-0.3%	-0.2%	0.1%	0.8%	4.59	-0.3%	5.3%
	2	-0.8%	-0.3%	0.0%	-0.1%	0.0%	0.8%	5.09	-0.2%	6.4%
	3	-1.0%	-0.3%	-0.3%	-0.2%	0.3%	1.3%	5.71	-0.3%	7.1%
	4	-1.0%	-0.3%	-0.1%	0.1%	0.7%	1.7%	8.32	-0.1%	8.3%
	5-high	-2.0%	-0.7%	-0.7%	-0.2%	-0.2%	1.8%	7.28	-0.8%	9.6%
	5–1	-1.3%	-0.4%	-0.4%	0.0%	-0.3%	1.0%		-0.5%	4.3%
	t-stat.	-5.84	-1.54	-2.26	-0.04	-1.59	4.26		-4.09	25.35

Table V (Continued…)

Panel C

Straddle returns

		End-user demand proxy (IV–HV)							*mean*	*sd*
		1-high	2	3	4	5-low	5–1	t-stat.	all	
Stock illiquidity	1-low	-6.5%	-2.2%	0.3%	0.1%	1.3%	7.8%	4.27	-1.4%	75.0%
	2	-5.5%	-1.8%	-0.4%	0.0%	2.0%	7.5%	4.09	-1.1%	75.7%
	3	-5.9%	0.1%	-0.8%	-0.1%	8.1%	14.0%	5.96	0.3%	77.3%
	4	-6.5%	-1.1%	0.8%	2.3%	4.5%	11.0%	5.60	0.0%	77.3%
	5-high	-8.2%	-3.1%	-2.5%	-1.0%	3.3%	11.5%	7.08	-2.3%	79.9%
	5–1	-1.7%	-0.9%	-2.8%	-1.1%	2.0%	3.7%		-0.9%	4.9%
	t-stat.	-0.91	-0.48	-1.37	-0.54	1.05	1.63		-0.69	3.41

Panel D

Synthetic future returns

		End-user demand proxy (Call implied VOL – Put implied VOL)							*mean*	*sd*
		1-high	2	3	4	5-low	5–1	t-stat.	all	
Stock illiquidity	1-low	-0.01%	0.01%	0.03%	0.05%	0.12%	0.13%	7.35	0.0%	0.3%
	2	-0.02%	0.02%	0.04%	0.08%	0.18%	0.20%	7.65	0.1%	0.3%
	3	-0.03%	0.02%	0.05%	0.10%	0.25%	0.28%	9.31	0.1%	0.4%
	4	-0.05%	0.01%	0.07%	0.12%	0.32%	0.37%	11.46	0.1%	0.5%
	5-high	-0.05%	0.03%	0.09%	0.16%	0.54%	0.59%	14.27	0.2%	0.7%
	5–1	-0.04%	0.02%	0.06%	0.11%	0.42%	0.46%		0.2%	0.4%
	t-stat.	-2.08	1.25	6.29	8.37	14.31	12.88		15.69	19.09

Table VI

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 implied and historical volatility (IV–HV). The implied volatility is the one resulting from Leland's adjustment. The historical volatility is measured from one year of simulated daily returns (with σ = 40%) for every option. The table reports the average delta-hedged returns for the combinations of transaction cost and IV–HV quintiles. We assume that the risk-premium increases with transaction costs. The risk premiums (above the risk-free rate of 5%) are 0%, 5%, 10%, 15%, and 20% from the lowest to the highest transaction cost category.

Delta-hedged call returns

		End-user demand proxy (IV–HV)						*mean*	*sd*
		1-high	2	3	4	5-low	5–1	all	
Transaction costs	1-low	-0.2%	-0.1%	0.0%	0.1%	0.2%	0.4%	0.0%	0.3%
	2	-0.6%	-0.5%	0.0%	0.6%	0.6%	1.2%	0.0%	0.6%
	3	-0.8%	-0.8%	0.1%	1.0%	1.0%	1.8%	0.1%	0.9%
	4	-1.1%	-1.1%	0.1%	1.3%	1.3%	2.4%	0.1%	1.2%
	5-high	-1.3%	-1.3%	0.2%	1.7%	1.7%	3.0%	0.2%	1.5%
	5–1	-1.1%	-1.2%	0.2%	1.6%	1.5%	2.6%	0.2%	1.2%

Table VII

Risk-adjusted post-formation returns with alternative volatility measures and stock illiquidity measures.

