Available online at www.sciencedirect.com
ScienceDirect
Journal of Financial Markets 13 (2010) 20–48
Journal of FINANCIAL MARKETS
www.elsevier.com/locate/finmar

# Option market liquidity: Commonality and other characteristics ☆

Melanie Cao[a,*], Jason Wei[b]

[a] *Schulich School of Business, York University, 4700 Keele Street, Toronto, Ontario, Canada M3J 1P3*
[b] *Joseph L. Rotman School of Management, University of Toronto, 105 St. George Street, Toronto, Ontario, Canada M5S 3E6*

Available online 10 September 2009

**Abstract**

This study examines option market liquidity using Ivy DB's OptionMetrics data. We establish convincing evidence of commonality for various liquidity measures based on the bid–ask spread, volumes, and price impact. The commonality remains strong even after controlling for the underlying stock market's liquidity and other liquidity determinants such as volatility. Smaller firms and firms with a higher volatility exhibit stronger commonalities in option liquidity. Aside from commonality, we also uncover several other important properties of the option market's liquidity. First, information asymmetry plays a much more dominant role than inventory risk as a fundamental driving force of liquidity. Second, the market-wide option liquidity is closely linked to the underlying stock market's movements. Specifically, the options liquidity responds asymmetrically to upward and downward market movements, with calls reacting more in up markets and puts reacting more in down markets.


*JEL classification:* G10; G12; D82

*Keywords:* Liquidity; Liquidity commonality; Option market liquidity; Stock market liquidity

Market liquidity has received much attention lately both in the media and in the academic literature. There are numerous studies that examine the liquidity characteristics and the pricing of illiquidity risk for stocks and bonds. In contrast, such research on the

☆ The initial version of this paper was titled "Commonality in Liquidity: Evidence from the Option Market."
*Corresponding author
*E-mail addresses:* mcao@schulich.yorku.ca (M. Cao), wei@rotman.utoronto.ca (J. Wei).

1386-4181/$ - see front matter © 2009 Elsevier B.V. All rights reserved.
doi:10.1016/j.finmar.2009.09.004

option market is still lacking or, at best, merely starting. Insofar as the ultimate goal is to determine how much premium illiquidity and illiquidity risk command, the first step is to study the liquidity characteristics and to investigate whether there exists an illiquidity risk. This is the focus of the current paper. We contribute to the literature by demonstrating the existence of illiquidity risk or liquidity commonality in the option market and by unveiling other important liquidity characteristics for options.

Using data from Ivy DB's OptionMetrics for the period from January 1, 1996 to December 31, 2004, we demonstrate strong evidence of liquidity commonality in the option market for such liquidity measures as the bid–ask spread, volume, and price impact. The commonality remains after controlling for the impact of the underling stock market and the individual determinants of liquidity such as volatility. Moreover, we find a size-effect and a volatility-effect in commonality, especially for the spread measure: Smaller firms and firms with a higher volatility exhibit stronger commonalities in liquidity.

Other than commonality, we also uncover several other important liquidity characteristics for the option market. First, employing various proxies and through different tests, we find that information asymmetry plays a much more important role than inventory risk as a driving force of the option market liquidity. One piece of supporting evidence is the *positive* correlation between changes in the bid–ask spread and the trading volume, in contrast to the more intuitive negative relation for stocks. Our findings are consistent with the notion that informed traders tend to trade in the option market (Black, 1975; Easley et al., 1998; Pan and Poteshman, 2006) and that market-makers infer information from volumes and protect themselves by widening the spread upon seeing an increase in the trading volume (Easley and O'Hara, 1992; Kim and Verrechia, 1994). Second, the market-wide liquidity is closely linked to the movements of the overall underlying stock market. Specifically, the option market liquidity responds asymmetrically to upward and downward market movements. For instance, the proportional bid–ask spread of calls decreases in up markets and increases in down markets; for puts, the spread remains roughly unchanged in up markets but decreases in down markets. More striking is how call and put options respond differently to the same market movement: Call options' liquidity mostly responds to upward market movements while put options' liquidity mostly responds to downward movements. Our results therefore suggest that options are favored by informed traders to realize their information value and are also the investors' choice to trade in response to general market movements.

