Journal of Banking and Finance 111 (2020) 105700

Contents lists available at ScienceDirect

Journal of Banking and Finance

journal homepage: www.elsevier.com/locate/jbf

Liquidity risk and expected option returns[☆]

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ARTICLE INFO

Article history:
Received 23 November 2017
Accepted 14 November 2019
Available online 19 November 2019

JEL classification:
G14

Keywords:
Liquidity risk
liquidity risk premium
Option returns

ABSTRACT

We establish the existence of liquidity risk premium in option returns via sorting analyses and Fama-MacBeth regressions. In leverage-adjusted, hedged returns, the alpha due to liquidity risk ranges from 8.5 to 14.6 basis points per month. In hedged returns unadjusted for leverage, the alpha ranges from 165.9 to 185.1 basis points per month. Compared with the option bid-ask spread, the premium is small in magnitude. In contrast to the findings for stocks and bonds, the liquidity risk premium uncovered in option returns is negative. We explain the negative premium by noting that option end-users write options in net and they might care more about liquidity risk than market makers.

1. Introduction

Liquidity can impact asset returns through a level effect and/or a risk effect. A level effect captures the premium in asset returns due to the expected future transaction costs; a risk effect captures the premium in returns due to the asset's sensitivity to shocks in aggregate liquidity.

The level effect of liquidity has been well established in stocks (e.g., Amihud and Mendelson, 1986; Amihud, 2002), Treasury bonds (e.g., Amihud and Mendelson, 1991), and corporate bonds (e.g., Chen, Lesmond and Wei, 2007; Bao et al., 2011). Although the level effect in options was first documented about two decades ago by Brenner et al. (2001), earnest research only started recently. For instance, Wei and Zheng (2010), Chou et al. (2011), and Christoffersen et al. (2018) further confirm the liquidity level effect in option prices and returns. Specifically, working with hedged returns, Christoffersen et al. (2018) demonstrate that less liquid options command a higher expected return.

The liquidity risk effect has been investigated in stocks and bonds. Motivated by the commonality in equity liquidity (e.g., Chordia et al., 2000; Hasbrouck and Seppi, 2001), Pastor and Stambaugh (2003) show that the aggregate liquidity is a state variable that commands a risk premium in stock returns. Lin et al. (2011) uncover a similar liquidity risk premium in corporate bond returns. Acharya and Pedersen (2005), via an equilibrium model, demonstrate the premia in stock returns due to various co-variation risks.

The current study examines the liquidity risk effect in option returns. Just as the stock-liquidity studies are motivated by the commonality in equity liquidity, this study is motivated by the commonality in option liquidity. Cao and Wei (2010) demonstrate a strong comovement in option liquidity after controlling for the comovement in stock liquidity. It is therefore natural to investigate whether the aggregate liquidity in the options market is also a priced state factor.

The potential liquidity risk in option returns deserves special attention for a unique reason. Unlike stocks and bonds, options are in zero net supply. While holders of stocks and bonds demand a higher expected return when the loadings on the aggregate liquidity factor, or liquidity beta, is higher (as shown respectively in Pastor and Stambaugh (2003) and Lin et al. (2011), it is not clear *a priori* whether a higher liquidity beta should be associated with a higher or lower excepted option return. For options, there are both a long and a short party. How do we interpret liquidity risk premium? From whose perspective?

We investigate the liquidity risk premium in option returns using data from OptionMetrics for the period of January 1, 1996 to December 31, 2017. Methodology-wise, we mostly follow

☆ Financial supports from King's College London and the Social Sciences and Humanities Research Council of Canada are gratefully acknowledged. For useful comments and suggestions, we thank Yakov Amihud, Peter Christoffersen, Madhu Kalimipalli, Di Luo, Radu Lupu, Neil Pearson, Danjue Shang, seminar participants at the University of Waterloo, and participants at the annual meeting of the Athens Institute for Education and Research, the Multinational Finance Society, and the Financial Management Association. We also thank two anonymous reviewers, an Associate Editor and the Managing Editor for comments and guidance in the review process.

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https://doi.org/10.1016/j.jbankfin.2019.105700
0378-4266/

Pastor and Stambaugh (2003), and Lin et al. (2011). We first estimate the liquidity factor loadings using the augmented Fama-French model, and then regress the cross-section of expected option returns on these loadings, all performed at the monthly frequency. We use three liquidity measures: the price impact measure, the return reversal measure, and the percentage bid-ask spread. The first two measures are based on, respectively, Acharya and Pedersen (2005) and Pastor and Stambaugh (2003); the third measure follows the spirit in Christoffersen et al. (2018).

The monthly stock market liquidity factors are constructed according to the standard methodology as in Pastor and Stambaugh (2003) and Acharya and Pedersen (2005). The construction of the option market liquidity factor is less straightforward due to the panel nature of daily observations and the finite maturity of options. To begin, we aggregate the contract-level option returns into a daily return through either equal-weighting or dollar-weighting where “dollar” stands for the dollar trading. Once we have the stock-day returns, we compound them into monthly option returns. While the common practice in the literature is to work with hedged returns, we adjust the option returns by “leverage” which is the absolute value of the option's elasticity (i.e., the absolute value of the option's delta multiplied by the ratio of stock price over the option price). Aside from being more suitable for regression analysis (due to the alleviated skewness and kurtosis), the leverage-adjusted, hedged returns also allow us to aggregate returns over call and put options and options with different moneynesses, which greatly simplifies the analysis and helps enhance the testing power.

Through sorting and Fama-MacBeth regression analyses, we demonstrate the existence of a liquidity risk premium in option returns. In leverage-adjusted, hedged returns, the alpha due to option liquidity risk premium ranges from 8.5 basis points to 14.6 basis points per month. When measured in hedged returns unadjusted for leverage, the (statistically significant) alpha ranges from 165.9 basis points to 185.1 basis points per month, which is much smaller in magnitude than the level effect premium demonstrated in Christoffersen et al. (2018). Our results are largely robust to alternative data screening criteria and liquidity measure/factor constructions. The liquidity risk premium generally holds up after controlling for the stock market liquidity, aggregate volatility, and many firm/stock characteristics such as liquidity level, stock return volatility, and firm size. However, the risk-neutral skewness and kurtosis weaken the results substantially. When the empirical tests are performed on disaggregated returns (e.g., call and put options separately or options in different moneyness and maturity buckets), the results are also weak possibly due to increased noise.

While the alpha analyses are carried out via a double-sort based on the implied volatility and liquidity beta, we have also repeated the analyses using the conventional single-sort based on liquidity betas only. The results are weaker, possibly due to the lack of dispersion in portfolio liquidity betas.

The uncovered liquidity risk premium carries a negative sign, in contrast to that for stocks and bonds. The negative risk premium can be explained by the empirical evidence that end-users are option writers in net (i.e., on the short side) and by the argument that they care more about liquidity risk than do market makers. Option end-users might be more concerned with liquidity risk for at least two reasons. First, while market makers usually hedge their positions through offsetting positions in options or stocks, end-users don't hedge or hedge much less often since they take option positions for a reason – speculation or informed trading. Thus, end-users are exposed to more risk, including liquidity risk. Second, margin calls affect end-users more than market makers since the latter are usually allowed to use their positions in other securities to offset margin requirements. Coupled with being option writers in net, the differential margin requirements would make end-users attach a negative risk premium to returns. To illustrate, suppose the liquidity beta is positive and the market liquidity experiences a positive shock. The option value would go up and the end-users (being on the short side) face a margin call. But this margin call ensues when the market liquidity improves. Other things being equal, this scenario is a desirable outcome, which justifies a negative risk premium as a reward.

Our study adds to the literature in several dimensions. To begin, in the standard Black-Scholes world, option liquidity doesn't play a role in valuation. Even in the pricing models with liquidity elements (e.g., Çetin et al., 2004; Çetin et al., 2006), the focus is on the direct impact of illiquidity on the value of options, just as the empirical studies (e.g, Christoffersen et al., 2018) only focus on the level effect of liquidity. The role of liquidity risk stemming from the option market per se has not been well understood. Second, insofar as equity options are derived securities from the underlying stocks, empirical studies of option liquidity usually focus on the impact of the underlying stocks' liquidity via the hedging channel (e.g., Cho and Engle, 1999). It is not yet known if option returns contain a premium due to options' own liquidity risk. Third, the existence of liquidity risk premium in option returns will have implications for pricing as well as hedging. For instance, if index put options are used to hedge a portfolio and the options are subject to liquidity risk, then the usual Black-Scholes delta-hedging would lead to errors.

The rest of the paper is organized as follows. Section 2 describes the data and the details in option return calculations and liquidity measure constructions. Section 3 establishes the existence of liquidity risk premium in option returns via both sorting analyses and the standard Fama-MacBeth asset pricing tests. Section 4 reports the main results of robustness checks and other additional tests. Some results of the auxiliary tests are placed in an internet appendix. Section 5 provides the explanation for the negative sign of the liquidity risk premium. Section 6 concludes.

2. Data, option returns, and liquidity measures

2.1. Data

The main data source is OptionMetrics from which we obtain, among other things, the daily bid and ask quotes, trading volume, open interest, delta, and implied volatility for each contract. The initial dataset contains options on all individual stocks for the period of January 1, 1996 to December 31, 2017. We screen the dataset according to the following criteria: maturity is between 7 and 365 days; moneyness (defined as the exercise price over the stock price) is in the range of (0.8, 1.2); the bid quote and bid-ask spread are positive; the percentage bid-ask spread (i.e., bid-ask spread divided by the midpoint) is less than 100%; both trading volume and open interest are positive (we also include bid and ask quotes with zero trading volume when constructing the liquidity factor based on the bid-ask spread). To avoid look-ahead bias that may be correlated with realized liquidity and option returns, the above screening is performed based on day $(t-1)$ information. Prices, bid-ask spreads, returns and trading volume of the underlying stocks are obtained from CRSP. Accounting data is obtained from Compustat.

2.2. Option returns

To focus on the liquidity risk in options, we need to first calculate returns with the impact of the underlying being stripped away. The logical choice is to calculate hedged returns as done in Christoffersen et al. (2018). Recognizing that options with different degrees of moneyness tend to have different leverages (and hence potentially different liquidity premiums), Christoffersen et al. (2018) examine options liquidity for specific moneyness buckets (i.e., in-the-money, at-the-money and out-of-the-money) of calls and puts. In contrast, inspired by Frazzini and Pedersen (2012) and Constantinides et al. (2013), and following Karakaya (2014), we calculate leverage-adjusted, hedged returns. Once the option position is de-levered and hedged against the underlying, there is no need to separate the options into calls and puts in different moneyness ranges.

We first fix some notation before describing the return calculations. Let R_{raw}, R_{hedged} and $R_{\text{lev\_adj}}$ be the raw, hedged and leverage-adjusted returns respectively. Let $R_{\text{hed\&lev}}$ stand for the leverage-adjusted, hedged return. Let R_s and r_f be the stock return and risk-free rate. Finally, let $E = \frac{\partial O}{\partial S}\frac{S}{O} \equiv \Delta\frac{S}{O}$, where O is the option price for a call or a put, and S is the stock price. In this study, the option price is simply the midpoint of the bid and ask quotes. With the above notation, the option returns for a particular contract on day t are calculated as:

$$
\begin{aligned}
R_{raw} &= \frac{O_t - O_{t-1}}{O_{t-1}}, \\
R_{hedged} &= \frac{O_t - O_{t-1} - \Delta_{t-1}(S_t - S_{t-1})}{O_{t-1}} + \frac{\Delta_{t-1}}{O_{t-1}}S_{t-1}r_f \\
&\equiv R_{raw} - E_{t-1}\left(R_s - r_f\right), \\
R_{lev\_adj} &= \frac{1}{|E_{t-1}|}\frac{O_t - O_{t-1}}{O_{t-1}} + \left(1 - \frac{1}{|E_{t-1}|}\right)r_f \\
&\equiv \frac{R_{raw}}{|E_{t-1}|} + \left(1 - \frac{1}{|E_{t-1}|}\right)r_f, \\
R_{hed\&lev} &= \frac{1}{|E_{t-1}|}\frac{O_t - O_{t-1}}{O_{t-1}} + \left(1 - \frac{1}{|E_{t-1}|}\right)r_f \pm R_s \mp r_f \\
&\equiv R_{lev\_adj} \pm \left(R_s - r_f\right).
\end{aligned}
$$

Please note that all returns are based on one-dollar investment to facilitate compounding. In the hedged return expression, the term $\frac{\Delta_{t-1}}{O_{t-1}}S_{t-1}r_f$ represents interest income/cost due to the cash balance in the margin account used to offset the stock's position. For instance, we need to short $\frac{\Delta_{t-1}}{O_{t-1}}$ units of the underlying stock to hedge $\frac{1}{O_{t-1}}$ units of a call option. The shorting proceed earns an interest of $\frac{\Delta_{t-1}}{O_{t-1}}S_{t-1}r_f$. For the leverage-adjusted return, we invest $\frac{1}{|E_{t-1}|}$ dollars in the option and $(1 - \frac{1}{|E_{t-1}|})$ dollars in the risk-free asset to mimic one dollar exposure to the stock. Finally, to hedge the delta exposure in the leverage-adjusted position, we need to long or short $\frac{\Delta_{t-1}}{|E_{t-1}|O_{t-1}}$ units of the stock, which amounts to one dollar. This is why we augment R_{lev_adj} by $\pm(R_s - r_f)$ which represent the return on the short stock position and the interest income from the margin account offsetting the short position. In the compound sign expression $\pm$, the positive sign corresponds to puts and the minus sign corresponds to calls. Evidently, the leverage-adjusted, hedged return for an option is simply the linear combination of the leverage-adjusted return and the underlying stock's excess return. It is therefore more reasonable to apply the linear pricing models such as the Fama-French factor model to the leverage-adjusted, hedged returns.

To estimate the liquidity risk premium at the stock level, we need to aggregate the contract returns to the stock-month level. To this end, we need to first aggregate the contract-level returns within the day for the same stock. This is done in two ways: averaging the contract-level returns based on either equal-weighting or dollar-weighting. In the latter, each contract-level return is weighted by the dollar trading volume which is the midpoint of the bid and ask quotes multiplied by the number of options being traded. We use equal-weighting in the base analyses in order for all contracts to exert an equal influence on the total return. Dollar-weighting allows the total return to be influenced mostly by the liquid contracts and results of this case are examined in the robustness analyses.

Once the contract-level returns are aggregated to the stock level for each day, we compound the daily returns within the calendar month to obtain a monthly return. We require at least 10 daily returns for a valid monthly return to be calculated. As shown below, this requirement is modified when constructing liquidity measures.

To avoid the impact of outliers due to potential calculation errors (e.g., erroneous option quotes or deltas from OptionMetrics), we remove the top and bottom 1% of the entire sample of stock-month observations. In other words, observations outside the 1st and 99th percentiles are eliminated. Table 1 reports the summary statistics for three cases: calls, puts and all options combined.

It should be noted that the entire procedure of return calculations and the outlier removals described above are applied separately to the three cases. For instance, for the case of all options combined, we aggregate both call and put returns within the day. This is why the means of the returns don't always lie between those of calls and puts. To understand this, suppose Stock XYZ has six daily call returns and seven daily put returns within a particular month, and suppose the days don't overlap. This stock would be screened out in both the call and put samples, but it will be present in the combined sample since it has 13 daily returns.

Several observations are in order. To begin, all the higher moments of raw option returns are much larger than their stock counterparts, reflecting the highly nonlinear and leveraged nature of option returns.[1] Once the returns are hedged, the higher moments shrink somewhat, but not to a large extent. Deleveraging brings the biggest bang in reducing the higher moments. In particular, the standard deviation of the de-levered returns is quite comparable to stocks'. With both deleveraging and hedging, the skewness and kurtosis lie between those of the leverage-adjusted and the hedged returns. But the second moment is now the lowest.