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 illiquidity quintiles are constructed as in Table III, 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 III. The t-statistics for the coefficients in brackets are calculated with Newey and West (1987) standard errors.

Panel A

	Delta-hedged calls			Delta-hedged puts		
	5–1 low ill.	5–1 high ill.	5–1 high ill. - 5–1 low ill.	5–1 low ill.	5–1 high ill.	5–1 high ill. - 5–1 low ill.
GARCH(1,1)	0.3%	1.2%	0.9%	0.3%	1.2%	0.8%
	(1.35)	(4.12)	(2.47)	(1.61)	(5.01)	(2.65)
6-month	0.7%	2.1%	1.5%	0.6%	2.1%	1.5%
	(2.52)	(7.65)	(4.01)	(2.84)	(7.44)	(4.72)
2-year	0.7%	2.0%	1.3%	0.7%	2.0%	1.4%
	(2.98)	(6.72)	(4.17)	(3.48)	(7.54)	(5.44)

	Straddles			Synthetic futures		
	5–1 low ill.	5–1 high ill.	5–1 high ill. - 5–1 low ill.	5–1 low ill.	5–1 high ill.	5–1 high ill. - 5–1 low ill.
GARCH(1,1)	2.7%	8.3%	5.6%	0.1%	0.5%	0.5%
	(1.29)	(4.26)	(2.25)	(6.81)	(13.16)	(13.85)
6-month	5.9%	14.9%	8.9%	0.1%	0.7%	0.6%
	(2.36)	(8.05)	(3.15)	(7.19)	(13.21)	(13.87)
2-year	6.6%	13.1%	6.6%	0.1%	0.7%	0.6%
	(3.19)	(7.06)	(2.50)	(7.19)	(13.21)	(13.87)

Table VII (Continued…)

Panel B

	Delta-hedged calls			Delta-hedged puts		
	5–1 low ill.	5–1 high ill.	5–1 high ill. - 5–1 low ill.	5–1 low ill.	5–1 high ill.	5–1 high ill. - 5–1 low ill.
ln(Size)	0.9%	2.1%	1.1%	0.8%	2.5%	1.6%
	(4.46)	(6.85)	(3.29)	(4.99)	(8.65)	(5.72)
Dollar Volume	1.0%	2.3%	1.3%	0.9%	2.3%	1.5%
	(3.25)	(9.31)	(3.70)	(3.91)	(9.22)	(5.34)
Roll	0.9%	2.8%	1.9%	1.0%	2.5%	1.5%
	(3.67)	(6.51)	(4.01)	(4.71)	(6.94)	(4.04)
Corwin–Schultz	1.1%	2.5%	1.4%	0.9%	2.4%	1.6%
	(5.38)	(7.73)	(3.99)	(4.39)	(8.03)	(4.64)

	Straddles			Synthetic futures		
	5–1 low ill.	5–1 high ill.	5–1 high ill. - 5–1 low ill.	5–1 low ill.	5–1 high ill.	5–1 high ill. - 5–1 low ill.
ln(Size)	9.5%	15.7%	6.2%	0.1%	0.7%	0.6%
	(4.44)	(8.31)	(2.35)	(7.52)	(13.96)	(14.63)
Dollar Volume	8.6%	16.7%	8.2%	0.1%	0.6%	0.5%
	(4.42)	(8.25)	(3.41)	(8.92)	(12.77)	(12.60)
Roll	11.7%	19.2%	7.5%	0.3%	0.5%	0.2%
	(4.65)	(8.20)	(2.44)	(9.52)	(11.57)	(5.49)
Corwin–Schultz	11.5%	16.3%	4.8%	0.2%	0.6%	0.4%
	(4.44)	(9.94)	(1.70)	(6.76)	(15.48)	(9.78)

Table VIII

Post-formation returns for alternative sample periods.

The sample between January 1996 and August 2015 includes 153,381 delta-hedged call returns, 142,267 delta-hedged put returns, 135,149 pairs of call and put options for the straddle returns, and 134,525 pairs of call and put options with the same ATM moneyness for the synthetic future returns. 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. The 5–1 portfolios within the stock illiquidity quintiles are constructed as in Table I. 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: Delta-hedged call returns (5–1)				
Stock illiquidity	1-low	0.7%	0.3%	0.3%
	2	1.0%	0.5%	0.6%
	3	1.4%	0.7%	0.9%
	4	1.9%	0.9%	0.8%
	5-high	2.3%	1.5%	1.6%
	5–1	1.6%	1.2%	1.3%
	t-stat.	4.32	4.43	4.17
Panel B: Delta-hedged put returns (5–1)				
Stock illiquidity	1-low	0.7%	0.3%	0.4%
	2	0.7%	0.4%	0.4%
	3	1.0%	0.5%	0.7%
	4	1.9%	1.0%	1.1%
	5-high	2.4%	1.6%	1.5%
	5–1	1.7%	1.3%	1.1%
	t-stat.	6.46	5.15	3.80