The literature on liquidity commonality originated from the seminal work of Chordia, Roll, and Subrahmanyam (2000) (CRS hereafter). They examined 1,169 NYSE stocks and found strong evidence of commonality. Independent of CRS (2000) and using different methodologies, Hasbrouck and Seppi (2001) and Huberman and Halka (2001) also showed the existence of common liquidity factors across stocks. Subsequent studies generally confirmed or rationalized the early evidence. For instance, Coughenour and Saad (2004) demonstrated that the covariation in liquidity is induced on the supply side since each NYSE specialist firm provides liquidity for many stocks and the firm's specialists share the same capital pool and relevant information; Brockman and Chung (2002), Fabre and Frino (2004), and Zheng and Zhang (2006) showed that commonality in liquidity also exists in order-driven markets; Brockman et al. (2009) confirmed the existence of liquidity commonality for stocks on 47 exchanges around the world; finally, Domowitz et al. (2005) showed that commonality in liquidity is a manifestation of the co-movements in supply and demand, which, in turn, are caused by the cross-sectional correlation in order types.

The evidence of commonality or covariation in liquidity provides a strong motivation for a more general asset pricing framework. Although the literature is still in its infancy with respect to pricing models that encompass liquidity risk, some promising frameworks have emerged. For equities, Pástor and Stambaugh (2003) investigated and confirmed that the market-wide liquidity is a priced state factor; Acharya and Pedersen (2005) proposed a liquidity-adjusted capital asset pricing model and empirically verified the impact of liquidity on asset returns; Sadka (2006) extended the above studies by identifying the component of liquidity risk that can explain asset-pricing anomalies such as momentum and post-earnings-announcement drift; finally, Korajczyk and Sadka (2008) showed that commonality exists for each of the liquidity measures under their consideration and that there indeed exists a priced, aggregate latent liquidity factor across all measures. As for derivatives, Çetin et al. (2004, 2006) and Jarrow and Protter (2007) developed an option pricing framework that incorporates both the price risk and the liquidity risk, the latter of which is modelled as a stochastic supply curve. Çetin et al. (2006) showed that liquidity costs could account for a significant portion of the option price.[1]

The importance of liquidity in asset pricing is not without doubters. Some researchers have presented evidence that questions the effectiveness of liquidity in explaining cross-section returns. For instance, Hasbrouck (2006) estimated the effective cost of trading using daily close prices and showed that a stock's return covariation with the market liquidity is not a determinant of expected returns. Reconciling with the findings of the above-mentioned studies, he tempered his conclusion by pointing out the potential importance of other liquidity measures such as the trading volume. Spiegel and Wang (2005) compared the contributions of idiosyncratic risk and liquidity in explaining the cross-sectional patterns in stock returns. They found that stock returns are increasing in both idiosyncratic risk and illiquidity, but that idiosyncratic risk plays a more dominate role and it often eliminates illiquidity's explanatory power. Our study is not about the pricing of illiquidity risk in options; rather, we take the first step toward that direction by demonstrating the existence of liquidity commonality.

The rest of the paper is organized as follows. In Section 1, we describe the data and define the liquidity measures. Section 2 presents the main results concerning commonality. Section 3 demonstrates other liquidity characteristics of the option market. Section 4 concludes the paper.

## 1. Data and liquidity measures

### 1.1. Data

The main data source is Ivy DB's OptionMetrics, which covers all exchange-traded options on U.S. stocks. The sample period is from January 1, 1996 to December 31, 2004. Among other things, the database provides end-of-the-day bid and ask quotes, open interest, volume, delta, and implied volatility for all options (the last two items are calculated via a binomial tree with a constant interest rate). For the underlying stocks, the database provides the daily high/low/close prices and trading volume. The bid and ask

[1]Other studies that examine the general properties of liquidity for the derivatives market include (Vijh, 1990; Cho and Engle, 1999; Mayhew et al., 1999; Brenner et al., 2001; Kalodera and Schlag, 2004; Deuskar et al., 2008; Tang and Yan, 2008).

quotes for stocks are retrieved from TAQ (Trade and Quote). For each stock, we take the average bid/ask price in the last 5 min of trading as the end-of-the-day bid/ask price.