As for correlations, the results mostly conform to our common-sense priors. For instance, the call (put) raw returns are highly positively (negatively) correlated with the stock returns, and this correlation is further enhanced with leverage-adjusted option returns; the hedged returns are highly correlated with leverage-adjusted, hedged returns, and so on. Incidentally, the correlation matrix in Panel C seems to bear more resemblance to Panel A than to Panel B, indicating that the combined sample is dominated by call options. This is indeed true. The ratio of call to put contracts in our sample is 1.27, and as shown in the auxiliary analysis, the liquidity risk premium manifests itself more in call options than in put options.

2.3. Liquidity measures and aggregate liquidity factors

In the studies of liquidity risk premium in stocks and bonds, the most commonly used liquidity measures are the price impact measure (which we denote as Amihud) based on Amihud (2002) and the return reversal measure (which we denote as PS) developed by Pastor and Stambough (2003). While Pastor and Stambough (2003) use their PS measure to study liquidity risk premium in stocks, Acharya and Pedersen (2005) examine stocks' liquidity risk premium with the Amihud measure. Lin et al. (2011) use both measures to study risk premium in corporate bonds. We therefore also employ these two liquidity measures. Since both mea-

[1] One should not over-interpret the raw returns and the leverage-adjusted returns of the combined sample of calls and puts since we lump together negative and positive returns within the day. Our subsequent analyses don't make use of these returns. They are summarized in the table for comparison purposes. Hedged returns (and leverage-adjusted, hedged returns) are not subject to this complication.

Table 1
Summary Statistics – Option and Stock Returns.
This table presents the first four moments of, and the pair-wise correlations between the stock return and various versions of option returns. All returns are monthly, compounded from daily returns. In addition, they are net of the risk-free rate, i.e., the monthly risk-free rate is subtracted from the compounded raw returns. There are four versions of option returns: raw returns (Raw), hedged returns (Hedged), leverage adjusted returns (Lev_Adj) which are raw returns adjusted by the option's elasticity or leverage, and leverage adjusted, hedged returns (Hed&Lev) which are leverage adjusted returns with the delta exposure being hedged away. All returns are for one-dollar initial investment. For each version of the option returns, we first calculate the contract-level returns within each day and then average them to obtain the stock-day option return. These aggregated daily returns are finally compounded into monthly returns. We require at least 10 daily returns in order for a valid monthly return to be calculated. The summary statistics represent the typical or average stock. In other words, we first compute the moments and pair-wise correlations for each stock, and then average the computed quantities across stocks. Before computing summary statistics, we remove observations outside the 1st and the 99th percentiles. Panels A and B are for calls and puts separately, while Panel C is for all options combined where the call and put returns are lumped together at the contract level and are aggregated to a daily option return (therefore, the raw option returns in Panel C should be interpreted with caution). The sample period is from January 1, 1996 to December 31, 2017.

	Panel A: Call options				
	Stock return	Option return			
		Raw	Hedged	Lev-adj	Hed&Lev
Mean	0.002	0.030	0.039	0.003	0.003
STD	0.115	0.805	0.388	0.097	0.041
Skewness	0.302	2.021	1.749	0.730	1.138
Kurtosis	3.048	7.217	6.505	2.452	4.422
	Correlation				
Stock Return	1.000				
Option_Raw	0.663	1.000			
Option_Hedged	−0.147	0.217	1.000		
Option_Lev_Adj	0.756	0.851	0.213	1.000	
Option_Hed&Lev	−0.153	0.205	0.894	0.239	1.000
	Panel B: Put options				
	Stock return	Option return			
		Raw	Hedged	Lev-adj	Hed&Lev
Mean	0.002	−0.010	0.019	0.001	0.002
STD	0.115	0.663	0.340	0.097	0.045
Skewness	0.302	2.057	1.670	1.039	1.146
Kurtosis	3.048	8.680	6.421	4.855	5.074
	Correlation				
Stock Return	1.000				
Option_Raw	−0.541	1.000			
Option_Hedged	0.009	0.375	1.000		
Option_Lev_Adj	−0.622	0.854	0.362	1.000	
Option_Hed&Lev	0.002	0.358	0.868	0.425	1.000
	Panel C: All options				
	Stock return	Option return			
		Raw	Hedged	Lev-adj	Hed&Lev
Mean	0.002	0.055	0.058	0.005	0.004
STD	0.115	0.629	0.425	0.077	0.049
Skewness	0.302	1.876	1.887	0.997	1.268
Kurtosis	3.048	6.198	7.018	3.457	5.042
	Correlation				
Stock Return	1.000				
Option_Raw	0.302	1.000			
Option_Hedged	−0.098	0.460	1.000		
Option_Lev_Adj	0.256	0.846	0.436	1.000	
Option_Hed&Lev	−0.096	0.419	0.884	0.494	1.000

sures are based on prices or returns, a potential mechanical link between option returns and liquidity measures might exist. To bypass this potential link, we also employ a third liquidity measure – the percentage bid-ask spread (denoted as BidAsk), which is the bid-ask spread divided by the mid-quote. This measure is used by Christoffersen et al. (2018) to study the liquidity premium in options returns. We first describe the construction of the aggregate liquidity factor Amihud.

The initial, raw ingredient is the contract-level price impact: $\frac{|R_{hed\&lev}|}{\log(1+dollar\ volume)}$, where we use logarithm to smooth out the large variations in options trading volume, and we add one to the dollar volume to avoid a zero from the logarithm (note: since each contract contains 100 options and the minimum bid is \$0.01, the lowest possible dollar volume is \$1). The idea behind this measure is analogous to the original Amihud measure: option prices might be moved by liquidity even after removing the impact of the stock price movement. To avoid the aggregate liquidity factor being driven by extreme values, we use only a subset of the previously screened data. Specifically, we restrict the maturity to the range of seven days to 120 days and the moneyness to the range between 0.45 and 0.55 in the absolute value of delta.[2] We aggregate the

[2] In this case, we follow the literature (e.g., Bollen and Whaley, 2004; Christoffersen, Goyenko, Jacobs and Karoui, 2018) to define moneyness based on the option's delta. Please note the following. First, the additional screening only applies to the construction of liquidity factors. The actual sorting and regression analyses

contract-level price impact (over both calls and puts) to the daily level by equal-weighting. Dollar-weighting using log(1+dollar volume) as the weight is considered in the robustness checks. The daily price-impact measure is then averaged within the month for each stock by requiring at least five observations. The aggregate market-level price impact for each month is either the cross-sectional mean or median of the individual stocks' price impacts. When taking the cross-sectional mean, we first trim the price impacts at the 1st and the 99th percentiles to avoid the undue influence of potential outliers.

Following Acharya and Pedersen (2005), we take as the aggregate liquidity factor the residuals or innovations from an AR(2) process of the monthly aggregate market-level price impacts. Specifically, to remove the impact of the rising trend in option trading volume, we adjust the market-level price impact by the average dollar volume of the previous month.[3] The AR(2) process is run in an expanding-window manner: The initial innovations are estimated using data from 1996 to 2000, and are subsequently appended each year by progressively adding more observations (this methodology is employed by Pastor and Stambaugh, 2003). Since price impact itself measures illiquidity, we reverse the sign of the AR(2) residuals or innovations so that they measure shocks in liquidity. This is to make the price-impact measure consistent with the PS measure of Pastor and Stambaugh (2003), which we now turn to.

To construct the aggregate liquidity factor based on Pastor and Stambaugh (2003), we use contracts with an absolute delta between 0.4 and 0.6, and a maturity between seven and 120 days.[4] We require at least 10 valid observations within the month in order to run the return-reversal regression, i.e., Eq. (1) in Pastor and Stambaugh (2003). Since many of the options expiring in the current month have fewer than 10 daily returns available, we exclude options expiring in the current month. To calculate the excess leverage-adjusted, hedged return for each contract, we subtract the average leverage-adjusted, hedged return for the day (over the entire options market). Once the return-reversal regression is run for each contract within the month for the same stock, we aggregate the reversal coefficient by equal-weighting, consistent with the treatment in the construction of the Amihud-based factor (the dollar-weighted-average of the PS measures is considered as a robustness check). Additionally, similar to the Amihud-based factor, we obtain the monthly aggregate market-level PS by taking either the mean (after trimming at the 1st and 99th percentiles) or the median of the individual stock PS measures. Finally, using the same value-adjustment in the Amihud-based factor estimation, we run the autoregressive process in Eq. (7) of Pastor and Stambaugh (2003) and treat the residual as our aggregate liquidity factor. Hereinafter, for ease of exposition, we refer to these two aggregate liquidity factors as Amihud and PS factors.

The construction of the aggregate liquidity factor based on the percentage bid-ask spread (BidAsk) is relatively straightforward. Similar to the case of Amihud, we first aggregate the contract-level BidAsk's to a stock-month measure, and then use either the cross-section mean or median to represent the aggregate liquidity (after putting a negative sign in front of the mean or median BidAsk). It should be noted that when constructing the BidAsk measure and its aggregate factor, we also include option quotes with zero trading volume. Arguably, illiquidity is best manifested in no-trade quotes. Therefore, our BidAsk measure not only severs the potential mechanical link between option returns and liquidity, but also encompasses an additional aspect of liquidity that the Amihud and PS measures cannot (since they rely on quotes with non-zero trading volumes). At any rate, once we have the aggregate BidAsk liquidity factor, we also perform the expanding window AR(2) procedures to obtain the residuals used to proxy the aggregate liquidity shocks. Since BidAsk is a unit-less measure, we no longer need to adjust for the changes in market capitalization over time.

While the BidAsk measure can overcome the potential mechanical link between option returns and liquidity, one might wonder what role the option trading volume plays in the Amihud and PS measures. In the case of stocks and bonds, a smaller price movement accompanied by a higher trading volume indicates high liquidity or lower illiquidity. However, in the case of options, option price movements don't have to be accompanied by trading if the price movements are purely due to the price change in the underlying asset. In other words, the role of option trading volume appears ambiguous. Thankfully, delta-hedging automatically addresses this concern. Our de-levered, hedged option returns measure option price movements due to factors other than the price change in the underlying stock. In this sense, given the size of an option return, a higher trading volume also means higher liquidity as in the stock Amihud measure. By the same token, a smaller option-return reversal per-dollar trading volume also indicates higher liquidity as in the stock PS measure.

Aside from option liquidity factors, we also need the corresponding stock market liquidity factors in our analysis. To this end, we download from WRDS the monthly series of the PS factor for the stock market. For the stock market Amihud factor, we follow the procedures in Acharya and Pedersen (2005) and construct it using all stocks on the NYSE and AMEX (as opposed to only the optioned stocks in the universe of OptionMetrics). For the stock market BidAsk factor, we also use NYSE and AMEX stocks and follow the same procedure as in the construction of the Amihud factor, except that we no longer need to adjust for the changes in market capitalization over time. It is worth noting that we include dummy variables in the AR(2) regression to account for the regime changes in the minimum tick size. Specifically, from 8th to 16th: AMEX in September 1992, February 1995, and May 1997; NYSE: June 1997; then decimalization in January 2001. Once again, we reverse the sign of the stock Amihud and BidAsk factors so that they measure shocks in the stock market liquidity.

Fig. 1 presents the plots of the three option liquidity factors for both the raw levels and the innovations. Compared with the Amihud and BidAsk factors, the PS factor exhibits much wider variations over time in the raw level series. There are at least two potential reasons. First, as discussed in Pastor and Stambaugh (2003), the return-reversal coefficient is a noisy measure of liquidity since returns may reverse due to reasons other than order flow pressures. Second, we require a minimum of 10 valid observations within each month to run the return-reversal regression (Pastor and Stambaugh require 15 in the case of stocks). The small sample necessarily leads to more noise in the coefficient estimation.

Notwithstanding the wider variations in the PS factor, the three measures are indeed positively correlated. As will be seen in Table 2, the pairwise correlations are: 0.408 (PS vs. Amihud), 0.448 (Amihud vs. BidAsk), and 0.219 (PS vs. BidAsk). They agree with each other on occasions of large liquidity shocks such as the market crashes in October 2008 (financial crisis), May 2010 (flash

are for the overall screened sample, i.e., maturity is between 7 and 365 days and moneyness (defined as the exercise price over the stock price) is in the range of (0.8, 1.2). Second, "moneyness in the range between 0.45 and 0.55 in the absolute value of delta" means: retaining calls whose delta is between 0.45 and 0.55 and puts whose delta is between −0.55 and −0.45.

[3] Note that we essentially follow Eq. (22) in Acharya and Pedersen (2005) without the conversions involving 0.25 and 0.30 since matching the price impact measure to the cross-sectional behavior of the actual transaction costs is not our objective. Moreover, we have also used the median dollar trading volume to make the adjustment, and the results are similar.

[4] We widen the moneyness range slightly from (0.45, 0.55) to (0.4, 0.6) in order to facilitate the PS estimation. Since the monthly estimation of the return reversal coefficient entails a regression for each particular option series, too narrow a moneyness range tends to screen out some deep in-the-money and/or deep out-of-the-money options, leaving too few observations to run the regression.

Table 2
Summary Statistics – Correlations among Liquidity and Volatility Factors.
This table presents pair-wise correlations between the stock liquidity factors, the option liquidity factors, and the market volatility factor measured by hedged straddle returns of S&P 500 index options. All factors are at the monthly frequency. PS_stock and PS_stock_tf are, respectively, the aggregate liquidity-innovation factor and the traded liquidity factor of Pastor and Stambaugh (2003), both of which are downloaded from WRDS. Amihud_stock and Amihud_stock_tf are the Amihud illiquidity (Amihud, 2002) counterparts of PS_stock and PS_stock_tf. Amihud_stock is constructed following the procedure in Acharya and Pedersen (2005), and Amihud_stock_tf is constructed in the same way as PS_stock_tf is constructed out of PS_stock, i.e., it is the return difference between the highest-liquidity-beta decile portfolio and the lowest-liquidity-beta decile portfolio. Likewise, BidAsk_stock and BidAsk_stock_tf are the proportional bid-ask spread (i.e., bid-ask spread divided by the mid-quote) counterparts of Amihud_stock and Amihud_stock_tf. PS_option, Amihud_option, and BidAsk_option are the option counterparts of PS_stock, Amihud_stock and BidAsk_stock and are constructed using option price, volume, and bid-ask spread. Straddle_tf is the excess return (over and above the monthly risk-free rate) on hedged straddles constructed using short-term, near-the-money S&P 500 index options. Please see the text for details. The sign of Amihud_stock, BidAsk_stock, Amihud_option, and BidAsk_option is reversed so that they represent shocks in liquidity (as opposed to illiquidity) as do PS_stock and PS_option. The sample period is from January 1, 1996 to December 31, 2017. With the exceptions below, the correlations are calculated for the period from January 1, 2001 to December 31, 2017 since the first five years are used to estimate the liquidity betas for the initial five-year rolling window period. The pair-wise correlations between the stock's PS and Amihud liquidity factors pertain to the period of January 1, 1962 to December 31, 2017, with the first five years (1962– 1966) being used to estimate liquidity betas for the initial five-year rolling window period. The pair-wise correlations between the stock's BidAsk liquidity factor and the other two stock liquidity factors (i.e., PS and Amihud) pertain to the period of January 1, 1993 to December 31, 2017, with the first five years (1993–1997) being used to estimate liquidity betas for the initial five-year rolling window period.

