Stock illiquidity and option returns

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A B S T R A C T

We provide evidence of a strong effect of the underlying stock's illiquidity on option returns. Conditional on end-user demand, illiquidity premiums are negative and decrease in stock illiquidity for options where end users are net buyers, 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. The observed pattern is consistent with an intermediary hedging cost channel and the magnitudes of our illiquidity premiums are in line with reasonable transaction costs.

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1. Introduction

There is growing evidence that intermediaries play an important role in determining asset prices, particularly in option markets, where trading is dominated by specialized intermediaries, the market makers (He and Krishnamurthy, 2013; He et al., 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 sparse empirical literature shows conflicting evidence. Results in Cao and Han (2013), Karakaya (2014), and Cao et al. (2022) suggest that delta-hedged option returns decrease with stock illiquidity, however,

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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: if end users are net sellers and dealers have to maintain a net long position in an option series, there are 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 end users being net buyers, 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 users being net short in options. If there is an indication for end users being net long, option returns decrease with stock illiquidity. To our knowledge, we are the first to uncover this relation between stock illiquidity and option returns 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 end users being net sellers (buyers). However, empirical evidence on net demand by Ni et al. (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. Note that such demand effects are not simply temporary dislocations but they may well lead to asset pricing phenomena that persist even until the option matures. 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, delta-hedged put options, and straddles 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 the bid–ask spreads of options can explain our results. A final test uses a simulation study to assess whether 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 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 et al. (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. According to this line of reasoning, delta-hedging costs show up exclusively in option spreads only if the market maker position is close to zero. In all other cases, there should always be an effect on mid prices and thus expected option returns.[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

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

[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. (2022) report similar results.

option returns are more negative when the underlying stock is less liquid …".[5] 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,[6] 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 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.[7] This positive relation is confirmed in multivariate Fama-MacBeth regressions.[8] 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 (2022) 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. (2021) find empirical evidence for a margin premium in the cross-section of option returns. They explain their findings using a model of funding-constrained derivatives dealers that require compensation for satisfying end-user option demand.

The remainder of the paper is organized as follows. In Section 2, we provide background on the empirical design and the data used in our empirical study. In Section 3, we present our main results on the relation between option returns and the underlying stock's illiquidity. In Section 4, we investigate different explanations for the observed patterns. In Section 5, we discuss robustness analyses and we conclude in Section 6.

2. Empirical design, data set, and data processing

2.1. 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 provide insight on the linkages between demand and option prices and guide the empirical design to investigate our research questions. Following Gârleanu et al. (2009), Hitzemann et al. (2021) 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:

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

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

Equation (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 $F_t \quad F_t^0$, 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 buyers 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 that 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[9]

[5] See Cao and Han (2013), p. 242.

[6] See Karakaya (2014), Table 9, Panel H. Note that Karakaya's actual analysis uses sold options.

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

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

[9] 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 equation (2) see Hoggard et al. (1994).

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

In equation (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 $\sigma_m^2 \quad \sigma^2$ 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, the models above 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.

2.2. Data sources and filters

Our primary data source is the OptionMetrics Ivy DB database. This database contains information on all exchange-listed individual equity options in the United States, 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.[10] 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. 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 $S \geq C \geq \max(S \quad Ke^{-rT}, 0)$ for call price C, underlying stock price S, strike K, risk-free rate r, and time to maturity T.

2.3. 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 two kinds of portfolios. The first kind contains either delta-hedged call or put options. The second, which does not rely on model-dependent deltas, consists of straddles. The formation of portfolios of delta-hedged options and straddles is based on information available on the first trading day (usually a Monday) after the expiration day of the month.[11] 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, and 135,149 straddle pairs of calls and puts. 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 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.

2.3.1. Delta-hedged option returns

We calculate the 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. The return of a delta-hedged call is calculated as follows:

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

where $C_{t+\tau}$ 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 equation (3), except that the call option price and call delta are replaced by the price and delta of the put.

2.3.2. 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

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

[11] 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.

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 follows:

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

2.4. *Measuring stock illiquidity*

Our main measure of underlying stock illiquidity is the average of the daily Amihud (2002) illiquidity measures over the month preceding the portfolio formation date. Goyenko et al. (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 three stock spread estimates based on average spreads from CRSP, Roll's (1984) measure, and Corwin and Schultz's (2012) measure in our robustness checks, as well as the stock's trading volume and market capitalization. Details on the illiquidity measure calculatiosn are in Appendix A.

2.5. *Measuring end-user demand*

Our main proxy for net end-user option demand 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 Subsection 2.1 and shown empirically by Bollen and Whaley (2004), Gârleanu et al. (2009), and Fournier and Jacobs (2020), there is a positive relation between demand and expensiveness. The more expensive an option, the higher the net end-user options 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*.