The option data are screened in the following way:

- Observations associated with a zero trading volume are deleted (OptionMetrics provides quotes even when the option is not traded). Furthermore, to avoid the undue impact of very small trades, we delete options that have five or fewer contracts traded.
- To ensure the representativeness of the sample, we avoid options whose maturity is too short or too long. Specifically, options with a maturity shorter than nine days or longer than 365 days are deleted.
- To avoid potential pricing structure issues associated with the deep in-the-money and deep out-of-the-money options, we delete options whose moneyness (defined as the exercise price divided by the stock price) is outside the range of $[0.9, 1.1]$.
- To minimize the impact of tick size on bid–ask spreads, we delete observations where the bid is lower than \$0.125 or \$1/8. Prior to 2001, the tick size was \$1/16 and \$1/8, respectively, for option prices below and above \$3; after 2001, the corresponding tick size was \$0.05 and \$0.10, respectively. Therefore, our screening criterion is conservative.
- Once the above criteria are met, we screen the sample further by keeping only those stocks that have an option listing at both the beginning and the end of the year. Moreover, we delete stocks that have fewer than 500 option observations within a calendar year. The count is over all options available in the year. The goal is to have at least two observations a day on average to facilitate time-series analyses.

Once the option file is created, we merge it with the corresponding stock file that contains the bid/ask quotes, the closing price, and the trading volume. The resulting dataset contains on average about 620 stocks each year. The total number of distinct stocks in the entire sample that meet all the screening criteria is 1,589.

### *1.2. Liquidity measures*

CRS (2000) used five liquidity measures, two of which are based on transaction prices and one on the guaranteed quantity associated with each quote. Since we have neither the transaction price nor the guaranteed quantity for each quote, we are left with only the first two measures used in CRS (2000): the dollar bid–ask spread and the proportional bid–ask spread. The panel nature of the option data rules out the dollar bid–ask spread as a liquidity measure, since an out-of-the-money option will have a smaller bid–ask spread than its in-the-money counterpart and this smaller spread in no way indicates better liquidity. In the end, we can adopt only one of the five measures used in CRS (2000): the proportional bid–ask spread. For stocks, we have only one observation per day; for options, we calculate a volume-weighted average of the proportional spreads within each day and use this average to conduct time-series analysis.

For completeness, we also include several measures used in other studies. In particular, we include contract volume and dollar trading volume as transaction-based measures (Mayhew et al., 1999; Hasbrouck and Seppi, 2001; Kalodera and Schlag, 2004) and Amihud's *ILLIQ* as a price impact measure (Amihud, 2002; Acharya and Pedersen, 2005). Again, for stocks, we have only one observation per day. For options, the contract volume is the total number of options traded during the day; the dollar trading volume is the midpoint of the bid and ask quotes times the volume summed over all the options within the day. We create two versions of the *ILLIQ* measure: the absolute *ILLIQ* (*AILLIQ* in short) and the percentage *ILLIQ* (*PILLIQ* in short). For stocks, *AILLIQ* (*PILLIQ*) is the absolute (percentage) change in daily closes divided by the dollar volume. For options, the *AILLIQ* and *PILLIQ* measures are constructed similarly with the following two modifications: (1) the daily change in option prices is adjusted by the option's delta times the change in the stock price (i.e., on the first order, we remove the part of option price change purely due to the change in the underlying stock price); and (2) we use the trading volume of each option to arrive at a volume-weighted average for each measure. Panel A of Table 1 defines and describes the five liquidity measures used in this study.

### 1.3. Summary statistics

The last three panels of Table 1 report the summary statistics. Panel B contains the mean, median, and standard deviation for each measure over the entire sample. For each measure, we first calculate the time-series average for each stock and then average across all stocks. The mean, median, and the standard deviation are from the cross-sectional calculations. Panel B shows that the average percentage bid–ask spread and the standard deviation are both smaller than what CRS (2000) reported. CRS (2000) included all intraday quotes for the calendar year 1992, whereas we use the day-end quotes for a nine-year period. The average percentage bid–ask spread is 13.44% for options, much larger than its stock counterpart of 0.81%. Compared with put options, call options have a smaller bid–ask spread and a larger trading volume in terms of both the mean and the median. Similar observations also apply to *AILLIQ* and *PILLIQ*. On the basis of per-dollar trading volume, the price impact is smaller for calls.[2] Thus, the overall statistics point to a relatively higher liquidity in call options, which is consistent with the stylized fact that, on average, more calls are being traded than puts.