	PS_stock	PS_stock_tf	Amihud_stock	Amihud_stock_tf	BidAsk_stock	BidAsk_stock_tf	PS_option	Amihud_option	BidAsk_option	Straddle_tf
PS_stock	1.000									
PS_stock_tf	−0.034	1.000								
Amihud_stock	0.164	−0.044	1.000							
Amihud_stock_tf	−0.011	−0.038	0.031	1.000						
BidAsk_stock	0.102	−0.038	0.235	0.141	1.000					
BidAsk_stock_tf	−0.104	0.274	0.017	0.502	0.092	1.000				
PS_option	−0.006	−0.009	0.230	0.023	0.130	0.051	1.000			
Amihud_option	0.278	0.189	0.363	0.084	0.268	−0.050	0.408	1.000		
BidAsk_option	0.113	0.069	0.239	0.132	0.137	0.084	0.219	0.448	1.000	
Straddle_tf	−0.122	−0.076	−0.275	−0.084	−0.229	0.047	−0.290	−0.581	−0.246	1.000

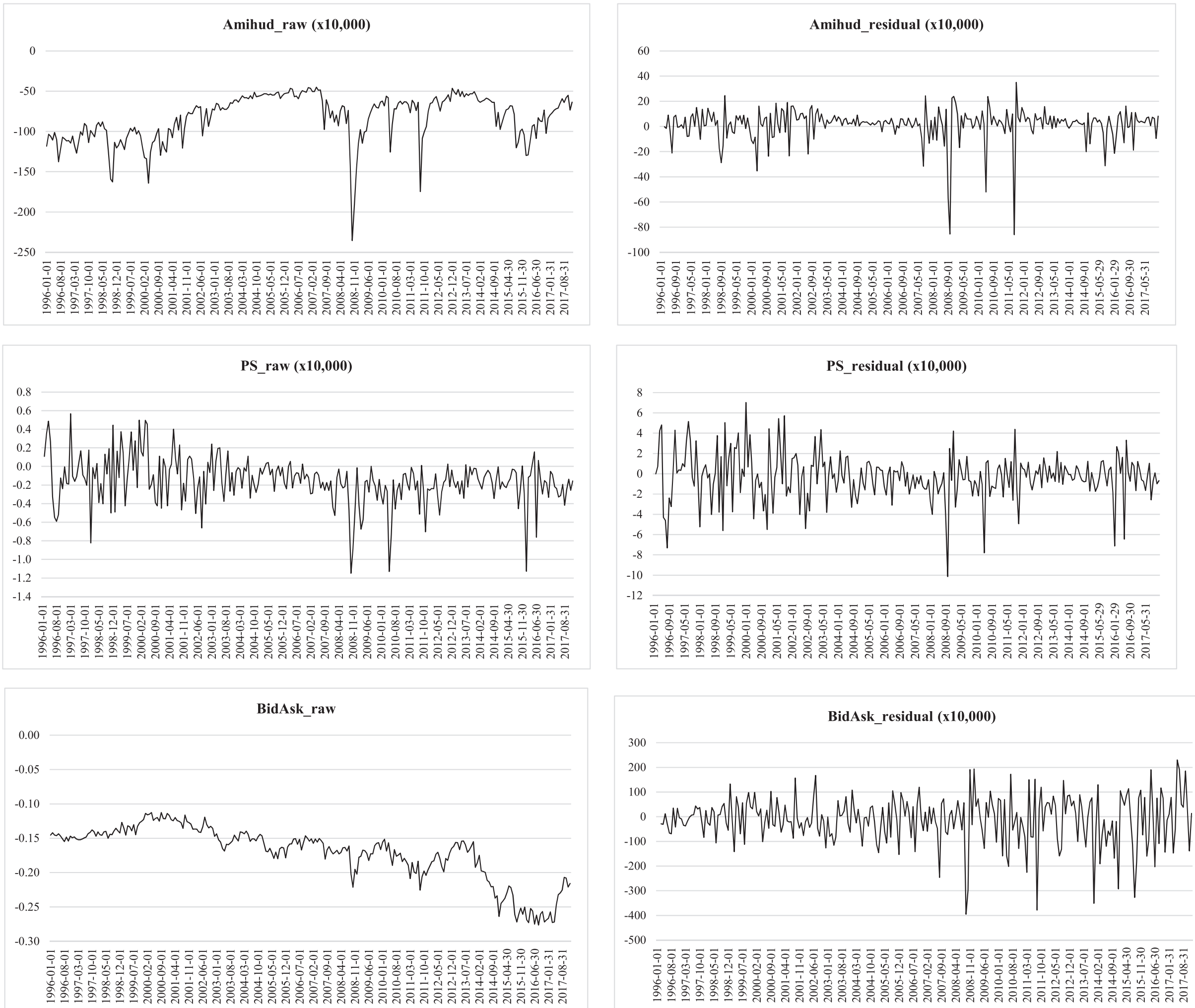

Fig. 1. Plots of Aggregate Option Liquidity Factors.
This figure presents the plots of the monthly series of the three aggregate option liquidity factors. The top two charts are for the Amihud factor, with the left depicting the raw levels of the factor and the right depicting the residuals of the factor. The middle two charts, and the bottom two charts are respectively the PS and BidAsk counterparts. We reverse the sign of the original price impact measure and the proportional bid-ask spread so that Amihud and BidAsk gauge liquidity just as PS. Please see the text for details of the factor constructions. The sample period is from January 1, 1996 to December 31, 2017.

crash), and August 2011 (fear of European sovereign debt crisis and the slowdown of the U.S. economy). That the three factors are not perfectly correlated is arguably a desirable thing, for they presumably capture different aspects of the dynamics of the option market's aggregate liquidity.[5]

Although the leverage-adjusted, hedged option returns are immune to the directional movements of the stock prices, they might still be subject to the impact of volatility. We therefore need a market volatility factor. To this end, we create a tradeable factor: the monthly excess return on delta-hedged straddles constructed from short-term, near-the-money S&P 500 index options. On each day, we calculate the return on a delta-hedged straddle (note: the delta-hedging is to remove the residual exposure to the underlying when the deltas of the call and put don't exactly cancel each other). We then compound the daily returns into a monthly return and subtract the monthly risk-free rate to arrive at an excess straddle return. To ensure smoothness in straddle returns within the calendar month, we use next-month options (as opposed to current month options) to form the straddle. Moreover, to maximize the natural hedge between the call and put, we choose the pair with an exercise price closest to the forward price of the index.

Finally, we need traded liquidity factors corresponding to stocks' PS, Amihud, and BidAsk in order to calculate alphas for the options liquidity risk via the Fama-French factor model. In other words, in order to assess the impact of options liquidity risk, we need to control for the impact of stock market liquidity. To help facilitate the interpretation of alphas, we need the stock market liquidity factor to be a traded one. For the PS measure, this traded liquidity factor is already available on WRDS. Essentially, the traded factor is the return difference between the decile portfolio with the highest liquidity betas and the decile portfolio with the lowest-liquidity betas (updated annually from decile sorting), where the portfolio return is the value-weighted average return of the constituent stocks. For the Amihud and BidAsk measures, we follow

[5] Incidentally, although a discernible pattern cannot be detected from the raw levels of Amihud and PS, the percentage bid-ask spread in options seems to exhibit an upward trend starting from the early 2000's (please be mindful of the negative sign we have placed in front of BidAsk), culminating in 2014, and then starts to trend down in 2017 after a relatively stable period. This phenomenon itself may warrant a separate study. However, the trend doesn't concern us in the current study since we only work with the innovations from an AR(2) process, which are trend-free as shown in Figure 1.

exactly the same procedure and construct the traded factors accordingly (using the Fama-French three factors and the momentum factor as the base).

Table 2 reports the pair-wise correlations between all the liquidity factors and the volatility factor.[6] Several observations are in order. First, all of the stock market liquidity factors are negatively correlated with the volatility factor, consistent with the fact that liquidity generally deteriorates when the market is more volatile. The correlation weakens for the traded factors. In fact, it becomes positive for the traded BidAsk factor. Moreover, the original PS factor and the traded PS factor are negatively correlated, although the correlation itself (i.e., –0.034) is not sizeable. Although the correlation between the non-traded and traded factors is positive for both the Amihud and the BidAsk measure, the correlation for the latter is larger than the former (0.092 versus 0.031). As mentioned repeatedly in this paper, BidAsk's complete disconnect with the option prices and returns makes a desirable liquidity measure supplementary to Amihud and PS.

Second, as already mentioned earlier, the three option liquidity factors are indeed positively correlated, with correlations ranging from 0.219 to 0.448. The three non-traded stock liquidity factors are also positively correlated, with correlations ranging from 0.102 to 0.235.

Third, similar to their stock counterparts, the option liquidity factors are also negatively correlated with the volatility factor. In fact, the correlation between the Amihud factor and the volatility factor is −0.581, presumably because of the fact that the Amihud measure is the closest to the raw option prices. Perhaps for the opposite reason (i.e., not directly related to option prices), the BidAsk factor is the least correlated with the volatility factor. This low correlation will help us isolate the pure liquidity risk premium in option returns using the BidAsk factor.

3. Is there a liquidity risk premium in option returns?

3.1. Liquidity level effect

Using the effective bid-ask spread as a proxy for option's illiquidity, Christoffersen et al. (2018) find that illiquid options command a higher expected return than liquid ones. Although the focus of the current paper is on liquidity risk premium in option returns, it is of interest to see whether the liquidity level effect in Christoffersen et al. (2018) also exists in our liquidity measures. To this end, we perform sorting analyses similar to Christoffersen et al. (2018). Specifically, we sort each month's option returns ($R_{hed\&lev}$) into quintiles on last month's liquidity measures; we then calculate the equal-weighted average return for each quintile and the difference between the average returns of the lowest-liquidity quintile and the highest-liquidity quintile, which we call the "low-high" portfolio; finally, the sample average and the corresponding Newey–West adjusted t-value are calculated for each quintile and the low-high portfolio. We also calculate the corresponding alpha and t-value for each quintile and the low-high portfolio relative to the Fama-French four-factor model (with the four factors being MKT, SMB, HML, and UMD).[7]

Panels A, B and C of Table 3 report the results. Under the Amihud and PS measures, neither the raw return nor the alpha of the low-high portfolio is statistically different from zero. However, under the BidAsk measure, the t-value for both the raw return and the alpha of the low-high portfolio is highly significant. Therefore, with leverage-adjusted, hedged returns, the liquidity level effect reported by Christoffersen et al. (2018) does exist in the BidAsk measure, but not in the other two liquidity measures.

Although our results are consistent with Christoffersen et al. (2018) under the BidAsk measure, one naturally wonders why the liquidity level effect doesn't exist under the Amihud and PS measures. The difference in horizons could be one reason: Their horizon is daily while ours is monthly. The difference in return calculations could be another: Christoffersen et al. (2018) examine hedged returns while we examine leverage-adjusted, hedged returns. To ascertain whether the difference in return calculations is at play, we repeat the sorting analyses with hedged returns (note: the Amihud and PS liquidity measures are also re-estimated using hedged returns). As seen in Panels D and E, under the Amihud and PS measures, lower liquidity (or higher illiquidity) is now indeed associated with higher option returns, consistent with Christoffersen et al. (2018). Although the association is somewhat weak under the PS measure, it is extremely strong under the Amihud measure. Under the BidAsk measure, the association not only remains, but also strengthens in terms of statistical significance.[8]

Evidently, whether to de-lever the option returns matters for the study of liquidity level effect. As shown later, this is also the case for the study of liquidity risk premium. Specifically, with the leverage-adjusted, hedged returns, the liquidity risk premium manifests itself in both the alpha analysis and the Fama-MacBeth analysis. In contrast, with the hedged returns (that are not adjusted for leverage), the liquidity risk premium only shows up in the alpha analysis. Insofar as the liquidity level effect matters more for the raw or hedged option returns, the focus on hedged returns in Christoffersen et al. (2018) is indeed appropriate. However, the study of liquidity risk premium relies on linear pricing models (such as the Fama-French factor model) in a regression setting. Properly removing leverage in option returns is therefore essential. Thus Christoffersen et al. (2018) and the current study complement each other in terms of both the focus – level effect versus liquidity risk premium – and the specific forms of returns being examines – hedged returns versus leverage-adjusted, hedged returns.

3.2. Liquidity risk premium – sorting analysis

As a first step of the liquidity risk premium investigation, in this section, we detect the risk premium in option returns via sorting analysis. To this end, we need to first estimate the option return's loading on the aggregate option market liquidity factor. This is accomplished via the following augmented Fama-French factor model:

$$\begin{aligned} R^{excess}_{hed\&lev} = {} & \beta_0 + \beta_1 MKT + \beta_2 SMB + \beta_3 HML + \beta_4 UMD + \beta_5 STRD \\ & + \beta_6 STOCK_{LF} + \beta_7 OPTION_{LF} + \varepsilon, \end{aligned} \tag{1}$$

where $R^{excess}_{hed\&lev}$ is the leverage-adjusted, hedged return net of the risk-free rate, $STRD$ is the market volatility factor constructed from straddle returns, and $STOCK_{LF}$ and $OPTION_{LF}$ are the aggregate liquidity factors for the stock market and the option market, respec-

[6] Please note that the pairwise correlations between the stock liquidity factors are calculated over a longer sample period. Specifically, the correlation between the Amihud and PS factors pertains to the period of 1967 to 2017; the correlations between the BidAsk factor and either of the other two pertain to the period of 1998 to 2017.

[7] The Fama-French four-factor model is chosen in order to be consistent with Christoffersen, Goyenko, Jacobs and Karoui (2018).

[8] One may notice some inconsistencies in the quintile returns across liquidity measures. For instance, all the raw quintile returns in Panel E are negative whereas most of the raw quintile returns in Panel D are positive, seemingly impossible. The apparent inconsistency results from sample differences. Simply put, for a particular stock in a specific month, one liquidity measure (e.g., Amihud) may exist in the previous month (so that the stock would be included in the sorting) while another (e.g, PS) may not. This leads to different samples under different liquidity measures. It should be noted that this concern does not extend to our main results since in the risk premium investigations, option returns are sorted according to beta sensitivity to market-wide option liquidity factors.

Table 3
Liquidity Level Effect – Sorting Option Returns on Lagged Option Liquidity.
This table presents the liquidity level effect based on sorting analyses. The specific procedure is as follows. We sort this month's option returns into quintiles based on last month's liquidity measure. The equal-weighted average option return is calculated for each quintile. The return difference between the quintile with the lowest liquidity and the quintile with the highest liquidity ("low-high" in short) is also calculated. The sorting is repeated for each month during the sample period of January 1996 to December 2017. The average quintile returns and the low-high returns are then obtained from the monthly time-series of quintile returns. Their corresponding Newey–West adjusted *t*-values are also calculated. For all the quintiles and the low-high portfolio, we also calculate their alphas based on the four-factor Fama-French model (with the factors being MKT, SMB, HML, and UMD) with Newey-West adjusted *t*-values. The returns and alphas are already in percentage form. The sign of Amihud and BidAsk is reversed so that they measure liquidity. Panels A, B and C are for leverage-adjusted, hedged option returns; Panels D, E and F are for hedged returns. Please see the text for details in the calculation of monthly option returns and liquidity measures Amihud, PS and BidAsk. *, **, and *** indicate significance at, respectively, the 10%, 5% and 1% levels.