As an alternative proxy of end-user net demand, we use a measure of order imbalance obtained from public order imbalance data from the International Securities Exchange (ISE). Starting in May 2005 and ending in August 2015, the data contains daily end-user buy and sell orders that were executed on the ISE. We calculate the order imbalances for each option series as the sum of the end-user buys minus the end-user sells from the initiation of series trading, at date i, until the portfolio formation date at t - 1. We then aggregate the option series order imbalances at the stock level. Following Chordia and Subrahmanyam (2004) and Muravyev (2016), we scale this net demand measure by the total number of trades to eliminate the impact of total trading activity. The order imbalance for the underlying stock at the portfolio formation date t - 1 is:

$$OrdImb_{t-1} = \frac{\sum_{\kappa \in N} \sum_{\tau=i}^{t-1} \left[\#Buys_{\kappa,\tau} - \#Sells_{\kappa,\tau}\right]}{\sum_{\kappa \in N} \sum_{\tau=i}^{t-1} \left[\#Buys_{\kappa,\tau} + \#Sells_{\kappa,\tau}\right]}, \tag{5}$$

where N is the set of calls and puts for the stock at date t - 1, which we include in our option return calculations.

Table 1 presents descriptive statistics for the option returns, illiquidity measures, and demand proxies. Delta-hedged call and put returns are broadly consistent with previous studies (e.g., Cao and Han, 2013) and show negative mean and median returns. With respect to our illiquidity and demand measures, patterns are also similar to what has been reported in previous work for the Amihud- (Cao and Han, 2013), the Roll- and high/low spread measures (Corwin and Schultz, 2012), the CRSP spread measure (Chung and Zhang, 2014), and the expensiveness measure (Goyal and Saretto, 2009).

3. Main results

We examine 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*. 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 2 reports the time series averages of these monthly means. For each demand quintile, we also calculate the 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 (5-low quintile) and sell options with the highest demand (1-high quintile). The corresponding average returns are presented in the 5–1 column. The last two columns of Table 2 show the time series averages of the mean 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 are calculated as described in Subsection 2.3.

If stock illiquidity affects the 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

Table 1

Summary statistics. This table shows summary statistics for the sample between January 1996 and August 2015, which includes 153,381 delta-hedged call returns, 142,267 delta-hedged put returns, and 135,149 pairs of call and put options for the straddle returns. Panel A shows the mean, median, standard deviation, and the 10th and 90th percentile of the delta-hedged call, delta-hedged put, and straddle returns. Panel B shows statistics on our illiquidity measures for the underlying stocks of the 135,149 observations where pairs of call and put options were available. We use Amihud's (2002) illiquidity measure, the Roll (1984), Corwin and Schultz (2012) and average CRSP spread estimates, the dollar trading volume, and the market capitalization. Panel C shows statistics on our end-user demand proxies. The implied volatility minus the historical volatility (*IV–HV*) is reported for the sets of call and put observations and the option order imbalance aggregated on stock level is reported for the observations where pairs of call and put options were available. The data period for option order imbalance is May 2005 to August 2015.

Variable	Mean	Median	Std.dev.	10th percentile	90th percentile
Panel A: Option returns					
Delta-hedged calls	−0.1%	−1.3%	9.0%	−8.2%	9.0%
Delta-hedged puts	−0.2%	−1.3%	8.0%	−7.7%	8.1%
Straddles	−0.3%	−18.2%	82.6%	−85.9%	106.5%
Panel B: Illiquidity measures					
Ln*(Amihud)*	−7.50	−7.58	1.80	−9.71	−5.16
Roll (incl. zeros)	1.2%	0.7%	3.6%	0.0%	3.1%
Corwin-Schultz	0.8%	0.7%	0.5%	0.3%	1.4%
CRSP spread	0.3%	0.1%	0.5%	0.0%	0.7%
Dollar trading volume/10^6	92.42	27.79	296.58	3.12	204.41
Size (Dollar Market cap./10^{9})	12.14	3.17	30.91	0.50	27.09
Panel C: Demand measures					
Call IV–HV	−2.0%	−1.0%	14.3%	−15.9%	10.9%
Put IV–HV	−1.0%	−0.4%	14.5%	−14.6%	12.0%
OrdImb	−0.18	−0.17	0.53	−0.97	0.55

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. Overall, the results in Table 2 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 (penultimate column in all three panels of Table 2), 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. However, the relation is generally not monotonous and essentially results from the relatively low (high) returns of the highest illiquidity quintile. By contrast, the standard deviation (last column in all three panels of Table 2) smoothly increases for all three options strategies, which is in line with the idea of stock illiquidity being important for option returns but working in 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 relation 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 three return measures (delta-hedged calls, delta-hedged puts, straddles), 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, for example, the average monthly return difference is 9.6%.[12]

To obtain a deeper understanding of the illiquidity effect on option returns, we refine the sorting on our illiquidity measure. For Fig. 1, we repeat our analysis from Table 2 but sort the options every month into deciles instead of quintiles on the stock illiquidity measure.[13] 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 that do not account for differences in expensiveness. The lower plots in Fig. 1 show these values for calls and straddles. The overall negative relation between

[12] 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%).