Panel C of Table 1 reports the average correlations among the liquidity measures for calls and puts. As in Panel B, we first calculate correlations using time-series data for each stock and then average the correlations across stocks. To gauge the significance of each average correlation, we report the *t*-value for the average, as well as the percentage of correlations sharing the same sign as the average itself. Several observations are in order. First and foremost, judging by the *t*-values, the correlations are significantly different from zero and, judging by the percentage, the sign is consistent among the vast majority of stocks. Second, the correlation structure appears identical for calls and puts. In other words, between each pair of measures, the correlation is of roughly the same magnitude for calls and puts. Third, not surprisingly, the highest correlation is between the contract volume (*VOL*) and the dollar volume (*DVOL*). The second highest correlation is between the two price impact measures, *AILLIQ* and *PILLIQ*. The percentage bid–ask spread (*PBA*) is correlated more with the price impact measures than with other measures. Fourth, as expected, the *PBA* measure is negatively correlated with the volume measures and positively correlated with the price impact measures. Naturally, the volume measures

[2]All the aforementioned differences are statistically significant. We tested the hypothesis that the mean of a liquidity measure for calls is larger than that of puts and we obtained the following *t*-values for *PBA*, *VOL*, *DVOL*, *AILLIQ*, and *PILLIQ*: $-5.570, 5.743, 6.136, -21.959$, and $-18.892$.

Table 1
Definitions and summary statistics for liquidity measures.

Panel A: Definitions

| Liquidity measure | Notation | Option: Definition | Option: Unit | Stock: Definition | Stock: Unit |
|---|---|---|---|---|---|
| Proportional bid–ask spread | *PBA* | $\dfrac{\sum_{j=1}^{J} VOL_j^* \frac{ask_j - bid_j}{(ask_j + bid_j)/2}}{\sum_{j=1}^{J} VOL_j}$ | None | (ask − bid)/[(ask + bid)/2] | None |
| Trading volume | *VOL* | $\sum_{j=1}^{J} VOL_j$ | Contracts | Number of shares | Shares |
| Dollar trading volume | *DVOL* | $\sum_{j=1}^{J} VOL_j^*(\mathrm{ask}_j + \mathrm{bid}_j)/2$ | \$ | $VOL * (\mathrm{ask} + \mathrm{bid})/2$ | \$ |
| Absolute *ILLIQ* | *AILLIQ* | $\dfrac{\sum_{j=1}^{J} VOL_j^* \frac{\lvert (P_t^j - P_{t-1}^j) - \Delta_{t-1}^j (S_t - S_{t-1}) \rvert}{DVOL_t^j}}{\sum_{j=1}^{J} VOL_j}$ | \$ / (\$ volume) | $\dfrac{\lvert S_t - S_{t-1} \rvert}{DVOL_t}$ | \$/(\$ volume) |
| Percentage *ILLIQ* | *PILLIQ* | $\dfrac{\sum_{j=1}^{J} VOL_j^* \frac{\lvert (P_t^j - P_{t-1}^j) - \Delta_{t-1}^j (S_t - S_{t-1}) \rvert / P_{t-1}^j}{DVOL_t^j}}{\sum_{j=1}^{J} VOL_j}$ | Return/(\$ volume) | $\dfrac{\lvert (S_t - S_{t-1}/S_{t-1}) \rvert}{DVOL_t}$ | Return/(\$ volume) |

Panel B: Summary statistics—size of liquidity measures

| | Call options | | | Put options | | | All options | | | Stocks | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | Median | STD | Mean | Median | STD | Mean | Median | STD | Mean | Median | STD |
| *PBA* | 0.1311 | 0.1267 | 0.0399 | 0.1393 | 0.1345 | 0.0428 | 0.1344 | 0.1303 | 0.0405 | 0.0081 | 0.0071 | 0.0044 |
| *VOL* ($\times 10^4$) | 5.476 | 2.222 | 11.911 | 3.412 | 1.381 | 7.962 | 8.430 | 3.163 | 19.473 | 156.177 | 85.193 | 254.702 |
| *DVOL* ($\times 10^4$) | 15.437 | 5.157 | 39.722 | 8.500 | 3.017 | 21.292 | 22.839 | 7.238 | 59.646 | 5,685.833 | 2,791.655 | 10,816.547 |
| *AILLIQ* ($\times 10^{-5}$, $\times 10^{-9}$) | 3.738 | 3.436 | 2.460 | 6.301 | 5.804 | 3.949 | 3.869 | 3.599 | 2.487 | 5.266 | 3.379 | 5.480 |
| *PILLIQ* ($\times 10^{-5}$, $\times 10^{-9}$) | 2.852 | 2.503 | 2.112 | 4.539 | 4.146 | 2.865 | 2.987 | 2.692 | 2.027 | 0.236 | 0.116 | 0.308 |