	Panel A: Sorting leverage-adjusted hedged returns on last month Amihud measure					
	Low	2	3	4	High	Low–High
Return	−0.174	−0.117	−0.086	−0.106	−0.187	0.013
t-value	−0.85	−0.59	−0.44	−0.62	−1.28	0.13
FF alpha	0.040	0.091	0.117	0.075	−0.034	0.074
t-value	0.20	0.49	0.62	0.45	−0.24	0.74
	Panel B: Sorting leverage-adjusted hedged returns on last month PS measure					
	low	2	3	4	high	low - high
Return	−0.281	−0.274	−0.314*	−0.270*	−0.270	−0.012
t-value	−1.42	−1.60	−1.87	−1.67	−1.41	−0.38
FF alpha	−0.073	−0.090	−0.136	−0.096	−0.071	−0.002
t-value	−0.38	−0.54	−0.82	−0.62	−0.38	−0.07
	Panel C: Sorting leverage-adjusted hedged returns on last month BidAsk measure					
	low	2	3	4	high	low - high
Return	0.245*	−0.046	−0.203	−0.244	−0.228	0.473***
t-value	1.78	−0.28	−1.08	−1.31	−1.19	4.97
FF alpha	0.383***	0.130	−0.011	−0.043	−0.030	0.413***
t-value	2.89	0.85	−0.06	−0.24	−0.16	4.43
	Panel D: Sorting hedged returns on last month Amihud measure					
	low	2	3	4	high	low - high
Return	5.140***	1.869	0.701	0.178	−0.814	5.954***
t-value	2.78	1.04	0.39	0.10	−0.46	10.91
FF alpha	6.885***	3.635**	2.501	1.975	0.893	5.992***
t-value	3.92	2.20	1.54	1.21	0.55	11.05
	Panel E: Sorting hedged returns on last month PS measure					
	low	2	3	4	high	low - high
Return	−1.081	−2.118	−2.401	−2.559	−1.850	0.769*
t-value	−0.57	−1.25	−1.35	−1.43	−1.08	1.68
FF alpha	0.919	−0.414	−0.672	−0.837	−0.111	1.030**
t-value	0.53	−0.26	−0.42	−0.51	−0.07	2.13
	Panel F: Sorting hedged returns on last month BidAsk measure					
	low	2	3	4	high	low - high
Return	7.502***	3.784**	1.314	−0.610	−2.239	9.741***
t-value	5.03	2.24	0.72	−0.34	−1.22	9.53
FF alpha	8.884***	5.422***	3.033*	1.257	−0.452	9.335***
t-value	6.38	3.45	1.77	0.76	−0.27	10.29

tively. The above regression is run in a time-series manner for each stock and we omit the time index for brevity. $STOCK_{LF}$, being the traded liquidity factor, is added to the Fama-French factor model to control for the potential sensitivity of the option returns to the stock market liquidity. Our main focus is on β_7, the loading of option returns on the aggregate liquidity factor in the options market.[9]

The regression is run for month t with a 60-month rolling window covering $(t-60,\ t-1)$ with at least 30 monthly returns. Starting from January 2001, each month, we first sort all the stocks into quintiles according to their last month's average implied volatility and then sort each quintile into sub-quintiles according to β_7, the estimated loadings on $OPTION_{LF}$. The five lowest-beta sub-quintiles and the five highest-beta sub-quintiles are, respectively, grouped together, resulting in the lowest-beta portfolio and the highest-beta portfolio. The leverage-adjusted, hedged option return for these two portfolios are then calculated in month t with either equal-weighting or contract-weighting where "contract" is the logarithm of open interest in month $(t-1)$. The contract-weighting mimics the value-weighting in equity studies where "value" is typically the market capitalization of the stock.[10, 11] The

[9] In this and all subsequent analyses, we have also examined an alternative version of the augmented Fama-French factor model in which the factor $OPTION_{LF}$ is first orthogonalized against $STOCK_{LF}$ and then added to the four-factor model together with the volatility factor. Results are similar and are omitted for brevity.

[10] As in the calculation of the price impact measure, we use logarithm to smooth out influence of extreme values. Moreover, we have also employed $\log(1 + \textit{dollar value of open interest})$ as the contract weight and the results are similar qualitatively.

[11] Aside from being a robustness check, the contract-weighting will hopefully also reduce the microstructure biases in option returns as discussed in Duarte, Jones and Wang (2019). They argue that the errors in stock and option

choice of the 5 × 5 double sort is justified in Section 4.1 when we examine other alternative sorting procedures. We use implied volatility as the other sorting dimension mainly due to the fact volatility a major determinant of option liquidity (e.g., Wei and Zheng, 2010). Results of single sorting are presented at the end of this sub-section.

The quantity of interest is the return of the "high-low portfolio," which is simply the return difference between the highest-beta portfolio and the lowest-beta portfolio. The above estimation and sorting procedure is repeated every month from January 2001 to December 2017, resulting in a time-series of high-low portfolio returns. Finally, to obtain alpha, the high-low portfolio returns are regressed on the Fama-French three factors, the UMD factor, the market volatility factor STRD, and the traded factor $STOCK_{LF}$. Table 4 reports the results of this regression, with different weighting/factor/factor construction combinations. "Factor construction" (i.e., LF_mean versus LF_median) refers to how the cross-section of liquidity measures are aggregated in each month, as discussed in the data section. Under "LF_mean" (or "LF_median"), the mean (or median) of liquidity measures is taken as the aggregate market liquidity. Several observations are in order.

First and foremost, all of the alphas are significant and all but one are significant at either the 5% level or the 1% level. The alpha ranges from 8.5 basis points to 14.6 basis points per month, much smaller than the liquidity level effect in Christoffersen et al. (2018) who report a return spread of 3.4% for calls and 2.5% for puts *per day*. It turns out that how the option returns are measured matters a great deal. For instance, with hedged returns in Panel F of Table 3 under the liquidity measure BidAsk, the level effect is more than 9% per month. In fact, as we will see in Table 12, for hedged returns, the alpha due to liquidity risk premium is indeed multi-fold larger compared with that for leverage-adjusted, hedged returns. The obvious implication is: In general, much of the hedged return comes from the leverage of the option.

Second, the negative sign is surprising since such alpha is positive in the stock market (Pastor and Stambaugh, 2003) and the bond market (Lin et al., 2011). The negative alpha implies that options with a higher sensitivity to the aggregate liquidity shocks command a lower expected return. Ultimately, this result has to do with the zero net supply of options and the interaction among the main players, viz., option traders and the market makers. We will postpone further discussions on this point to the end of this paper.

Third, option returns don't load significantly on the aggregate liquidity factor for the stock market, implying that the two markets are somewhat "disconnected" when it comes to the dynamics of liquidity and the interactions between returns and liquidity. This finding is broadly consistent with Cao and Wei (2010) who find a very low correlation (0.066) in the percentage bid-ask spreads between the stock and options markets. It is also consistent with Cho and Engle (1999) who fail to find unambiguous support for the derivative-hedge theory of option liquidity, and Christoffersen et al. (2018) who show a generally weak association between options returns and the level of the stock market liquidity.

Finally, the high-low portfolio returns by and large load positively on the Fama-French MKT factor and the HML factor. As for the market volatility factor, the loading is negative under the Amihud and PS measures, but positive under the BidAsk factor. Regardless, the above findings stress the importance of controlling for the Fama-French factors and the market volatility factor when estimating the liquidity risk premium in option returns.

As discussed in Section 4.1, we follow the literature and use double-sort to increase dispersion among portfolios. We have used the same double-sort in Table 4 to ensure the comparability between the results of the sorting and Fama-MacBeth regression analyses. Nevertheless, for completeness, we have also performed single-sort analyses and examined the pattern of alphas across sorting portfolios. Specifically, we perform single sort of various groups (viz., quintiles, deciles, 25 and 30) on liquidity betas. Table 5 presents the results for the Amihud liquidity measure (results for other liquidity measures are similar). The table shows that the alphas are mostly monotonic with respect to liquidity betas. The monotonicity maintains until the last portfolio. In other words, an approximate linear relationship exists between alphas and liquidity betas for most of the sorting portfolios. Although the alpha of the high-low portfolio is significant in all alternative sorts, the significance level is generally low – e.g., under quintile and decile single sorts, the *t*-values are only −1.85 and −1.78 respectively. Last but not least, the double-sort employed in Table 4 produces the highest *t*-value for the alpha of the high-low portfolio, indicating that a double-sort ensures a wider dispersion and a more reliable test (thanks to the inclusion of more assets in the high-low portfolio). Please refer to Section 4.1 and Table 8 for detailed discussions on the rationale of the double-sorts.

3.3. Liquidity risk premium – Fama-MacBeth regression

Having established the preliminary evidence of liquidity risk premium in option returns, we now proceed to a formal asset pricing test using the Fama-MacBeth methodology. The initial step is identical to the analysis in the previous section. In other words, each month, we estimate β_7 via (1) for each stock in a 60-month rolling window (up to last month) that has at least 30 monthly option returns. We also perform double sorting and form 25 portfolios based on last month's implied volatility and option liquidity beta. Portfolio returns for month *t* are calculated with either equal-weighting or contract-weighting. Meanwhile, the corresponding portfolio-level loadings are also calculated (with either equal-weighting or contract-weighting) and they are taken as the predicted liquidity betas for month *t*. The following cross-section regression is then run over the 25 portfolios:

$$R^{excess}_{hed\&lev} = \gamma_0 + \gamma_1\beta_1 + \gamma_2\beta_2 + \gamma_3\beta_3 + \gamma_4\beta_4 + \gamma_5\beta_5 + \gamma_6\beta_6 + \gamma_7\beta_7 + e, \tag{2}$$

where $\beta_1, \beta_2, \beta_3, \ldots, \beta_7$ are estimated from the aforementioned first-pass regression via (1). The above cross-section regression is run for every month starting from January 2001. The average of each regression coefficient and its corresponding Newey–West adjusted *t*-value are calculated. Our interest is in γ_7, the premium per unit of liquidity risk. Table 6 reports the results with the same column headings as in Table 4. To save space, we only report results under LF_mean. Results under LF_median will be reported later in robustness checks.

As shown in the two lines headed by "$OPTION_{LF}$," the option liquidity risk premium is negative, consistent with the alphas in Table 4 (once again, we will postpone the discussions of the risk premium's negative sign to the end of this paper). All of the risk premium estimates are statistically significant, which is quite remarkable in that we have only 204 monthly observations (i.e., from January 2001 to December 2017). The *t*-values of the risk premium estimates in Pastor and Stambaugh (2003) are comparable to ours, but their sample period is from 1966 to 1999, with 408 monthly observations (please refer to their Table 7 for details). Throughout this paper, when assessing statistical significance, the smaller sample size should always be kept in mind.

prices (e.g., errors due to the use of bid-ask midpoints to proxy the actual transaction prices) lead to errors in not only option returns but also hedge ratios, the correlation between which can lead to errors in hedged returns of equally-weighted option portfolios. They propose two methods to correct the potential error: 1) constructing hedge ratios independent of option prices, and 2) replacing equal-weighting with return-weighting.

Table 4
Alpha of the High-Low Portfolio Based on Option Liquidity Beta.
This table presents the alpha of the high-low portfolio formed from 5 × 5 double sorts. Each month, we first sort all stocks into quintiles according to their last month's average implied volatility; we then sort each volatility group into sub-quintiles according to their option liquidity betas. Here, liquidity beta is the option return's sensitivity to the aggregate *liquidity* factor. It is estimated by regressing the leverage-adjusted, hedged returns (over and above the monthly risk-free rate) on the aggregate option liquidity factor, the corresponding traded liquidity factor for the stock market (denoted by $STOCK_{LF}$), the Fama-French four factors (viz. MKT, SMB, HML, UMD), and the market volatility factor (denoted by STRD) which is the monthly hedged return (over and above the monthly risk-free rate) of the S&P 500 index straddles. The five lowest-beta sub-quintiles and the five highest-beta sub-quintiles are grouped together, which we name as the lowest-beta portfolio and the highest-beta portfolio. The leverage-adjusted, hedged option return is then calculated for each portfolio with either equal-weighting or contract-weighting where "contract" is the logarithm of last month's total open interest. The return of the high-low portfolio is simply the return of the highest-beta portfolio minus the return of the lowest-beta portfolio. This sorting procedure is repeated every month to obtain a time-series of the high-low portfolio returns. Finally, the high-low portfolio return is regressed on the Fama-French four factors as well as $STOCK_{LF}$ and STRD. The reported alphas are already in percentage form. Two sets of estimates are presented under each weighting-factor combination: LF_mean and LF_median. The suffixes "mean" and "median" indicate how the option liquidity factor is aggregated in each month. Under LF_mean (LF_median), the aggregate liquidity factor is the mean (median) of the individual stocks' liquidity measure. The liquidity beta is estimated using a 60-month rolling window. Since our dataset starts in January 1996, the time-series of high-low portfolio returns commences in January 2001. *, **, and *** indicate significance at, respectively, the 10%, 5% and 1% levels.

Panel A: Equal-weighting

		LF: PS		LF: Amihud		LF: BidAsk	
		LF_mean	LF_median	LF_mean	LF_median	LF_mean	LF_median
ALPHA	**coeff.**	**−0.135****	**−0.099****	**−0.142*****	**−0.146*****	**−0.106****	**−0.131****
	***t*-value**	**−1.98**	**−2.28**	**−3.28**	**−3.56**	**−2.36**	**−2.49**
$STOCK_{LF}$	coeff.	0.13	−1.48*	−0.34	−0.10	0.57	0.55
	t-value	0.10	−1.92	−0.28	−0.09	0.56	0.58
STRD	coeff.	−0.44	−0.25	−0.37**	−0.37**	0.32**	0.20
	t-value	−1.39	−1.32	−2.40	−2.56	2.21	1.63
MKT	coeff.	0.62	−0.25	2.54*	2.80**	2.68**	2.37*
	t-value	0.46	−0.20	1.78	2.12	2.29	1.67
SMB	coeff.	0.24	2.55	−1.72	−1.69	0.76	0.06
	t-value	0.13	1.33	−0.78	−0.85	0.50	0.04
HML	coeff.	2.66	0.21	4.89*	4.18*	2.19	2.86
	t-value	1.30	0.12	1.95	1.88	0.99	1.28
UMD	coeff.	−0.97	−0.69	1.04	1.22	−0.22	−0.25
	t-value	−1.12	−0.71	0.87	1.22	−0.28	−0.25
Adj-R^2		5.8%	1.9%	9.6%	10.1%	3.4%	1.7%

Panel B: Contract-weighting

		LF: PS		LF: Amihud		LF: BidAsk	
		LF_mean	LF_median	LF_mean	LF_median	LF_mean	LF_median
ALPHA	**coeff.**	**−0.130***	**−0.085****	**−0.141*****	**−0.143*****	**−0.096****	**−0.114****
	***t*-value**	**−1.91**	**−1.96**	**−3.17**	**−3.43**	**−2.12**	**−2.19**
$STOCK_{LF}$	coeff.	0.41	−1.80**	−0.56	−0.28	0.60	0.71
	t-value	0.33	−2.40	−0.48	−0.25	0.55	0.72
STRD	coeff.	−0.42	−0.21	−0.41***	−0.41***	0.32**	0.20*
	t-value	−1.26	−1.08	−2.73	−2.98	2.12	1.77
MKT	coeff.	0.50	−0.34	3.17**	3.26**	3.05***	2.66*
	t-value	0.40	−0.26	2.14	2.35	2.74	1.92
SMB	coeff.	0.19	2.14	−1.75	−1.74	0.69	0.00
	t-value	0.11	1.14	−0.80	−0.88	0.45	0.00
HML	coeff.	2.80	0.18	4.19	3.54	1.94	2.87
	t-value	1.35	0.10	1.68*	1.61	0.84	1.24
UMD	coeff.	−1.21	−0.86	1.08	1.30	−0.18	−0.34
	t-value	−1.32	−0.77	0.86	1.23	−0.25	−0.39
Adj-R^2		5.7%	1.4%	11.0%	11.7%	3.7%	2.4%

The premium in option returns due to the stock market liquidity risk is indistinguishable from zero statistically, again implying that the option market possesses its own liquidity risk dynamics after we remove the direct influence from the stock market via hedged returns. The HML factor seems to command a negative, albeit statistically weak, risk premium in option returns. The MKT and SMB factors, and the momentum factor UMD do not command a risk premium.

The magnitude of the coefficient itself (e.g., −1.649 under equal-weighing) is meaningless since the liquidity measures are in arbitrary units. What is meaningful is the contribution of the product of the coefficient and the liquidity beta. To this end, we follow Pastor and Stambaugh (2003) and calculate the spread in option returns between the high-beta and low-beta portfolios. In other words, in each month, we calculate the value of $\gamma_7(\beta_7^H - \beta_7^L)$, where β_7^H and β_7^L are, respectively, the average betas for the highest-beta portfolio and the lowest-beta portfolio constructed in the same way as in Table 4. The average of the time-series of $\gamma_7(\beta_7^H - \beta_7^L)$ is then the estimate of the contribution of option liquidity risk premium to the return spread between the two extreme-beta portfolios. It turns out that, at the 5% or 1% significance level, this quantity ranges from −0.159% (for the case of LF_median, contract-weighting, PS measure) to −0.477% (for the case of LF_mean, contract-weighting, Amihud measure). Evidently, the magnitude is much larger than that of the alphas in Table 4. The reasons are actually quite simple, as we discuss below.