[13] 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.

Table 2

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, and 135,149 pairs of call and put options for the straddle returns. Each month, option observations are first sorted into quintiles based on Amihud's illiquidity measure. Within these quintiles, options are sorted into quintiles based on the difference between the implied and historical volatility. 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

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

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. By 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, Fig. 1 illustrates the main contribution of the paper: By long–short trading strategies that condition on end-user demand, we have uncovered a clear connection between stock illiquidity and option returns.

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.

4. Potential explanations for the main results

4.1. 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

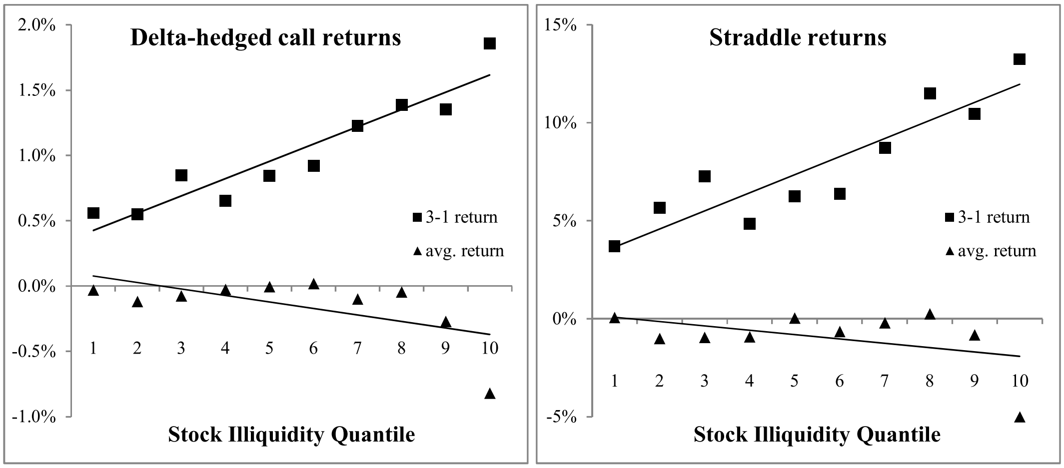

Fig. 1. Average monthly post-formation returns of delta-hedged calls and straddles for Amihud deciles. The 3–1 return is calculated as for Table 2, but with a decile sorting on the Amihud measure and a second sorting on *IV–HV* into three portfolios. The average return for the Amihud decile is the equally-weighted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

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.[14] 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.[15] 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 et al. (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.

Table 3 shows the regression alphas of the 5–1 demand strategies within the low illiquidity quintiles and the high illiquidity quintiles together with the differences between these alphas. Overall, the alphas of the portfolios are all significant and very close to the average raw returns reported in Table 2. The differences for the alphas of the high and low illiquidity delta-hedged call, delta-hedged put, and straddle portfolios are 1.4%, 1.8%, and 9.3%, 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.

4.2. *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.[16] To check this possibility, we repeat our main analysis but control for historical volatilities. Panel A of Table 4 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 Panel A of Table 4 are qualitatively the same as in Table 2. The returns of delta-hedged calls, delta-hedged puts, and straddles 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 monotonously increase in illiquidity (5–1 columns) and the return differences between the options in the highest and the lowest

[14] Goyal and Saretto (2009), Schürhoff and Ziegler (2011), Cao and Han (2013), Buraschi et al. (2014), Christoffersen et al. (2018), and Frazzini and Pedersen (2022) also include these four factors as control variables for option returns.

[15] Bollerslev et al. (2009) present a general equilibrium model of the market variance risk premium.

[16] 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.