Panel C: Cross-sectional means of time-series, pair-wise correlations between liquidity measures for calls and puts

| | | | *PBA* | *VOL* | *DVOL* | *AILLIQ* | $\rho_{\text{call-put}}$ |
|---|---|---|---|---|---|---|---|
| *PBA* | | Correlation | | | | | 0.186 |
| | | *t*-Value | | | | | 43.117* |
| | | Percentage (%) | | | | | 87.791 |
| *VOL* | Calls | Correlation | −0.054 | | | | 0.286 |
| | | *t*-Value | −25.305* | | | | 61.470* |
| | | Percentage (%) | 75.960 | | | | 96.916 |
| | Puts | Correlation | −0.036 | | | | |
| | | *t*-Value | −16.230* | | | | |
| | | Percentage (%) | 68.848 | | | | |
| *DVOL* | Calls | Correlation | −0.174 | 0.859 | | | 0.271 |
| | | *t*-Value | −98.501* | 336.469* | | | 59.981* |
| | | Percentage (%) | 99.434 | 100.000 | | | 95.784 |
| | Puts | Correlation | −0.155 | 0.870 | | | |
| | | *t*-Value | −87.654* | 409.674* | | | |
| | | Percentage (%) | 98.490 | 100.000 | | | |
| *AILLIQ* | Calls | Correlation | 0.165 | −0.168 | −0.149 | | 0.130 |
| | | *t*-Value | 57.306* | −114.184* | −101.605* | | 36.942* |
| | | Percentage (%) | 92.826 | 99.622 | 99.308 | | 87.854 |
| | Puts | Correlation | 0.200 | −0.157 | −0.145 | | |
| | | *t*-Value | 63.055* | −103.492* | −100.378* | | |
| | | Percentage (%) | 95.091 | 99.308 | 99.497 | | |
| *PILLIQ* | Calls | Correlation | 0.311 | −0.145 | −0.143 | 0.791 | 0.109 |
| | | *t*-Value | 108.411* | −117.611* | −110.414* | 320.715* | 34.113* |
| | | Percentage (%) | 99.434 | 99.811 | 99.937 | 100.000 | 84.393 |
| | Puts | Correlation | 0.349 | −0.140 | −0.141 | 0.805 | |
| | | *t*-Value | 113.434* | −107.587* | −103.371* | 338.604* | |
| | | Percentage (%) | 100.000 | 99.622 | 99.937 | 100.000 | |

Panel D: Cross-sectional means of time-series, pair-wise correlations between liquidity measures for options and stocks