In alpha calculations, the option liquidity betas only serve the purpose of sorting and their magnitude is irrelevant once the quintile membership is assigned. In contrast, in the risk premium estimations and calculations, the option liquidity betas play a central role. They not only serve the purpose of sorting, but also serve as the raw ingredients of the explanatory variable (i.e., be-

Table 5
Alphas for Individual Sorting Portfolios and the High-Low Portfolio.
This table presents the alphas for the high-low portfolio as well as the individual sorting portfolios, all sorted by option liquidity beta only. For brevity, we only report the results for the Amihud liquidity measure and for the case of LF_mean and equal-weighting in portfolio return calculations. Please see Table 4 for related definitions and descriptions. Panel A corresponds to the results in Table 4. In other words, the five portfolios shown in Panel A are averaged from the corresponding portfolios in each of the second sort by liquidity beta (the first sort is by implied volatility). For instance, portfolio 3 is the average of the five 3rd quintiles (from sorting by liquidity beta), each in turn coming from a quintile sorted by implied volatility. The sorts in Panels B through E are for comparison purposes. The alphas in Panel B result from a single quintile sort. Likewise, those in Panel C result from a single decile sort, and we report deciles 1, 3, 5, 8, and 10, roughly corresponding to quintiles 1, 2, 3, 4, and 5 in the quintile sorting. Panels D and E follow the same logic, except that they are for 25 and 30 portfolios. *, **, and *** indicate significance at, respectively, the 10%, 5% and 1% levels.

	A. Double-sort (5 × 5)					
	low(1)	2	3	4	high(5)	high-low
Alpha	0.458***	0.337**	0.296**	0.275**	0.315***	−0.142***
t-value	3.96	2.46	2.30	2.37	2.96	−3.28
	B. Single sort - quntiles					
	low(1)	2	3	4	high(5)	high-low
Alpha	0.401***	0.353***	0.282**	0.241**	0.299***	−0.103*
t-value	3.14	2.61	2.16	2.21	2.92	−1.85
	C. Single sort - deciles					
	low(1)	3	5	8	high(10)	high-low
Alpha	0.425***	0.384***	0.300**	0.249**	0.313***	−0.113*
t-value	3.16	2.60	2.19	2.31	2.96	−1.78
	D. Single sort - 25 portfolios					
	low(1)	7	13	19	high(25)	high-low
Alpha	0.495***	0.414***	0.287**	0.200*	0.305***	−0.191**
t-value	3.63	2.90	2.24	1.91	2.68	−2.21
	E. Single sort - 30 portfolios					
	low(1)	8	15	22	high(30)	high-low
Alpha	0.465***	0.423**	0.319**	0.313***	0.301***	−0.164**
t-value	3.58	2.56	2.54	2.83	2.68	−1.94

Table 6
Option Liquidity Risk Premium.
This table presents the risk premium of option liquidity beta. The specific estimation procedure is as follows. To begin, the option liquidity beta is estimated for each stock on a 60-month rolling-window basis. Here, liquidity beta is the option return's sensitivity to the aggregate *liquidity* factor. It is estimated by regressing the stock's leverage-adjusted, hedged returns (over and above the monthly risk-free rate) on the aggregate option liquidity factor, the corresponding traded liquidity factor for the stock market (denoted by $STOCK_{LF}$), the Fama-French four factors (viz. MKT, SMB, HML, UMD), and the market volatility factor (denoted by STRD) which is the monthly hedged return (over and above the monthly risk-free rate) of the S&P 500 index straddles. Please see the text for details. Starting in January 2001 (note: the dataset starts in January 1996), 25 portfolios are formed each month by double-sorting the stocks on their last month's average implied volatility (quintiles) and their option liquidity beta (quintiles). The leverage-adjusted, hedged option return is then calculated for each of the 25 portfolios using either equal-weighting or contract-weighting where "contract" is the logarithm of last month's total open interest. The portfolio's option liquidity beta, stock liquidity beta, the four Fama-French factor loadings, and the loading of the market volatility factor are also calculated by equal-weighting or contract-weighting its constituent stocks' betas and loadings. This procedure is repeated for every month until the end of the sample period (i.e., December 2017), resulting in a time-series of portfolio returns and loadings. Fama-MacBeth regressions are then run whereby portfolio returns are cross-sectionally regressed on the loadings, and the coefficients are averaged with corresponding Newey-West adjusted *t*-values. As in Table 4, two sets of estimates are obtained under each weighting-factor combination: LF_mean and LF_median. The suffixes "mean" and "median" indicate how the option liquidity factor is aggregated in each month. Under LF_mean (LF_median), the aggregate liquidity factor is the mean (median) of the individual stocks' liquidity measure. For brevity, the table only presents the results under LF_mean. Results under LF_median will be reported in robustness checks. Each of the original regression coefficient is multiplied by 10,000 for ease of presentation. *, **, and *** indicate significance at, respectively, the 10%, 5% and 1% levels.

		Equal-weighting			Contract-weighting		
		LF: PS	LF: Amihud	LF: BidAsk	LF: PS	LF: Amihud	LF: BidAsk
$OPTION_{LF}$	**coeff.**	**−0.158****	**−1.649*****	**−1.118****	**−0.145***	**−1.791*****	**−1.039****
	***t*-value**	**−1.98**	**−2.58**	**−2.54**	**−1.90**	**−2.75**	**−2.52**
$STOCK_{LF}$	coeff.	5.42	79.80	5.93	−5.95	83.94	−12.22
	t-value	0.12	1.20	0.12	−0.14	1.22	−0.24
STRD	coeff.	−115.11	337.17	−462.33	−176.21	361.80	−449.67
	t-value	−0.43	0.93	−1.56	−0.66	0.98	−1.57
MKT	coeff.	−42.14	45.15	−31.25	−21.82	58.26	8.73
	t-value	−0.81	0.86	−0.58	−0.39	1.11	0.17
SMB	coeff.	5.49	28.17	−0.83	5.51	26.78	20.43
	t-value	0.15	0.91	−0.02	0.15	0.89	0.48
HML	coeff.	−61.89*	−53.89	−71.72**	−55.24	−60.60	−79.04**
	t-value	−1.72	−1.55	−2.27	−1.43	−1.61	−2.38
UMD	coeff.	48.30	−1.65	−4.47	18.83	−11.62	−13.02
	t-value	0.95	−0.03	−0.10	0.35	−0.22	−0.27
Adj-R^2		25.1%	26.2%	26.8%	27.8%	28.0%	29.3%

Table 7
Impact of the Market Volatility Factor.
This table presents abridged results from alternative analyses of Tables 4 and 6. We repeat the alpha analysis in Table 4 and the risk premium analysis in Table 6 by omitting the market volatility factor STRD. All procedures are otherwise identical to those in Tables 4 and 6. For brevity, we only report results for LF_mean under equal-weighting. Please refer to Tables 4 and 6 for detailed procedures and the definition of LF_mean and equal-weighting. The reported alphas are already in percentage form, and each of the original regression coefficient in the risk premium analysis is multiplied by 10,000 for ease of presentation. *, **, and *** indicate significance at, respectively, the 10%, 5% and 1% levels.

		Alpha			Risk premium		
		LF: PS	LF: Amihud	LF: BidAsk	LF: PS	LF: Amihud	LF: BidAsk
ALPHA/	**coeff.**	**−0.113***	**−0.095***	**−0.153****	**−0.286*****	**−1.262****	**−0.927****
RISK PREM.	***t*-value**	**−1.66**	**−1.65**	**−2.35**	**−3.07**	**−2.26**	**−2.10**
$STOCK_{LF}$	coeff.	0.80	−0.06	0.22	6.24	−63.33	−22.19
	t-value	0.41	−0.04	0.22	0.19	−1.28	−0.45
MKT	coeff.	4.79*	7.46***	4.86*	−8.01	34.43	12.35
	t-value	1.78	3.42	1.94	−0.15	0.59	0.21
SMB	coeff.	−1.67	−2.37	−0.39	30.25	6.11	22.58
	t-value	−0.86	−1.06	−0.24	0.81	0.15	0.55
HML	coeff.	4.13*	6.24**	4.26	−121.11***	−105.51***	−76.42**
	t-value	1.88	2.47	1.36	−3.31	−2.71	−2.07
UMD	coeff.	−0.33	0.93	0.29	113.06**	72.22	−11.34
	t-value	−0.42	0.79	0.37	2.41	1.30	−0.21
Adj-R^2		9.4%	17.7%	7.2%	23.5%	23.2%	25.0%

ing used to calculate the average beta of each sub-quintile) in the Fama-MacBeth cross-section regression. Outlier betas can potentially skew the average beta of a sub-quintile. However, as long as the outliers are more or less matched at both ends of the spectrum, they may cancel each other in the average, which means the estimation of the risk premium coefficient in the cross-section regression is not too much affected by the beta outliers after all. What really matters is how we calculate the actual risk premium using the beta difference between the highest-beta portfolio and lowest-beta portfolio. The product $\gamma_7(\beta_7^H - \beta_7^L)$ heavily depends on $(\beta_7^H - \beta_7^L)$, which is under the influence of outlier betas. More specifically, the outliers will exaggerate the true magnitude of $(\beta_7^H - \beta_7^L)$, resulting in $\gamma_7(\beta_7^H - \beta_7^L)$ being larger in magnitude than the corresponding alpha estimate. It should be noted that our key objective is to establish the existence, as opposed to the precise estimation, of liquidity risk premium in option returns. In that sense, the statistical significance of the $OPTION_{LF}$ coefficient in Table 6 already meets the objective. Should one wish to speak of the magnitude of liquidity risk premium in option returns, the alphas would better suit the purpose since they are not subject to the potential estimation error in γ_7 and are free of the influence of liquidity beta outliers. On that note, to recap Table 4, the liquidity risk premium ranges from 8.5 basis points to 14.6 basis points per month. It should be kept in mind that the risk premium resides in the leverage-adjusted, hedged option returns. As seen later, the risk premium is much larger in hedged returns unadjusted for leverage.

Before closing this section, it is instructive to examine the impact of the market volatility factor on the liquidity risk premium estimation. To this end, we repeat the analysis in Tables 4 and 6 without the market volatility factor. In other words, we omit the *STRD* factor in regressions (1) and (2) but otherwise follow exactly the same procedures as before. Table 7 reports the results. For brevity, we only report the alpha (i.e., sorting analysis) and Fama-MacBeth regression results for the combination of LF_mean as the aggregate liquidity measure and equal-weighting at the portfolio level. Interestingly, the presence of the market volatility factor not only preserves the statistical significance of the alpha and risk premium coefficient estimates, it actually enhances the significance. Other than the risk premium estimate under the PS measure, the *t*-value for all other estimates actually increases in magnitude when the market volatility factor is present. This means the market volatility factor helps sharpen the relationship between option returns and the aggregate liquidity risk.

4. Robustness checks and auxiliary tests

Through sorting analyses and Fama-MacBeth regressions in the previous section, we have established the existence of a negative liquidity risk premium in the leverage-adjusted, hedged option returns. In this section, we perform robustness checks and some additional tests. The auxiliary tests proceed along the following avenues: 1) subsample analysis around the 2007-08 financial crisis, 2) liquidity risk premium in disaggregated returns (i.e., stratification along the dimensions of option type (calls vs. puts), maturity, and moneyness), 3) liquidity risk premium in hedged returns, 4) controlling for firm characteristics, 5) comparing the liquidity level effect and the risk effect, and 6) risk premium persistence. We place the tests in 4), 5) and 6) and the associated discussions in an internet appendix for two reasons: 1) these tests are somewhat unconventional with respect to typical asset pricing studies, and 2) to conserve space in the regular text.

4.1. Robustness checks

Table 6 presents results under the combination of LF_mean (i.e., using the cross-section mean as the measure of aggregate liquidity) and equal-weighting (i.e., aggregating the contract-level liquidity to the daily level using equal-weighting). We therefore need to check the robustness of each. Since we also need to examine the robustness of other aspects of the liquidity factor construction, for brevity, we report all robustness results under LF_median.

Our first robustness check involves relaxing the moneyness screening criterion in the construction of the aggregate liquidity factors. Instead of screening out contracts with moneyness outside the range between 0.45 and 0.55 in the absolute value of delta (for the PS measure, the range is between 0.4 and 0.6), we now remove this restriction to allow more in-the-money and more out-of-the-money options to exert their influence in the construction of aggregate liquidity factors. The left portion in Table A1 (in the appendix) reports the results under equal-weighting for portfolio construction (Panel A) and contract-weighting (Panel B). Several observations are in order. First, for the aggregate liquidity factor Amihud, the risk premium remains significant in that the *t*-value is −2.65 under equal-weighting and −2.62 under contract-weighting, compared with the previous −2.58 and −2.75. Second, for the aggregate liquidity factor PS, the risk premium estimate becomes more significant, with the *t*-value going from −1.98 and −1.90 to −2.78 and −2.25 respectively. In this case, expanding the moneyness range helps improve the precision of the risk premium estimation since more contract series now have enough observations for us to run the time-series regression within each month to estimate PS. Third, for the BidAsk measure, removing the moneyness screen renders the risk premium estimate insignificant (the t-value is –0.87 or –0.80) whereas if we maintain the moneyness screen but only change LF_mean to LF_median, the risk premium would still be significant, with a t-value of –2.30 or –2.41, comparable to the LF_mean case t-value of –2.54 or –2.52. The loss of estimation power is mostly due to the noise in the BidAsk measure coming from deep out-of-the-money options. To illustrate, suppose an option has a bid of \$0.05 and an ask of \$0.10. Then the BidAsk is $(0.10 - 0.05)/(0.05 + 0.10)/2 = 66.67\%$, a lofty spread for an otherwise trivial option with a mid-quote of only \$0.075. In contrast, the Amihud and PS measures are less affected by wider spreads since we use mid-quotes to calculate returns. At any rate, putting BidAsk aside, widening the moneyness range either doesn't materially affect the risk premium estimate (in the case of Amihud) or actually improves the estimation of liquidity risk premium (in the case of PS).

Our second robustness check also has to do with the construction of the aggregate liquidity factors. As described in Section 2, in the construction of the aggregate liquidity factors, the contract-level liquidity measures are averaged within the day with equal-weighting to arrive at a stock-day liquidity measure. In this robustness check, we use dollar-weighting – the contract-level liquidity measures are averaged within the day with log(1+dollar trading volume) being the weight. All other procedures remain the same, including the original moneyness screening criterion. While equal-weighting allows less liquid contracts to equally influence the aggregate liquidity factor, the dollar-weighting scheme allows more liquid contracts – mostly at-the-money options with large trading volumes – to dominate the aggregate liquidity factor.

The right portion of Table A1 contains the results. Comparing the results against those in Table 6, we see that the risk premium estimation under the BidAsk measure is largely unaffected.[12] Under the PS measure, the significance of the liquidity risk premium strengthens, with its t-value changing from –1.98 and –1.90 to –2.77 and –2.43. The reason for the improvement under the PS liquidity measure is two-fold: 1) more liquid options afford more accurate PS estimates, and 2) using the cross-section median to gauge the aggregate liquidity avoids the influence of PS outliers. As for the Amihud measure, dollar-weighting slightly weakens the significance of the estimate of the liquidity risk premium, with a t-value of –2.02 or –2.14 compared with the previous –2.58 or –2.75. In fact, a moment of reflection leads to an interesting realization: dollar-weighting the Amihud measure is not a valid exercise after all. The Amihud measure is the absolute leverage-adjusted, hedged return divided by log(1+dollar trading volume). In other words, Amihud measures the extent to which one dollar worth of trade (in logarithmic form) can move the return. It is already a per-dollar measure. Weighting Amihud by log(1+dollar trading volume) amounts to removing the trading volume dimension, leaving us with absolute returns only. In any event, when we retain equal-weighting but use the cross-section median to approximate the aggregate liquidity, the liquidity risk premium remain significant at the 5% (with a t-value of –2.13 or –2.12).