Table 3

Risk-adjusted post-formation returns. This table presents the alphas 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 2. The *t*-statistics for the alphas 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)
	Straddles					
	5–1 low ill.	5–1 high ill.	5–1 high ill.- 5–1 low ill.			
Alpha	7.4%	16.7%	9.3%			
	(3.51)	(8.64)	(3.64)			

Table 4

Average monthly post-formation returns of three-way sorted portfolios. The sample between January 1996 and August 2015 includes 153,381 delta-hedged call returns, 142,267 delta-hedged put returns, and 135,149 pairs of call and put options for the straddle returns. Each month, option observations are sorted on three variables. For Panel A (Panel B), option observations are first sorted into quintiles based on the individual historical volatility (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. This table reports the average of the 25 second and third sort portfolios along the 5 volatility (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: Hist. Volatility							
		Delta-hedged calls		Delta-hedged puts		Straddles	
		5–1	*t*-stat.	5–1	*t*-stat.	5–1	*t*-stat.
Stock illiquidity	1-low	0.5%	2.83	0.5%	3.02	5.0%	2.59
	2	0.7%	3.64	0.9%	4.91	5.3%	2.70
	3	1.1%	5.15	1.2%	7.35	8.6%	4.20
	4	1.4%	4.96	1.6%	6.90	13.5%	6.44
	5-high	2.1%	8.37	1.8%	7.85	13.7%	6.26
	5–1	1.6%		1.3%		8.7%	
	t-stat.	5.03		4.47		3.73	
Panel B: Option Spread							
		Delta-hedged calls		Delta-hedged puts		Straddles	
		5–1	*t*-stat.	5–1	*t*-stat.	5–1	*t*-stat.
Stock illiquidity	1-low	0.8%	4.58	0.8%	4.59	7.8%	4.27
	2	0.9%	4.65	0.8%	5.09	7.5%	4.09
	3	1.6%	5.37	1.3%	5.71	14.0%	5.96
	4	1.6%	5.52	1.7%	8.32	11.0%	5.60
	5-high	2.0%	7.91	1.8%	7.28	11.5%	7.08
	5–1	1.2%		1.0%		3.7%	
	t-stat.	4.21		4.26		1.63	

illiquidity quintile are highly significant in all three cases. So, we conclude that cross-sectional differences in stock volatility cannot explain the effect of stock illiquidity on option returns.

An alternative explanation for our findings might be the higher bid–ask spreads of options associated with less liquid stocks (Christoffersen et al., 2018). Panel B of Table 4 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. We next average the 125 portfolios along the relative bid-ask spread quintiles leaving us with 25 illiquidity/end-user demand portfolios with roughly the same average bid-ask spreads. Again, the corresponding long–short returns increase with greater illiquidity and the return differences between the highest and the lowest illiquidity portfolios are positive in all cases and highly significant except for the straddle case. For the latter, the significance is roughly at the 10% level. 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.

Portfolio sorts are a flexible and transparent method to analyze dependencies without relying on any restrictive parametric specifications. However, sorts come to their limits when several control variables are considered simultaneously. Therefore, we check whether cross-sectional differences in stock volatility and option's illiquidity jointly explain the documented effect of stock illiquidity on option returns via Fama-MacBeth regressions. Because equation (1) shows that the sign of end-user demand is crucial for the relation between stock illiquidity and option returns, we check whether an option is in the first *IV–HV* quintile (highest end-user demand) or in the fifths *IV–HV* quintile (lowest end-user demand) interacts with the stock illiquidity measure. Specifically, we define a variable that takes a value of 1 if *IV–HV* is in the first quintile and takes a value of 1 if it is in the fifth quintile. This variable is multiplied with the illiquidity measure to capture the interaction effect. Our hypothesis is that the interaction term loads with a positive coefficient. In addition to the interaction term, the Fama-MacBeth regressions contain the demand variables themselves (dummy variables *IVHV high* and *IVHV low*), as well as the option spread and the stock volatility.

Table 5 reports the results of the Fama-MacBeth regressions. There are significant negative return effects of higher stock volatility and positive effects of low demand for delta-hedged calls and delta-hedged puts. Moreover, higher option spreads significantly reduce option returns for delta-hedged puts. Most importantly, there is still an interaction effect with stock illiquidity that has the expected positive sign: illiquidity leads to higher option returns for low end-user demand as compared to high end-user demand on average. The null hypothesis that the interaction term's coefficient is zero is rejected in all three cases, i.e. for delta-hedged calls, puts, and straddles, with *t*-statistics ranging from 2.68 to 5.13.

Overall, both portfolio sorts and Fama-MacBeth regressions indicate 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 et al. (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 et al. (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 et al. (2002). In addition, Christoffersen et al. (2018) empirically show 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 et al. (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.

4.3. *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 varying signs of end users' net positions across individual equity options. We provide further evidence on this explanation in this subsection.