Table VIII (Continued…)

		Jan. 1996 - Aug. 2015	May 2003 - Aug. 2015	May 2003 - Aug. 2015 excl. Jun. 2007 - Dec. 2009
Panel C: Straddle returns (5–1)				
Stock illiquidity	1-low	6.9%	3.4%	3.6%
	2	7.1%	4.7%	4.5%
	3	10.5%	5.9%	5.8%
	4	14.8%	9.3%	7.2%
	5-high	16.5%	12.4%	11.8%
	5–1	9.6%	9.0%	8.2%
	t-stat.	3.55	3.24	2.48
Panel D: Synthetic future returns (5–1)				
Stock illiquidity	1-low	0.1%	0.0%	0.0%
	2	0.2%	0.1%	0.1%
	3	0.3%	0.2%	0.1%
	4	0.4%	0.3%	0.3%
	5-high	0.7%	0.5%	0.5%
	5–1	0.6%	0.5%	0.5%
	t-stat.	13.88	12.30	12.69

Figure 1. Average monthly post-formation returns of delta-hedged calls and straddles for Amihud deciles.

The 3–1 return is calculated as in Table I, but with a decile sorting on the Amihud measure and a second sorting on IV–HV 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.

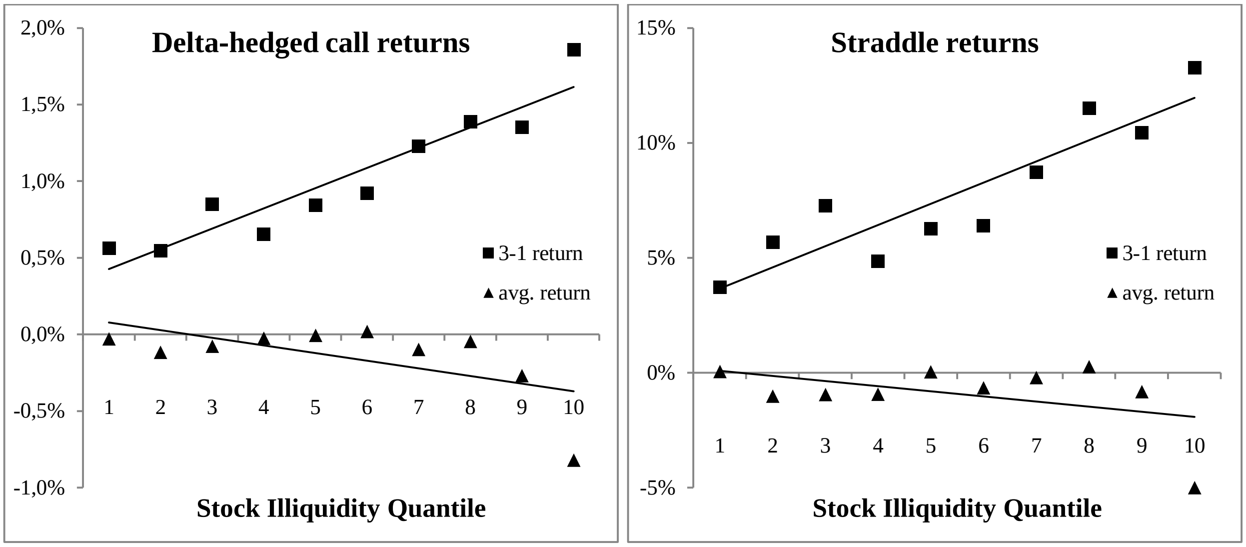
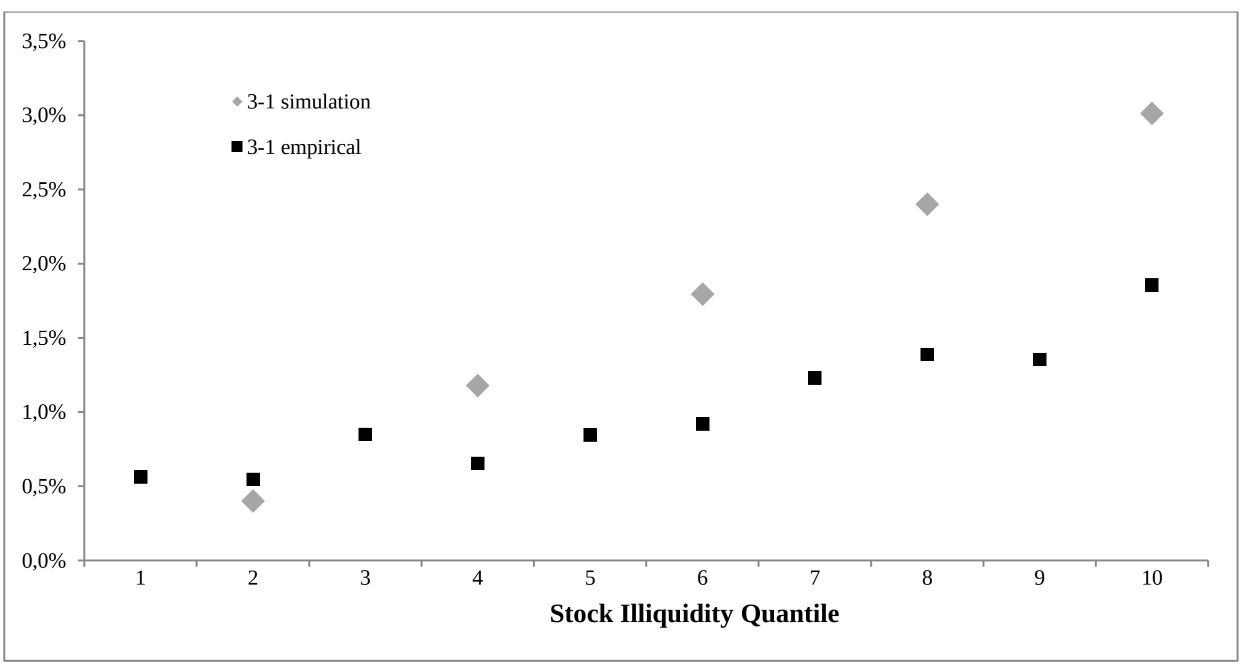