In a nutshell, our results remain largely robust under alternative constructions of the aggregate liquidity factors. We have performed some additional checks on the construction of the aggregate liquidity factors and our results also remain robust. For instance, all of our results so far are based on option returns aggregated at the contract level using equal-weighting. Dollar-weighting (where "dollar" is the midpoint of bid and ask quotes times the trading volume) leads to similar results. Moreover, when calculating the portfolio-level returns and factor loadings with contract-weighting, our base case uses the logarithm of last month's open interest as the weight. In the robustness checks, we have replaced the weight by 1) the logarithm of one plus last month's dollar value of open interest, 2) the current month's counterparts of the two versions, and 3) the current month open interest itself. The results remain the same qualitatively. For brevity, results of the above additional checks are omitted in the table.

Our last robustness check is on the formation of testing portfolios: the 5 × 5 double sort. Following the seminal study of Fama and French (1993), many researchers have used double-sort to form asset portfolios when examining alphas. Arguably, the double-sort has at least two advantages: 1) achieving a potentially wider dispersion, and 2) including more assets in the high-minus-low portfolio (e.g., in a 5 × 5 sort, 40% of the assets will enter into calculations, whereas the high-minus-low portfolio will involve only 8% of the assets if we single-sort the asset universe into 25 portfolios). Our choice of the 5 × 5 double sort is guided by the above thinking and convention.

To see how other asset portfolios work, we repeat the alpha and risk premium analysis with four separate univariate sorts on: 1) last month liquidity beta, 2) last month firm size, 3) liquidity level of the past 12 months (which is the average of the monthly liquidity measure), and 4) volatility of the liquidity level in the past 12 months (which is the standard deviation of the monthly liquidity measure in the past 12 months). The last three choices are motivated by the study of Acharya and Pedersen (2005). We investigate two scenarios of each single sort, one with 25 portfolios, and one with 30 portfolios. Table 8 contains the results.

With 25 portfolios formed according to liquidity beta, we achieve statistical significance for five of the six cases shown in the table. Sorting into 30 portfolios doesn't always improve the significance. In fact, most of the t-values weaken slightly. The net effect of increasing the number of portfolios is due to a trade-off. On one hand, more portfolios help increase the dispersion in returns; on the other hand, more portfolios also mean fewer stocks in each portfolio, increasing the noise in average returns. Regardless, by and large, the significance levels are comparable to those in Tables 4 and 6.

Moving on to the sorting by firm size, again, more portfolios (i.e., 30) don't improve the results, and some of the risk premium estimates are insignificant. When sorting along the liquidity level, more portfolios do help (turning insignificance to significance in two cases), but once again, we fail to achieve uniform significance in all cases. Additionally, it is apparent that more occasions of significance are present with alphas than with the risk premium estimates. This is not a coincidence. To obtain a significant risk premium estimate, it is not enough for the two extreme portfolios to be significantly different. Instead, a wider dispersion among all portfolios is required.

The most interesting and important results are in Panel D where the liquidity volatility is used for sorting. Here, statistical significance is uniformly achieved for all cases, and the t-values are much larger in magnitude than their counterparts in Tables 4 and 6. This is important in that the results of our 5 × 5 double sort are not the strongest among possible portfolio formations. In other words, the main results presented in our paper are not selected because they are the most favorable. Stronger evidence for liquidity risk premium does exist with alternative asset portfolio formations.

The upshot of the alternative portfolio-formation analysis is the following. Notwithstanding the lack of a uniform significance in

[12] It should be noted that the dollar-weighting has implicitly introduced another change in the construction of the aggregate liquidity factor BidAsk. In the base case, we include zero-volume quotes in the BidAsk measure. Dollar-weighting automatically excludes zero-volume quotes. In this sense, it is comforting to know that our results don't depend on zero-volume quotes.

Table 8
Robustness Checks – Alternative Sorting Portfolios.
This table also presents results of robustness checks. The estimation procedures are identical to those in Tables 4 and 6, except that, instead of a 5 × 5 double sort, we now use alternative sorting procedures to form testing portfolios. Specifically, we present the alpha and risk premium estimates for portfolios resulting from a single sort on 1) last month liquidity beta, 2) last month firm size, 3) liquidity level of the past 12 months (i.e., average of the monthly liquidity measure), 4) volatility of the liquidity level in the past 12 months (i.e., standard deviation of the monthly liquidity measure in the past 12 months). Under each univariate sort, we report two sets of results: 25 portfolios and 30 portfolios. The alpha is always for the high minus low portfolio. Please consult Tables 4 and 6 for other descriptions and explanations. For brevity, we only report results for the LF_mean aggregate liquidity factor construction and equal-weighting option portfolios as in Table 7. For brevity, we also omit the coefficients of all other factors. *, **, and *** indicate significance at, respectively, the 10%, 5% and 1% levels.

		Alpha			Risk premium		
		LF: PS	LF: Amihud	LF: BidAsk	LF: PS	LF: Amihud	LF: BidAsk
		Panel A: Sorting on liquidity beta					
25 porfolios	coeff.	−0.222**	−0.191**	−0.238***	−0.195**	−0.707	−0.998***
	t-value	−2.45	−2.21	−2.88	−2.39	−1.07	−2.82
30 porfolios	coeff.	−0.206**	−0.164*	−0.218**	−0.202***	−0.872	−0.922**
	t-value	−2.00	−1.94	−2.23	−2.71	−1.41	−2.54
		Panel B: Sorting on firm size					
25 porfolios	coeff.	−0.312***	−0.279***	−0.278***	−0.394	−2.943**	−1.565
	t-value	−3.36	−3.10	−2.92	−1.39	−2.13	−1.10
30 porfolios	coeff.	−0.169*	−0.152*	−0.153*	−0.440*	−2.796**	−1.146
	t-value	−1.82	−1.65	−1.67	−1.80	−2.18	−0.92
		Panel C: Sorting on liquidity level of the past 12 months					
25 porfolios	coeff.	0.081	−0.386***	−0.450***	−0.087	−2.432	−5.458***
	t-value	0.92	−3.15	−3.07	−0.41	−1.57	−3.50
30 porfolios	coeff.	−0.327**	−0.423***	−0.477***	−0.211	−2.532*	−6.516***
	t-value	−2.45	−3.02	−3.76	−0.99	−1.93	−4.39
		Panel D: Sorting on volatility of liquidity level in the past 12 months					
25 porfolios	coeff.	0.297***	0.613***	0.455***	−0.573*	−5.130***	−4.417***
	t-value	3.65	5.05	4.18	−1.94	−4.47	−3.50
30 porfolios	coeff.	0.217***	0.469***	0.322***	−0.535**	−4.739***	−3.683***
	t-value	2.98	5.17	4.18	−2.24	−3.98	−3.64

the alpha and risk premium estimates, all alternative sorts produce consistent evidence of liquidity risk premium. With some asset portfolios (e.g., formed according to liquidity volatility), uniform significance at very high levels can be achieved, strongly validating the existence of a liquidity risk premium.

Incidentally, some remarks are in order concerning the sign of alphas. To begin, the negative sign under liquidity beta sorting is clearly consistent with the negative risk premium. The negative sign in Panels B and C indicates that, larger firms or higher option liquidity tend to be associated with a higher liquidity beta (which, in the presence of a negative risk premium, leads to a lower return). By the same token, the positive alphas in Panel D indicate that a higher liquidity volatility is associated with a lower liquidity beta. The above observations are consistent with Pastor and Stambaugh (2003) who observe and explain why more liquid stocks tend to have a higher liquidity beta. In our case, options of larger firms and lower liquidity volatility are generally more liquid and, as a result, tend to have a higher liquidity beta. To verify the above, we sort the option liquidity betas on firm size, liquidity level and some other firm characteristics. As an illustration, Panel B of Table 9 presents results for the Amihud measure, which confirm the aforementioned patterns in liquidity betas vis-à-vis firm size and liquidity level. Large firms are associated with larger betas, just as stocks with low stock and option illiquidity (i.e., high liquidity) and low liquidity volatility. Moreover, lower idiosyncratic volatility and turnover are also associated with higher liquidity betas. To have a sense of the general cross-section dispersion of liquidity betas, we also report in Panel A the pre- and post-ranking decile betas (please see the table notes for details). Since the correlation between the liquidity beta and each firm/stock characteristic is far from being perfect, the beta dispersion in Panel B is far narrower than the true dispersion in Panel A for both pre-ranking and post-ranking betas.

For completeness, we have also investigated whether and how the above stock characteristics are associated with high and low liquidity betas. In this investigation, we sort stocks into deciles according to option liquidity betas and then calculate the stock characteristics for each decile. Panel C presents the results. It turns out that the relationship between a particular stock characteristic and liquidity beta is rarely monotonic. In most cases, we observe a U-shaped or L-shaped (or the reverse of each) relationship. For instance, modest liquidity betas are associated with large firms whereas very low or very high liquidity betas are associated with small firms,

4.2. Crisis period versus non-crisis period

It is well known that liquidity generally deteriorates during market turmoil. Fig. 1 demonstrates the dramatic drop in liquidity during the 2007–2009 financial crisis. Christoffersen et al. (2018) have noted the same in their paper. Some researchers have examined whether liquidity affects asset prices more in the crisis period than in the non-crisis period, and the answer is generally affirmative. For instance, Friewald et al. (2012) find that the liquidity effects are far more pronounced in corporate bonds during the crisis period, especially for the more risky, high-yield bonds. In our study, it is of interest to know whether the liquidity risk premium in option returns also heightens during the financial crisis. To this end, we repeat the analysis in Tables 4 and 6 for two subsamples: the crisis period of January 2007 to December 2009, and the non-crisis period which is from January 2001 to December 2017 excluding the crisis period (the period from January 1996 to December 2000 is used to generate the initial liquidity betas on a rolling-window basis). The definition of the financial crisis period varies in the literature. In our case, to ensure a minimum number of observations for

Table 9

Liquidity Betas and Stock Characteristics.

This table presents, using the Amihud measure based on LF_mean as an illustration, the dispersion of option liquidity betas and stock characteristics sorted on liquidity betas. Panel A shows the standardized, pre- and post-ranking decile betas. Each month, the betas within each decile are averaged to obtain a time-series of decile betas. This time-series is further averaged to obtain the entries in the panel. Since the magnitude of the liquidity beta is arbitrary given the arbitrary unit of the liquidity factor, we first standardize the betas by subtracting the monthly mean and dividing by the cross-section standard deviation. Pre-ranking betas are estimated for month t as in Tables 4 and 5, whereas post-ranking ones are betas for month $(t+1)$ assuming the month t rank. Panel B presents the standardized betas sorted on various firm characteristics: the option and stock illiquidity and their standard deviations calculated using the past 12-month observations (we retain the original sign so that Amihud measures illiquidity), firm size, book-to-market ratio, idiosyncratic volatility calculated using daily returns in the past 12 months, the O/S ratio (Roll, Schwartz, and Subrahmanyam, 2010) which is the option volume (in number of options) divided by the stock trading volume (in number of shares), and stock turnover. Panel C presents stock characteristics sorted on option liquidity betas. Each month, all stocks are sorted into deciles according to their liquidity betas, and the average of each stock characteristic is then calculated for each decile. The panel shows the average of the time-series of each decile. Since the unit of the illiquidity measure is arbitrary, the entries associated with illiquidity are scaled for ease of exposition.

	Panel A: Dispersion of standardized liquidity beta									
Deciles of liquidity beta	1 (low)	2	3	4	5	6	7	8	9	high (10)
Pre-ranking beta	−1.935	−0.923	−0.537	−0.262	−0.035	0.169	0.375	0.602	0.904	1.642
Post-ranking beta	−1.917	−0.951	−0.551	−0.275	−0.039	0.173	0.391	0.624	0.933	1.611
	Panel B: Standardized liquidity betas sorted on firm characteristic									
Deciles of firm characteristic	1 (low)	2	3	4	5	6	7	8	9	high (10)
Option Amihud	0.215	0.168	0.115	0.075	0.063	0.009	−0.020	−0.094	−0.159	−0.206
STD of option Amihud	0.206	0.138	0.085	0.050	0.022	−0.021	−0.030	−0.042	−0.098	−0.148
Stock Amihud	0.157	0.105	0.088	0.032	0.005	−0.015	0.006	−0.053	−0.091	−0.208
STD of Stock Amihud	0.158	0.102	0.096	0.033	0.001	−0.008	−0.004	−0.047	−0.086	−0.218
Firm size	−0.197	−0.125	−0.027	−0.011	0.000	0.021	0.063	0.078	0.102	0.164
Book/market ratio	−0.056	0.018	0.013	0.010	0.002	0.010	0.000	0.023	−0.015	−0.090
Idiosyncratic volatility	0.223	0.171	0.144	0.091	0.047	−0.013	−0.053	−0.139	−0.235	−0.204
O/S	0.029	0.048	0.034	−0.027	−0.050	−0.047	−0.049	−0.008	0.023	0.103
Stock turnover	0.133	0.100	0.074	0.065	0.044	0.009	−0.046	−0.084	−0.131	−0.127
	Panel C: Firm characteristics sorted on liquidity beta									
Deciles of liquidity beta	1 (low)	2	3	4	5	6	7	8	9	high (10)
Option Amihud ($\times 10^4$)	12.302	10.338	9.229	8.579	8.148	7.933	7.981	8.310	9.033	11.060
STD of option Amihud ($\times 10^4$)	3.811	3.210	2.866	2.621	2.484	2.412	2.419	2.557	2.814	3.457
Stock Amihud ($\times 10^9$)	22.274	7.342	5.442	5.298	6.075	7.019	6.015	5.287	10.256	19.137
STD of stock Amihud ($\times 10^9$)	52.224	11.199	8.450	8.286	10.283	11.437	8.760	8.144	14.325	38.498
Firm size (in million $)	2,524	5,593	7,359	9,872	12,710	15,331	14,945	13,878	9,889	4,359
Book/market ratio	1.892	2.311	2.009	1.284	1.430	1.293	1.583	1.234	1.350	1.039
Idiosyncratic volatility	0.031	0.024	0.022	0.020	0.019	0.019	0.019	0.019	0.020	0.025
O/S	0.037	0.046	0.049	0.054	0.058	0.059	0.058	0.059	0.052	0.039
Stock turnover	0.018	0.019	0.019	0.020	0.018	0.018	0.020	0.021	0.018	0.016

statistical analysis, we choose to define the crisis period covering the entire three-year period, resulting in 36 monthly observations. Table 10 presents the results.

As far as alpha is concerned, the t-value under all three measures during the crisis period is larger in absolute value than its counterpart in the non-crisis period. This is remarkable in that we have far fewer observations in the crisis period. Therefore, by simply eyeballing the magnitude of alphas and their associated t-values, we can infer that the liquidity risk premium in option returns is much larger in the crisis period. This inference can be sharpened by a formal test of equality between two corresponding alphas. The null hypothesis is: The alphas are equal under each liquidity measure for the crisis and non-crisis periods. The alternative hypothesis is, e.g., under the PS measure, $-0.226 < -0.033$. As seen from the t-values of this test at the bottom of Panel A, the null is rejected only under the Amihud measure at the 10% significance level. The null cannot be rejected under the PS and BidAsk measures, even though the t-values are close to the 10% critical level.

Moving on to Panel B, we see that all three estimates of the risk premium in the non-crisis period are significant at the 5% level, an indication that our overall results are not driven by the crisis period. As for the magnitude of the estimates, although it appears much larger in the crisis period under the Amihud and BidAsk measures, the null hypothesis of equality cannot be rejected in either case.

Before drawing a broad conclusion about the impact of the crisis period on our analysis, we need to reconcile the seemingly opposite implications from the alpha and risk premium results: The former are more robust during the crisis period while the latter are more robust during the non-crisis period. To better understand the seemingly contradicting results, we need to realize the following. First, the testing power under the Fama-MacBeth procedure largely depends on the sample size or the number of observations when averaging the regression coefficients from the cross-section regressions. The standard error is inversely related to the square root of the number of observations. In our case, the crisis period has 36 observations while the non-crisis period has 168 (14×12) observations. Therefore, the lack of significance in the crisis period does not necessarily indicate the lack of robustness relative to the non-crisis period. Second, the testing power under the alpha analysis depends on the sample size as well as the linearity or overall trend of returns. If the returns do not display a simple linear ordering, then a shorter sample can help since it may capture a locally linear pattern which would boost the t-value. Therefore, the higher significance in the crisis period does not necessarily mean a stronger robustness relative to the non-crisis period.