Table 5

Fama-MacBeth regression of monthly post-formation returns. The sample between January 1996 and August 2015 includes 153,381 delta-hedged call returns, 142,267 delta-hedged put returns, and 135,149 pairs of call and put options for the straddle returns. This table reports the average coefficients from monthly Fama-MacBeth regressions of the post formation returns (straddles, delta-hedged calls, or delta hedged puts) on: *Illiq.* * (1 if *IVHV high*; 1 if *IVHV low*), which is the stock illiquidity measure multiplied with 1 or 1 if the option is in the high or low *IV–HV* quantile of the respective month; *IVHV high*, which is one if the option is in the high *IV–HV* quantile, else zero; *IVHV low*, which is one if the option is in the low *IV–HV* quantile, else zero; *Option spread*, the quoted closing option spread; *Volatility*, the yearly historical volatility of the option's underlying. Newey and West (1987) *t*-statistics are given in parentheses. The regressions exclude observations which are not in the first or fifth *IV–HV* quantile. Stock illiquidity is measured in monthly quintiles of the Amihud measure.

	Straddle	Delta-hedged calls	Delta-hedged puts
Illiq. * (−1 if *IVHV high*; 1 if *IVHV low*)	0.008	0.001	0.002
	(2.86)	(2.68)	(5.13)
Option spread	−0.078	−0.019	−0.039
	(-0.89)	(-1.05)	(-2.06)
Volatility	−0.039	−0.010	−0.012
	(-1.31)	(-2.63)	(-3.61)
IVHV high	−0.021	0.000	0.001
	(-0.86)	(-0.05)	(0.33)
IVHV low	0.051	0.009	0.007
	(1.52)	(2.62)	(2.60)

We use the order imbalance measure (*OrdImb*) from equation (5), as obtained from the ISE data set, to study the relation between our expensiveness measure and order imbalance. As a first indication, we calculate the average cross-sectional correlation between *IV–HV* and *OrdImb*, where *IV* is the average of the implied volatilities of calls and puts. The correlation coefficient is 7.08%, and the hypothesis of zero correlation is clearly rejected with a *t*-statistic of 9.81. To dig deeper into the relation between expensiveness and order imbalance, option observations are sorted into quantiles based on *IV–HV* each month. For these quantile portfolios, we calculate the measure *Avg(OrdImb)*, which is the monthly average *OrdImb*, and the measure *%OrdImb*$^+$, which is the monthly percentage of observations where *OrdImb* is positive (end user buys $>$ end user sells). The results in Table 6 show that *Avg(OrdImb)* declines monotonously with declining expensiveness and the differences in *Avg(OrdImb)* within the low and the high expensiveness quintile are significantly negative. This relation holds for calls, puts, as well as straddles. The negative average *Avg(OrdImb)* for all call, put, and straddle portfolios is in line with the empirical observation in Christoffersen et al. (2018) of market makers being on average net long in options on individual stocks. Moreover, the average percentage of observations with a positive order imbalance (*%OrdImb*$^+$) is highest for the high expensiveness quintile (around 40%) and declines monotonously with declining expensiveness to less than 30%. Again, this relation holds for calls, puts, and straddles. Thus, in line with Gârleanu et al. (2009), a higher fraction of positive (negative) end-user demand for an option leads to more expensive (cheaper) option prices.

A natural next step is to use the ISE dataset and also perform the sorts from Section 3 by conditioning on OrdImb instead of option expensiveness. It should be noted that this approach is subject to some limitations, and the nature of the available customer buy and sell volumes data does not allow the same analysis to be performed for a variety of reasons. First, the dataset is available only from 2005 and covers only a fraction of the options in our sample, leading to a shorter time series and smaller cross-section relative to our main analysis. Second, the open-close data available to us refers to the ISE, but ISE transactions represent only a subset of the total volume of trade in listed options, while option trading is organized in a national market with multiple exchanges participating. So, even for options within our smaller cross-section, we would actually need to source data from different data vendors to get a full picture. Note that the ISE market share is around 30% in 2005 (beginning of the ISE data) and declines to only around 10% in 2015 (Andersen et al., 2021). Third, the fragmentary nature of buy and sell volumes data requires an aggregation by stock or moneyness categories (see Muravyev, 2016; Christoffersen et al., 2018), such that we cannot assign a value for *OrdImb* to each individual option. This point is critical to our analysis as different options on the same stock may differ in their direction of end-user demand, such that the resulting positive and negative premia might wash out due to the aggregation. Finally, the computation of *OrdImb* depends on specific assumptions on the market structure, i.e., which groups of traders are categorized as option dealers and which are assumed to be end-users.