Figure 2. Average empirical and simulated delta-hedged call returns.

The 3–1 empirical returns are calculated as in Table I, but with a decile sorting on the Amihud measure and a three-quantile second sort on IV–HV. The 3–1 simulated returns are calculated as in Table VI, but with a tertile sorting on IV–HV. 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: Illiquidity 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: Simulation of Transaction Cost Effects

Our simulation study uses call option prices according to Leland's (1985) model. Leland 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:

$$\sigma_m^2 = \sigma^2 \left(1 + \frac{k}{\sigma} \sqrt{\frac{2}{\pi \delta t}} \;\; sign(V_{SS}) \right).$$

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 gamma ($sign(V_{SS})$) of the end-user's option position 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.[22] 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 important 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.

[22] In this setting, the half spread would also be equal to the Amihud measure for a trading volume of one.

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%.[23] 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 long in 50% of the call options and short in the other 50%. 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 proportion across stocks.[24] To capture potential illiquidity premiums of the underlying stocks, we consider drift rates that increase with transaction costs, taking values of 5%, 10%, 15%, 20%, and 25%, respectively, for the five transaction cost categories. Since we assume a risk-free rate of 5%, we therefore assume risk premiums of 0%, 5%, 10%, 15%, and 20%, respectively. It should be noted, however, that our results are very similar when we use a homogenous drift rate of 10%. Therefore, the resulting patterns do not stem from the heterogeneity of drift rates. Market makers are assumed to 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 II.C. The expected return for the delta-hedged call according to Eq. (3) is calculated as[25]

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

To obtain our results, we first sort options on their underlying liquidity costs into five groups, each consisting of 2,000 option observations. Within these groups, we sort the options again into quintiles based on their IV–HV values, where the historical volatilities are estimates based on one year of simulated daily return data with a true return volatility of 40%. Given the number of 400 observations in each portfolio, the required expectation is very well approximated by the mean value. For the results shown in Figure 2, we use a sorting that is based on deciles with respect to illiquidity and on tertiles with respect to IV–HV.

[23] The average implied volatility in our delta-hedged call sample of Table I is 41%.

[24] 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.

[25] We calculate the expected option payoff under the P-measure based on the geometric Brownian motion for the stock price process.

Appendix D: 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 equals

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

assuming 252 trading days per year.