How do we make a fair comparison then? A logical approach is to split the sample into halves, with one containing the crisis period. In our case, the precise midpoint of 01/2001–12/2017 is June/July 2009. To cover the entire crisis period in one subsample, we split the sample period into the following two roughly-equal halves: 01/2001–12/2009 and 01/2010–12/2017. We then repeat the analysis in Panels A and B and report the main results in Panel C.

Our conjecture is largely confirmed. For alphas, we lose one significance (BidAsk) in the sample containing the crisis, but gain one

Table 10
Alpha and Risk Premium in Crisis and Non-Crisis Periods.
This table presents abridged results from alternative analyses of Tables 4 and 6. We repeat the alpha analysis in Table 4 and the risk premium analysis in Table 6 by first separating the sample into two periods: crisis period of 01/2007–12/2009, and non-crisis period outside of 01/2007–12/2009. For the alpha analysis, the time-series regressions are run for the two separate periods; for the risk premium analysis, the coefficients from the first-pass Fama-MacBeth regressions are averaged within each of the two separate periods. All other procedures are otherwise identical to those in Tables 4 and 6. For brevity, we only report results for LF_mean under equal-weighting. Please refer to Tables 4 and 6 for detailed procedures and the definition of LF_mean and equal-weighting. The reported alphas are already in percentage form, and each of the original regression coefficient in the risk premium analysis is multiplied by 10,000 for ease of presentation. At the bottom of Panels A and B, we also report the *t*-value of the test of coefficient equality. Specifically, in Panel A, we test whether the alpha in the crisis period is smaller than its counterpart in the non-crisis period (e.g., −0.226 < −0.033); likewise, in Panel B, we test whether the risk premium estimate in the crisis period is smaller than its counterpart in the non-crisis period (e.g., −2.515 < −1.463). In Panel C, we repeat the analyses in Panels A and B by an alternative sample split and report the results for alphas and risk premium estimates. Specifically, we divide the entire period with liquidity beta estimates (viz. 01/2001–12/2017) into two roughly equal periods, with the former containing the crisis period. *, **, and *** indicate significance at, respectively, the 10%, 5% and 1% levels.

Panel A: Alpha

		Crisis period: 01/2007 - 12/2009			Period outside of crisis		
		LF: PS	LF: Amihud	LF: BidAsk	LF: PS	LF: Amihud	LF: BidAsk
Alpha	**coeff.**	**−0.226***	**−0.295*****	**−0.224****	**−0.033**	**−0.105****	**−0.063**
	***t*-value**	**−1.93**	**−2.89**	**−2.46**	**−0.76**	**−2.43**	**−1.22**
$STOCK_{LF}$	coeff.	3.04	−1.58	2.44	−1.57	1.29	0.89
	t-value	0.99	−0.58	0.91	−1.28	1.20	0.68
STRD	coeff.	−1.07***	−0.07	0.53**	0.29*	−0.46***	0.32
	t-value	−4.73	−0.25	2.25	1.87	−2.62	1.34
MKT	coeff.	1.87	6.20**	7.86***	0.28	0.55	0.82
	t-value	0.72	2.05	2.86	0.25	0.40	0.75
SMB	coeff.	8.22	7.07	1.84	0.21	−2.50	0.97
	t-value	1.18	1.07	0.42	0.12	−1.28	0.58
HML	coeff.	2.86	−1.56	2.12	2.34	1.76	0.76
	t-value	0.42	−0.25	0.35	1.08	0.68	0.32
UMD	coeff.	−1.65	−1.59	0.61	−0.22	3.86***	−0.16
	t-value	−0.91	−1.09	0.46	−0.23	3.44	−0.14
Adj-R^2		47.0%	25.0%	18.7%	0.6%	11.8%	−1.0%
Test of alpha equality	*t*-value	−1.64	−1.69*	−1.63			

Panel B: Risk premium

		Crisis period: 01/2007 - 12/2009			Period outside of crisis		
		LF: PS	LF: Amihud	LF: BidAsk	LF: PS	LF: Amihud	LF: BidAsk
$OPTION_{LF}$	**coeff.**	**−0.155**	**−2.515**	**−1.908***	**−0.159****	**−1.463****	**−0.949****
	***t*-value**	**−0.58**	**−1.42**	**−1.81**	**−2.06**	**−2.16**	**−1.98**
$STOCK_{LF}$	coeff.	−150.58	53.53	82.03	38.85	85.43	−10.38
	t-value	−1.40	0.37	0.81	0.83	1.16	−0.19
STRD	coeff.	−294.33	1843.6	524.13	−76.71	14.37	−673.71**
	t-value	−0.38	1.59	0.62	−0.28	0.04	−2.28
MKT	coeff.	−103.57	−149.82	−77.57	−28.97	86.92	−21.33
	t-value	−0.68	−1.16	−0.56	−0.54	1.59	−0.36
SMB	coeff.	−68.14	20.74	55.12	21.27	29.77	−12.82
	t-value	−1.00	0.26	0.62	0.50	0.90	−0.24
HML	coeff.	13.30	−50.52	−12.28	−78.00*	−54.61	−84.45**
	t-value	0.21	−0.74	−0.17	−1.93	−1.37	−2.41
UMD	coeff.	−232.92**	121.62	−219.20**	108.56**	−28.07	41.55
	t-value	−1.97	1.01	−2.42	2.15	−0.51	0.82
Adj-R^2		34.3%	38.0%	31.3%	23.2%	23.6%	25.8%
Test of risk prem. equality	*t*-value	0.02	−0.34	−0.84			

Panel C: Alpha and risk premium under alternative sample split

		01/2001 - 12/2009 (including crisis period)			01/2010 - 12/2017 (outside of crisis period)		
		LF: PS	LF: Amihud	LF: BidAsk	LF: PS	LF: Amihud	LF: BidAsk
Alpha	coeff.	−0.229**	−0.165***	−0.077	−0.016	−0.090*	−0.145**
	t-value	−2.45	−2.68	−1.15	−0.27	−1.67	−2.27
$OPTION_{LF}$	coeff.	−0.085	−1.323*	−0.972**	−0.240***	−2.016*	−1.283*
	t-value	−0.64	−1.86	−2.07	−3.09	−1.85	−1.66

significance in the half sample that excludes the crisis. For the risk premium estimates, as we shift more observations to the sample containing the crisis period, we gain one more significance (Amihud) in this period while the significance weakens in the other period, although all three estimates are still significant.

At a broad level, the statistical significance seems to be comparable between the two sub-periods. In fact, as far as the risk premium estimates are concerned, the results of the non-crisis period are still stronger (viz. three versus two occasions of significance). Therefore, the important upshot is: After controlling for the sample size, the results are not noticeably different between the sample that contains the crisis period and the sample that doesn't. In other words, we can say with a fair amount of confidence that our main results are not driven by the financial crisis period.

4.3. Liquidity risk premium in less-aggregated option returns

So far, our results are based on option returns aggregated to the stock-month level. We have lumped all options together and calculated a single option return for each stock within a particular month. While this aggregation allows us to utilize as many option observations as possible and reduce the potential impact of noises in contract returns, it might average away information at the same time. For instance, the aggregation might mask the potential dif-

Table 11
Alpha and Risk Premium Estimates for Disaggregated Option Returns.
This table presents the alpha and risk premium estimates for option returns disaggregated along the dimensions of call/put type (Panel B), moneyness (Panel C) and maturity (Panel D). The estimation procedure is the same as in Tables 4 and 6, except that the monthly leverage-adjusted, hedged returns are calculated separately for each specific bucket. In other words, the regressions in Tables 4 and 6 are re-run for the individual buckets. For instance, in Panel B, we use the same aggregate liquidity factors as in Tables 4 and 6, but the leverage-adjusted, hedged returns are only aggregated to the option-type level (as opposed to lumping call and put options together). The moneyness buckets in Panel C are defined according to the option's delta, δ. For calls, in-the-money (ITM): $\delta > 0.625$, at-the-money (ATM): $0.625 \geq \delta > 0.375$, out-of-the-money (OTM): $\delta \leq 0.375$. For puts, in-the-money (ITM): $\delta \leq -0.625$, at-the-money (ATM): $-0.375 \geq \delta > -0.625$, out-of-the-money (OTM): $\delta > -0.375$. The maturity buckets in Panel D are defined as: short (60 days or shorter), medium (61–180 days), and long (181 days or longer). Please see Tables 4 and 6 for other details of the estimation procedures. For brevity, we only report the coefficient and the *t*-value for the alpha or risk premium estimate, and do so for the case of LF_mean aggregate liquidity factor and the equal-weighted option portfolios. For ease of comparison, we extract the relevant results from Tables 4 and 6 for the fully aggregated case and present them in Panel A. *, **, and *** indicate significance at, respectively, the 10%, 5% and 1% levels.

		Alpha			Risk premium		
		LF: PS	LF: Amihud	LF: BidAsk	LF: PS	LF: Amihud	LF: BidAsk
		Panel A: Fully aggregated					
All	coeff.	−0.135**	−0.142***	−0.106**	−0.158**	−1.649***	−1.118**
	t-value	−1.98	−3.28	−2.36	−1.98	−2.58	−2.54
		Panel B: Call/put disaggregation					
Call	coeff.	−0.116***	−0.131***	−0.087**	−0.121*	−0.504	−0.628**
	t-value	−2.60	−3.60	−2.37	−1.73	−0.86	−2.18
Put	coeff.	−0.084	−0.070	−0.125***	0.047	−0.117	−0.198
	t-value	−1.25	−1.51	−3.23	0.49	−0.21	−0.54
		Panel C: Moneyness disaggregation					
ITM	coeff.	−0.057*	0.036	−0.034	0.011	0.033	−0.260
	t-value	−1.71	1.42	−1.43	0.24	0.11	−1.13
ATM	coeff.	−0.141**	−0.097***	−0.039	−0.008	−0.576	−0.495
	t-value	−2.01	−2.64	−0.92	−0.11	−1.10	−1.29
OTM	coeff.	−0.143	−0.130**	−0.058	−0.242**	−1.335	−1.092**
	t-value	−1.34	−2.01	−1.14	−2.40	−1.75	−2.02
		Panel D: Maturity disaggregation					
Short	coeff.	−0.176**	−0.118***	−0.127***	−0.129*	−0.771	−0.534
	t-value	−2.29	−2.76	−2.76	−1.65	−1.36	−1.43
Medium	coeff.	−0.077	−0.070*	0.014	−0.261***	−1.767***	−0.951***
	t-value	−1.05	−1.91	0.37	−3.50	−3.30	−2.89
Long	coeff.	−0.035	0.012	−0.030	−0.093	−1.637***	−0.481*
	t-value	−0.53	0.27	−0.63	−1.34	−3.55	−1.78

ference between call and put options in terms of how their returns react to the aggregate liquidity factor. A more important question is whether the alpha and risk premium estimates of the two types of options share the same sign. The same question can be asked about different maturity and moneyness buckets.

To shed light on this issue, we re-do the analysis in Tables 4 and 6 separately for subclasses of options, or for less-aggregated option returns. Specifically, we examine three dimensions of disaggregation: call/put option type, moneyness and maturity. We follow Christoffersen et al. (2018) and define the moneyness buckets by the option's delta, $\delta = \frac{\partial O}{\partial S}$. For call options, in-the-money (ITM): $\delta > 0.625$, at-the-money (ATM): $0.625 \geq \delta > 0.375$, out-of-the-money (OTM): $\delta \leq 0.375$. For put options, the buckets are defined analogously: in-the-money (ITM): $\delta \leq -0.625$, at-the-money (ATM): $-0.375 \geq \delta > -0.625$, out-of-the-money (OTM): $\delta > -0.375$. The maturity buckets are defined as: short (60 days or shorter), medium (61–180 days), and long (181 days or longer). Within each subclass or bucket, the contract-level option returns are averaged within each day and then compounded to the month. The subclass option returns are then used to repeat the analysis in Tables 4 and 6, with the original option liquidity factors (liquidity factors, by definition, are for the entire market).

In the previous analyses, for a stock to be included in the regressions, it must have at least 10 daily returns within the month, which might be from, e.g., either calls or puts, or both. In order to ensure comparability with the previous results, we still start with the 10-daily-return screen (where the daily returns result from grand aggregation) and then separate the sample into call/put, moneyness, and maturity buckets. To ensure reliability in the estimation, we then require that there must be at least 5 daily returns within each bucket. Requiring at least 10 daily returns in each bucket would lead to too small a sample for meaningful portfolio formation. Even with the screening criterion of 5 daily returns, we still end up with fewer stock-month observations. Table 11 presents the abbreviated results. There are several observations.

First and foremost, the statistically significant alpha and risk premium estimates are all negative among the various buckets, consistent with the results in the combined sample. This is reassuring in that the same sign of risk premium validates the amalgamation of call and put returns, and returns of different moneyness and maturity buckets.

Additionally, due to the loss of testing power resulting from the disaggregation, we do not achieve uniform significance across all buckets. In some cases, alphas are estimated with a higher statistical significance than their corresponding risk premiums (e.g., the short-term options); in some other cases, the opposite is true (e.g., the medium-term options). Generally though, we simply see a loss of testing power due to the smaller and noisier samples.

As for patterns among the subclasses of each dimension, only the call-put dichotomy leads to clearly noticeable differences: the alpha and risk premium estimates for call options enjoy a much higher statistical significance than put options. The weaker results for put options are mostly due to the smaller sample and presumably higher noises: the overall call/put ratio in our sample is 1.27. As for moneyness, the significance seems to progress from in-the-money to at-the-money to out-of-the-money, which makes intuitive sense since it is generally known in the literature (e.g. Wei and Zheng, 2010) that out-of-the-money options are less liquid than in-the-money options. Finally, in terms of maturity, short-

Table 12
Alpha and Option Liquidity Risk Premium Based on Hedged Returns.
This table is a combined version of Tables 4 and 6 with one important modification: The leverage-adjusted, hedged returns are replaced by hedged returns everywhere throughout the analysis. The option liquidity factors are also reconstructed using the hedged returns. Otherwise, the analysis follows exactly the same procedures as in Tables 4 and 6. As in Table 4, alphas are already in percentage form; as in Table 6, each of the original regression coefficient is multiplied by 10,000 for ease of presentation. For brevity, we only report results under LF_mean under equal-weighting. Results based on LF_median and dollar-weighting are similar. Please refer to Tables 4 and 6 for detailed procedures and the definition of.LF_mean, LF_median, equal-weighting and dollar-weighting. *, **, and *** indicate significance at, respectively, the 10%, 5% and 1% levels.

		Alpha			Risk premium		
		LF: PS	LF: Amihud	LF: BidAsk	LF: PS	LF: Amihud	LF: BidAsk
ALPHA/	**coeff.**	**−0.786**	**−1.851*****	**−1.659*****	**−0.732**	**−0.390**	**−0.177**
RISK PREM.	***t*-value**	**−1.45**	**−3.65**	**−2.91**	**−0.70**	**−0.08**	**−0.45**
$STOCK_{LF}$	coeff.	8.47	22.28**	11.58	51.92	138.30*	95.78*
	t-value	0.85	1.99	0.86	1.04	1.92	1.86
STRD	coeff.	−6.30*	−4.64**	3.89**	82.85	326.34	460.43*
	t-value	−1.91	−2.19	2.12	0.40	1.54	1.94
MKT	coeff.	−4.89	−4.55	27.73**	42.91	94.27**	12.35
	t-value	−0.37	−0.32	2.29	0.86	2.02	0.28
SMB	coeff.	−50.64***	6.97	18.60	−48.02	−20.88	−29.88
	t-value	−2.91	0.34	1.07	−1.37	−0.55	−0.90
HML	coeff.	14.22	48.07**	16.36	−104.19***	−169.72***	−97.74***
	t-value	0.87	2.25	0.65	−2.60	−4.25	−2.70
UMD	coeff.	4.77	−1.67	−4.85	−126.91**	7.53	−11.17
	t-value	0.65	−0.16	−0.66	−2.12	0.12	−0.19
Adj-R^2		9.4%	8.3%	3.1%	16.3%	20.1%	19.0%

term and medium-term options are comparable in that each subclass sees four out of six occasions of statistical significance. The significance is weaker for long-term options. We should refrain from interpreting this as evidence that liquidity risk premium is less important for long-term options. The weaker significance is most likely due to the lower testing power since we have fewer observations for thinly traded long-term options.