We nevertheless conduct portfolio double sorts based on OrdImb and illiquidity variables, assigning to each option the average *OrdImb* as aggregated on the underlying stock level. Due to the much smaller sample size than in our full sample, we use tertile sorts instead of quintiles. We first sort on the Amihud illiquidity measure for all the panels in Table 7. We use a second sort based on *OrdImb* and, for comparison, we also report the baseline second sort based on *IV–HV* for the ISE sample. Despite the described limitations, using order imbalance as an alternative proxy for demand leads to the same qualitative pattern as found in Section 3. Returns of the long–short (3–1) portfolios increase with stock illiquidity in all our three cases. Note that for both proxies (the option expensiveness measure and the alternative proxy of end-user demand), the returns show much weaker results than for the full sample. Besides the smaller sample size, this is also likely due to a sample selection effect because stocks are disproportionally liquid in the ISE sample. A more homogenous sample with respect to stock illiquidity makes it unfortunately more difficult to identify cross-sectional differences.

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 provide estimates of the upper bound for the price impact of the illiquidity of the underlying.[17] We simulate the prices of the 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. Finally, we calculate the delta-hedged option returns and perform the same sorting procedure that led to Table 2, this time using the simulated data.

Table 8 shows the results for the simulated data, which correspond to the results in Panel A of Table 2. 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 penultimate column shows that the differences between the 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. By 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 3.[18]

We now use our simulated data to check whether they lead to a similar pattern as the market data in Fig. 1. Fig. 2 shows the results.

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

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

Table 6

Relation between *OrdImb* and *IV–HV*. The sample between May 2005 and August 2015 includes 70,530 calls, 69,539 puts, and 68,872 pairs of call and put options for the straddles with available *OrdImb*. Each month, option observations are sorted into quantiles based on *IV–HV*. For these quantile portfolios, this table reports the averages of *Avg(OrdImb)*, which is the monthly average *OrdImb*, and *%OrdImb*$^{+}$, which is the monthly percentage of observations where *OrdImb* is positive (end user buys > end user sells). Associated *t*-statistics are corrected for autocorrelation following Newey and West (1987).

		Delta-hedged calls		Delta-hedged puts		Straddles	
		Avg(OrdImb)	*%OrdImb*$^{+}$	*Avg(OrdImb)*	*%OrdImb*$^{+}$	*Avg(OrdImb)*	*%OrdImb*$^{+}$
IV-HV	1-high	−10.7%	40.1%	−10.9%	39.8%	−10.6%	40.2%
	2	−15.5%	35.4%	−15.9%	35.4%	−15.6%	35.4%
	3	−18.6%	32.6%	−18.4%	32.5%	−18.5%	32.5%
	4	−21.3%	31.0%	−20.5%	31.5%	−20.4%	31.6%
	5-low	−23.6%	27.9%	−23.0%	28.4%	−23.2%	28.1%
	5–1	−12.9%	−12.1%	−12.1%	−11.4%	−12.6%	−12.0%
	t-stat.	−13.2	−13.1	−12.5	−12.0	−13.2	−12.6

Table 7

Average monthly post-formation returns of two-way sorted portfolios for alternative demand proxies (*OrdImb* and *IV–HV*). The sample between May 2005 and August 2015 includes 70,530 delta-hedged call returns, 69,539 delta-hedged put returns, and 68,872 pairs of call and put options for the straddle returns. Each month, option observations are first sorted into tertiles based on the Amihud illiquidity measure. Within these tertiles, options are sorted into tertiles based on the order imbalance (*OrdImb*) and the difference between the implied and historical volatility (*IV–HV*). 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 delta-hedged options and straddles 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 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 (*OrdImb*)							End-user demand proxy (*IV–HV*)				
		1-high	2	3-low	3–1	*t*-stat.			1-high	2	3-low	3–1	*t*-stat.
St. Illiq.	1-low	−0.1%	0.0%	−0.1%	0.0%	0.71	St. Illiq.	1-low	−0.3%	0.0%	0.0%	0.3%	2.98
	2	0.0%	0.2%	0.1%	0.1%	1.23		2	−0.1%	0.2%	0.2%	0.3%	2.18
	3-high	−0.1%	0.1%	0.2%	0.3%	1.42		3-high	−0.3%	0.1%	0.5%	0.8%	3.96
	3–1	0.0%	0.1%	0.3%	0.3%			3–1	0.0%	0.1%	0.5%	0.5%	
	t-stat.	0.19	0.77	1.60	1.22			*t*-stat.	0.03	0.21	2.62	2.48	

Panel B: Delta-hedged put returns

		End-user demand proxy (*OrdImb*)							End-user demand proxy (*IV–HV*)				
		1-high	2	3-low	3–1	*t*-stat.			1-high	2	3-low	3–1	*t*-stat.
St. Illiq.	1-low	−0.1%	−0.1%	−0.2%	−0.1%	−0.66	St. Illiq.	1-low	−0.3%	0.0%	−0.1%	0.2%	2.21
	2	−0.2%	0.0%	0.0%	0.2%	1.50		2	−0.3%	0.1%	0.0%	0.3%	2.55
	3-high	−0.4%	−0.2%	0.0%	0.4%	1.74		3-high	−0.5%	−0.3%	0.1%	0.6%	3.46
	3–1	−0.3%	−0.1%	0.2%	0.5%			3–1	−0.2%	−0.3%	0.2%	0.4%	
	t-stat.	−1.73	−0.70	0.87	1.95			*t*-stat.	−1.10	−1.96	1.29	2.13	

Panel C: Straddle returns

		End-user demand proxy (*OrdImb*)							End-user demand proxy (*IV–HV*)				
		1-high	2	3-low	3–1	*t*-stat.			1-high	2	3-low	3–1	*t*-stat.
St. Illiq.	1-low	0.3%	0.6%	−1.2%	−1.5%	−1.14	St. Illiq.	1-low	−3.2%	2.1%	0.8%	4.0%	2.47
	2	−0.4%	1.6%	1.6%	2.0%	1.38		2	−0.6%	1.7%	1.9%	2.5%	1.39
	3-high	−1.0%	0.4%	2.3%	3.3%	1.85		3-high	−1.4%	−0.8%	3.9%	5.3%	3.15
	3–1	−1.3%	−0.2%	3.5%	4.8%			3–1	1.8%	−2.9%	3.1%	1.3%	
	t-stat.	−0.72	−0.12	2.09	2.16			*t*-stat.	0.96	−1.54	1.90	0.56	

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.

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.

Table 8
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 $\sigma = 40\%$) 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								mean	sd
		End-user demand proxy (*IV–HV*)							
		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%

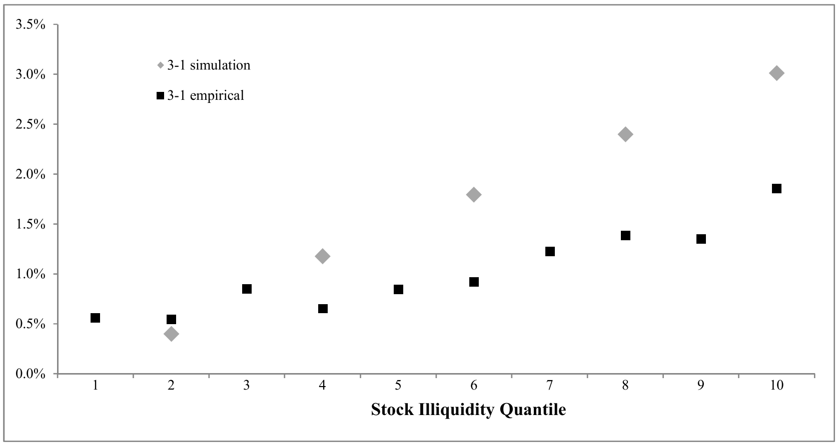

Fig. 2. Average empirical and simulated delta-hedged call returns. The 3–1 empirical returns are calculated as for Table 2, but with a decile sorting on the Amihud measure and a three-quantile second sort on *IV–HV*. The 3–1 simulated returns are calculated as for Table 7, but with a tertile sorting 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%.

5. Robustness checks

Finally, we address some additional robustness issues. A first issue is the measurement of end-user demand. We start by examining 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, thus we examine the robustness with respect to alternative illiquidity measures in Subsection 5.1. A third robustness issue refers to the sample period considered. In Subsection 5.2, we investigate this point. Finally, in a fourth robustness check in Subsection 5.3, we examine whether the results change when moving from a monthly to a daily holding period.

5.1. *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 and 24 most recent months.[19] With respect to the measurement of illiquidity, we replace Amihud's 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 and the average bid-ask spread from the CRSP database. We repeat the analysis for Table 3, but with the alternative measures and give the results in Table 9. 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 23

[19] Details on the GARCH(1,1) estimation process are in Appendix D.

Table 9

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 3, but in the regression for Panel A, the *HV* measure is replaced with alternative volatility estimates and in the regression for Panel B, alternative illiquidity measures are used instead of the Amihud measure. We use the same *HV* measure for Panel B as in Table 3. The *t*-statistics for the coefficients in brackets are calculated with Newey and West (1987) standard errors.