4.4. Liquidity risk premium in hedged returns

We have delineated the reasons for working with leverage-adjusted, hedged returns. However, it is useful to examine hedged returns for two reasons. First, the liquidity level effect in Christoffersen et al. (2018) is for hedged returns. For comparison purposes, it is instructive to also examine liquidity risk premium in hedged returns. Second, although leverage-adjusted, hedged returns are more suitable for asset pricing tests, they are not the kind of returns investors usually think about. In contrast, the concept of hedged returns is something most people are familiar with.

We re-do the analysis in Tables 4 and 6 based on hedged returns. We follow the same methodology and screening criteria as before. The only modification is to replace the leverage-adjusted, hedged returns by the hedged returns unadjusted for leverage. It should be noted that the aggregate liquidity factors under the PS and Amihud measures are also reconstructed using hedged returns. Table 12 reports the results based on LF_mean and equal-weighting at the quintile/portfolio level – those based on LF_median and contract-weighting are similar and are omitted for brevity.

To begin, the alphas are also negative and generally significant as in Table 4. However, the magnitude is multi-fold larger, with the smallest (in magnitude) being 0.786% per month and the largest being 1.851% per month. A monthly return of 0.786% corresponds to an annual return of 9.432% without compounding, and this is based on the smallest magnitude of alpha in Table 12. The magnitude of alpha is much smaller than that in Christoffersen et al. (2018) which is 3.4% for calls and 2.5% for puts per day. Nevertheless, one needs not be overly alarmed since the two types of premiums are not directly comparable. Christoffersen et al. (2018) measure the return premium due to the illiquidity level which directly depends on transaction costs such as the bid-ask spread, and the bid-ask spread is typically quite large for options (e.g., 13.4% as reported by Cao and Wei, 2010). In contrast, we measure the return premium due to the covariation risk in addition to the liquidity level effect. To obtain a rough idea about the relative magnitude of the two liquidity effects, we can divide the level-effect alpha in Panel F of Table 3 (9.335%) under the BidAsk measure by the corresponding risk-effect alpha in Table 12 (1.659%) to obtain a ratio of 5.6. This means the level effect is about six times the risk effect. Incidentally, 9.335% is much smaller than the number of trading days per month (e.g., 22) times the daily alpha in Christoffersen et al. (2018) mentioned above. Using the average of 3.4% and 2.5%, which is 2.95%, we obtain a ratio close to 3 (i.e., 9.335%/2.95% = 3.16). Insofar as the liquidity level effect captures the future expected transaction costs (Amihud and Mendelson, 1986), we may infer that investors trade options roughly three times per month. Admittedly, the difference between our monthly estimate and the daily estimate of Christoffersen et al. (2018) could also be due to other factors such as the sample scope (viz., member stocks of the S&P 500 index in their study versus the entire universe of the optioned stocks in our study) and how the bid-ask spread is measured (viz., they use intraday spreads while we use daily spreads).

The Fama-Macbeth regressions fail to produce a significant risk premium estimate for all three liquidity measures. The fact that alphas are significant but the risk premium coefficients are insignificant can be explained by the non-linearity in returns among the sub-quintiles. An examination of the average returns of the five portfolios (ranging from the lowest-beta portfolio to the highest-beta portfolio) reveals that the alpha is mostly contributed by the difference between the lowest-beta portfolio and the adjacent one. In other words, the returns of the four portfolios other than the lowest-beta one are similar to each other. The lack of return dispersion among most of the sub-quintile portfolios is the culprit for the absence of a significant coefficient estimate for the liquidity risk premium. Why, then, is the return dispersion low among most of the sub-quintile portfolios? The answer lies in the nature of option returns. Since the returns are not de-levered, extreme returns in each sub-quintile tend to overwhelm the rest, obscuring the true, nuanced difference in returns.

If we take the view delineated in Section 3.3 that alphas are more reliable in gauging the magnitude of liquidity risk premium, we can conclude that there is indeed a liquidity risk premium in hedged option returns. Additionally, the liquidity risk premium in hedged option returns is multi-fold larger than that in the leverage-adjusted, hedged returns.

Incidentally, the discussions in this section and in Section 3.3 underscore the supplementary nature of alphas and the risk premium estimates (from the Fama-MacBeth procedure) in asset pricing tests. When returns follow a linear pattern across assets/portfolios along the dimension of interest (e.g., ordering according to liquidity beta), the two analyses should lead to consistent results: The sign, the magnitude, and the statistical significance of the alpha and the risk premium from the Fama-MacBeth regression should agree with each other. When the returns are not linear along the ordering in question, we may obtain significant alphas but not risk premium coefficients, or vice versa. Table 12 is a case in point for the former. We may indeed also obtain significant risk premium coefficients, but not alphas. This can happen in, e.g., a situation where the nonlinearity in portfolio returns is such that the returns of the first $(n-1)$ portfolios are linear and increasing, but the return of the last portfolio n drops back to the level of the first portfolio. In this case, the risk-premium coefficient will be estimated with significance, but the alpha is zero. In most of the asset pricing studies (including the current one), the convention is to treat alphas as preliminary evidence of risk premium. Our insights here suggest that the alpha analysis and the Fama-MacBeth regression analysis are supplementary and equally useful.

5. Why is the liquidity risk premium negative?

As alluded to earlier, Christoffersen et al. (2018) find a positive illiquidity premium in hedged option returns, which we confirm under all of our three liquidity measures. The positive premium means that the expected returns on less liquid options are higher than those on more liquid options, and the premium is a compensation for illiquidity. Citing the empirical evidence that non-market-maker investors or end-users are option writers in net (e.g., Lakonishok et al., 2007; Garleanu et al., 2009), Christoffersen et al. (2018) rationalize their results by stating that market makers, who take a long position in net, demand the illiquidity premium.

We show that with the leverage-adjusted, hedged returns, the illiquidity premium or liquidity level effect only exists under the BidAsk measure; it is absent under the Amihud and the PS measures. However, a liquidity risk premium does exist under all three measures. More interesting is the fact that, in contrast to the positive liquidity risk premium found in, e.g., Pastor and Stambaugh (2003), Acharya and Pedersen (2005), and Lin et al. (2011), the liquidity risk premium we uncover in the option returns bears a negative sign. In other words, the higher the loading on the aggregate option liquidity factor, the lower the expected option return. This result would go against the conventional asset pricing wisdom if it were for assets in positive supply such as stocks and bonds. For assets in zero net supply such as options, the sign of the risk premium can indeed be either positive or negative, depending on who the marginal investors are and what influence they exert (e.g., Garleanu et al., 2009).

To our knowledge, there are only two studies in the literature that have direct bearings on the sign of liquidity premium in derivatives. Deuskar et al. (2011) show that illiquid interest rate caps and floors trade at higher prices. They rationalize their finding by noting the asymmetric hedging ability and need of the short and long parties of the same contract. Their focus is on the level effect of liquidity and therefore cannot shed direct light on our findings. The most relevant study is by Bongaerts et al. (2011) who show that, under certain conditions, a liquidity risk covariation for zero-net-supply assets can indeed command a negative risk premium. They extend the equilibrium model of Acharya and Petersen (2005) by introducing short-selling of the so-called hedge assets (e.g., derivatives) and agents' need to hedge a nontraded risk (e.g., credit risk). They show that when some agents optimally hedge their positive exposure to the nontraded risk, the covariation between the hedge asset's liquidity and the return on the nontraded risk factor can indeed lead to a negative risk premium. They are able to verify their theoretical prediction with credit default swaps (CDS). Because of the usage of CDS by financial institutions such as banks to hedge their exposure to credit risk, the covariation between CDS liquidity and the credit risk innovation indeed leads to a lower return on CDS.

While their study does demonstrate the possibility of a negative liquidity risk premium in derivatives, it would be far-fetched to use their theoretical framework to predict our findings. Although option end-users indeed take a short position in net (e.g., Lakonishok et al., 2007 Garleanu et al., 2009), it is unlikely that they do so to hedge certain nontraded risks. It is generally believed that end-users trade options due to private information (e.g., Amin and Lee, 1997; Cao et al., 2005), differences of opinion (e.g., Choy and Wei, 2012), or outright speculation such as writing covered calls to bet on a bearish view or a view of limited upside.

As in Pastor and Stambaugh (2003), and Lin et al. (2011), our starting point is a factor model, which takes a reduced form and abstracts away from the fundamental equilibrium elements. As such, we need to search for a plausible explanation of our finding from a heuristic angle, which we will attempt below.

Going back to the conventional thinking, if the marginal investors are long in options, then we should expect a positive liquidity risk premium, following the logic in Pastor and Stambaugh (2003), Acharya and Pedersen (2005), and Lin et al. (2011). This also means that, if the marginal investors are, in net, taking a short position in options then we should expect a negative liquidity risk premium. However, there is a crucial element missing in this logical argument, viz. the counterparty of the marginal investor. Insofar as options are in zero net supply, for every marginal investor with a net long position, there must be an investor with a net short position. According to Lakonishok et al. (2007) and Garleanu et al. (2009), market makers are taking the long position in net. Specifically, Lakonishok et al. (2007) show that the net short position is mostly held by end-users who are full-service customers.

To complete the above logical argument, we need the following to be true: As far as liquidity risk is concerned, option end-users care more about liquidity risk than market makers. Unfortunately, in the absence of a comprehensive theory and proprietary dataset on investors' trading of options, we are unable to ascertain this definitively. Nevertheless, we can think of at least two reasons why market makers might care less about liquidity risk compared with end-users, and these two reasons are not mutually exclusive. First, market makers usually hedge or neutralize their option positions via the underlying stocks. In contrast, end-users take an option position for a reason, be it informed trading or speculation. In other words, they usually don't hedge and therefore are exposed to more risks, including liquidity risk. Even when the market makers' hedge is imperfect due to, e.g., infrequent rebalancing and less accurate pricing models, the crude annihilation of risk still makes them less subject to various shocks.

Second, market makers are less affected by margin calls than end-users. Aside from the simple fact that market makers usually maintain both long and short positions in options, which helps alleviate the variations on their margin account, the most distinct advantage option market makers enjoy is the so-called "permitted offsets." Most exchanges (e.g., CBOE) allow market makers to use positions in other securities (e.g., stocks held to hedge short calls) to offset margin requirement. The favorable margin treatment enjoyed by market makers could become one of the reasons for market makers to care about liquidity risk less than end-users do. For ease of exposition, suppose the loading on the option market liquidity factor is positive. When the option market liquidity goes down, the option return is lower, entailing a lower option value, which is good for the end-users. This wouldn't necessarily lead to a negative risk premium since a symmetric, opposite effect also entails for the market markers. Asymmetric effects can occur when the market liquidity goes up. Here, the option value goes up which may trigger margin calls to the end-users. But the margin calls only occur when the market liquidity goes up, which is indeed a desirable outcome. Since margin calls matter more to option end-users, a negative liquidity risk premium therefore ensues as a reward for the desirable feature that margin calls come to the option users under better market liquidity conditions.

The above story rests on the premise that end-users care more about liquidity risk due to their different profile in, e.g. margin treatments. Another way of explaining the negative risk premium is directly via the pricing channel. Specifically, in contrast to Christoffersen et al. (2018), we may argue that, instead of the market makers, the option end-users dictate the pricing of options for reasons beyond, e.g., the realm of the demand-based option pricing model such as Garleanu et al. (2009). As long as this is true, the fact that the option end-users are on the short side in net is a sufficient explanation for the negative liquidity risk premium.

In summary, the negative liquidity risk premium we uncover in leverage-adjusted, hedged returns is consistent with the empirical finding that investors in net are taking a short position in options. More generally, our results support the notion conveyed in Bongaerts et al. (2011) and Deuskar et al. (2011) that, when the assets are in zero net supply, liquidity premium can be either positive or negative.

Before concluding the paper, we need to address a more general issue: How can we have an aggregate liquidity risk factor in the options market where net supply is zero? We have provided empirical evidence in support of such a factor without an enabling theory. As such, our paper merely provides evidence for the existence of liquidity risk premium in option returns. The absence of theories notwithstanding, we can think of intuitive reasons why there could be an aggregate liquidity risk factor over and above the liquidity risk factor of the stock market. Conceivably, the liquidity of the options market could be subject to collective shocks that affect option pricing. One such example is the 2008 short selling ban of financial stocks. Various studies (e.g., Battalio and Schultz, 2011; Grundy et al., 2012; Lin and Lu, 2016) have shown that the ban has led to a deterioration in option liquidity (in the form of wider bid-ask spreads and lower trading volume) and a deviation from fundamental pricing (in the form of more severe violations of the put-call parity). Liquidity shocks like this could affect all existing options, regardless who is on the short side and who is on the long side.

6. Conclusion

Using data from OptionMetrics for the period of January 1, 1996 to December 31, 2017, we examine the liquidity risk premium in option returns. The study employs three liquidity measures: the price impact measure, the return reversal measure, and the percentage bid-ask spread. The first two measures are based on, respectively, Acharya and Pedersen (2005) and Pastor and Stambaugh (2003). The methodology mostly follows that for liquidity risk studies on stocks (e.g., Pastor and Stambaugh, 2003) and bonds (e.g., Lin et al., 2011). We examine leverage-adjusted, hedged option returns in the monthly frequency.

Complementing the study by Christoffersen et al. (2018) who establish a liquidity level effect in hedged option returns —— more illiquid options command a higher expected return, we examine the liquidity risk premium in option returns. In other words, we investigate whether the option returns' sensitivity to the option market liquidity factor is priced, after controlling for the sensitivity to the stock market liquidity factor. The main findings can be summarized as follows.

First, our sorting analysis uncovers a statistically significant alpha due to exposures to the option market's liquidity risk. Depending on the liquidity measure and the weighting scheme in calculating portfolio returns, the monthly alpha ranges from 8.5 basis points to 14.6 basis points in the leverage-adjusted, hedged option returns. In contrast, when the hedged returns are not adjusted for leverage, the alpha ranges from 165.9 basis points to 185.1 basis points per month. Regardless, in magnitude, the uncovered liquidity risk premium is much smaller than the level effect premium demonstrated in Christoffersen et al. (2018).

Second, using the Fama-MacBeth methodology whereby expected option returns are regressed on the loadings on the Fama-French three factors, the momentum factor, a traded stock market liquidity factor, a traded market volatility factor, and the option market liquidity factor, we estimate a significant coefficient for the loading on the option market liquidity factor, corroborating the significant alphas.

Various robustness checks are performed and our results hold up under alternative data screening criteria and liquidity measure constructions. The results also hold for call options and put options separately, albeit weaker for the latter due to the fact that there are more calls in the sample period (the call-put ratio is 1.27). By the same token, the results are consistent (viz. a negative liquidity risk premium) among different moneyness and maturity buckets, with some weak evidence that the risk premium manifests itself more in out-of-the-money, and short- and medium-term options. But similar to the reason behind the difference between call and put options, the stronger presence of risk premium in the aforementioned buckets is most likely due to a higher testing power thanks to more observations in those buckets. Additionally, there is some evidence that the liquidity risk premium in option returns manifests itself more in the financial crisis period (viz. 2007–2009) than in other periods.

Last but not least, the liquidity risk premium in option returns is negative, in contrast to the positive liquidity risk premium uncovered in stock returns (Pastor and Stambaugh, 2003) and bond returns (Lin et al., 2011). The negative premium is consistent with the fact that option end-users take a short position in net – i.e., end-users write more options than they buy.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jbankfin.2019.105700.

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