Panel A: Alternative volatility estimates						
	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					
	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%			
	(1.29)	(4.26)	(2.25)			
6-month	5.9%	14.9%	8.9%			
	(2.36)	(8.05)	(3.15)			
2-year	6.6%	13.1%	6.6%			
	(3.19)	(7.06)	(2.50)			
Panel B: Alternative illiquidity measures						
	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)
CRSP Spread	1.2%	2.5%	1.3%	0.7%	2.1%	1.4%
	(3.56)	(10.45)	(3.42)	(3.11)	(9.59)	(4.67)
	Straddles					
	5–1 low ill.	5–1 high ill.	5–1 high ill.- 5–1 low ill.			
ln(Size)	9.5%	15.7%	6.2%			
	(4.44)	(8.31)	(2.35)			
Dollar Volume	8.6%	16.7%	8.2%			
	(4.42)	(8.25)	(3.41)			
Roll	11.7%	19.2%	7.5%			
	(4.65)	(8.20)	(2.44)			
Corwin–Schultz	11.5%	16.3%	4.8%			
	(4.44)	(9.94)	(1.70)			
CRSP Spread	9.0%	16.6%	7.6%			
	(4.49)	(8.63)	(3.55)			

out of 24 cases. Therefore, these findings are in line with the results and conclusions from Table 3.

5.2. *Alternative sample periods*

Until 1999, options were often listed only on one exchange, which governed all interactions between market participants. In October 1999, the SEC ordered the option exchanges to develop a plan to electronically link the various market centers. Battalio et al. (2004) show that option market efficiency improved during this period when 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 whether 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 10 are the same as for Table 2. The first column returns correspond to

Table 10

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, and 135,149 pairs of call and put options for the straddle 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 sample for 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 for Table 2. 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
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

the 5–1 column returns in Table 2. We then exclude observations before the option market structure changes up to May 2003 and give the results in the second column. Next, we additionally exclude the financial crisis from June 2007 to December 2009 and give the results in the third column.

The difference in 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 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.

5.3. Daily holding period

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 repeated our main analysis for Table 2 for a one-day holding period. The results are available upon request and show the same patterns as for the monthly holding period. Again, in the high demand columns, returns decrease in stock illiquidity while they increase in the low demand columns. This pattern holds for all three strategies and is even more pronounced than for the monthly holding period. 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.

6. Conclusion

This paper examines the relation between option returns and stock illiquidity. It is the first to present empirical evidence that the underlying stock's illiquidity is strongly related to option returns. We show in a cross-sectional analysis that the returns of delta-hedged calls, delta-hedged puts, and straddles 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. 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.

Appendix A. Illiquidity Measure Calculations

Amihud measure: Following Cao and Han (2013), we calculate Amihud's (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 $sp^{R}_{i,t}$ as:

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

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. For the descriptive statistics in Table 1, we set all observations with positive covariance equal to zero. To allow for a unique categorization in quintiles, we drop observations with positive covariance values for the analyses for Table 9.

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:

$$\beta = \left[\ln\left(\frac{H^{i,t}_{d}}{L^{i,t}_{d}}\right)\right]^2 + \left[\ln\left(\frac{H^{i,t}_{d+1}}{L^{i,t}_{d+1}}\right)\right]^2, \quad \gamma = \left[\ln\left(\frac{H^{i,t}_{d,d+1}}{L^{i,t}_{d,d+1}}\right)\right]^2,$$

where $H^{i,t}_{d}$ and $L^{i,t}_{d}$ are the high and low prices, respectively, for stock i on day d and $H^{i,t}_{d,d+1}$ and $L^{i,t}_{d,d+1}$ 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:

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

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. We set negative two-day spread estimates to zero before we calculate the average.

CRSP spread: We calculate the average bid-ask spread from daily CRSP data for the month preceding the trading initiation date t as:

$$CRSP\ Spread_{i,t} = {}^{1}/_{m_{i,t}} \sum_{d=t-m_{i,t}}^{t-1} \frac{Ask_d - Bid_d}{(Ask_d + Bid_d)/2},$$

where $m_{i,t}$ is the number of trading days from last month's trading initiation date until $t-1$. Following Chung and Zhang (2014), we exclude all daily spreads that are greater than 50% of the quote midpoint, to reduce the effect of data errors and outliers.

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 and 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:

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

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.[20] 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 et al. (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.

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%.[21] 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.[22] 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%,

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

[21] The average implied volatility in our delta-hedged call sample of Table 1 is 41%.

[22] 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.

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 Subsection 2.3. The expected return for the delta-hedged call according to equation (3) is calculated as[23]

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

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 Fig. 2, we use a sorting that is based on deciles with respect to illiquidity and on tertiles with respect to *IV–HV*.

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:

$$\sigma^2_{i,t-1,d} = \omega_{i,t-1} + \alpha_{i,t-1} u^2_{i,t-1,d-1} + \beta_{i,t-1} \sigma^2_{i,t-1,d-1},$$

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*, $\sigma^2_{i,t-1,d-1}$ is the estimated variance for stock *i* on day *d* within the estimation period, and $u^2_{i,t-1,d-1}$ 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:

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

assuming 252 trading days per year.

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

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