| | | | *PBA* | *VOL* | *DVOL* | *AILLIQ* | $\rho_{option-stock}$ |
|---|---|---|---|---|---|---|---|
| *PBA* | | Correlation | | | | | 0.066 |
| | | *t*-Value | | | | | 20.525* |
| | | Percentage (%) | | | | | 68.722 |
| *VOL* | Options | Correlation | −0.067 | | | | 0.411 |
| | | *t*-Value | −28.845* | | | | 98.821* |
| | | Percentage (%) | 79.610 | | | | 99.811 |
| | Stocks | Correlation | −0.019 | | | | |
| | | *t*-Value | −5.708* | | | | |
| | | Percentage (%) | 59.346 | | | | |
| *DVOL* | Options | Correlation | −0.185 | 0.870 | | | 0.453 |
| | | *t*-Value | −93.191* | 354.368* | | | 95.881* |
| | | Percentage (%) | 99.245 | 100.000 | | | 99.937 |
| | Stocks | Correlation | −0.091 | 0.879 | | | |
| | | *t*-Value | −28.680* | 259.548* | | | |
| | | Percentage (%) | 79.862 | 100.000 | | | |
| AILLIQ | Options | Correlation | 0.176 | −0.177 | −0.157 | | 0.153 |
| | | *t*-Value | 61.987* | −111.835* | −102.798* | | 52.958* |
| | | Percentage (%) | 94.588 | 99.308 | 98.993 | | 94.399 |
| | Stocks | Correlation | 0.124 | −0.215 | −0.199 | | |
| | | *t*-Value | 31.275* | −93.091* | −86.805* | | |
| | | Percentage (%) | 80.302 | 98.804 | 97.609 | | |
| *PILLIQ* | Options | Correlation | 0.312 | −0.159 | −0.156 | 0.809 | 0.133 |
| | | *t*-value | 113.202* | −116.366* | −113.491* | 333.611* | 44.370* |
| | | Percentage (%) | 99.748 | 99.497 | 99.811 | 100.000 | 91.378 |
| | Stocks | Correlation | 0.180 | −0.172 | −0.234 | 0.904 | |
| | | *t*-value | 49.167* | −69.421* | −113.296* | 313.892* | |
| | | Percentage (%) | 91.630 | 95.469 | 99.622 | 100.000 | |

This table contains the definitions and summary statistics for the liquidity measures. Panel A contains the definitions where $\Delta$ stands for the option's delta and the summation is over the distinct options that are traded during the day. Panel B contains the mean, median, and standard deviation (STD) for each liquidity measure (the volume measures need to be multiplied by $10^4$; the *AILLIQ* and *PILLIQ* measures need to be multiplied by $10^{-5}$ for options and by $10^{-9}$ for stocks). We first obtain the time-series average for each stock and then average across stocks. Panel C reports the average pair-wise correlations between the liquidity measures. For each pair of liquidity measures, we calculate the correlation separately for calls and puts. We first calculate time-series correlations for each stock and then average across all stocks. Each cell in the table contains three numbers, with the upper being the average correlation, the middle the *t*-value for the average and the lower the percentage of correlations having the same sign as the average. The last column contains the average correlation between the calls and the puts for a particular liquidity measure. Panel D has the same structure as Panel C except that the correlations are calculated for all options combined and the stocks. The *t*-values in both panels are all significant at the 1% level or higher for two-tail tests and are indicated by $*$.

are negatively correlated with the price impact measures. Finally, the correlation between calls and puts for the same measure (the last column of the table) is not high, indicating that the liquidity dynamics of calls and puts are not identical. In the subsequent analyses, when warranted, we will treat calls and puts separately.

Panel D of Table 1 reports the average correlations and associated statistics for call and put options combined, as well as for stocks. Similar to Panel C, all the average correlations are highly significant and representative of the vast majority of stocks. For the volume and price impact measures, the correlations for stocks appear stronger than those for options; it is the opposite for the bid–ask spread measure. Across markets, volume-based liquidity measures exhibit the highest correlation (shown in the last column of the table), followed by the price impact measures. The two markets have the lowest correlation for the percentage bid–ask spread measure, suggesting that spreads are driven by potentially different factors in the two markets. Nonetheless, the positive correlation is consistent with the derivative-hedge theory proposed by Cho and Engle (1999), who showed that the market-maker's hedging activity through the underlying market will make the spreads in the two markets positively correlated.

## 2. Empirical analysis of liquidity commonality in the option market

### 2.1. Basic evidence of commonality

To detect commonality in liquidity, we follow CRS (2000) and run a time-series, "market-model" regression for each stock:

$$PL_{i,t} = \beta_{0,i} + \beta_{1,i}PSL_{i,t} + \beta_{2,i}PL_{m,t} + \beta_{2_{lag},i}PL_{m,t-1} + \beta_{3,i}PSL^{res}_{m,t} + \beta_{3_{lag},i}PSL^{res}_{m,t-1} + \alpha X + \sum_{j=1}^{8}\gamma_j YearDummy_{j,t} + \varepsilon_{i,t}, \tag{1}$$

where $PL_{i,t}$ is the daily percentage change of the option's liquidity measure ($PBA$, $VOL$, $DVOL$, $AILLIQ$, or $PILLIQ$), $PSL_{i,t}$ is the percentage change of the stock's corresponding liquidity measure, $PL_{m,t}$ ($PL_{m,t-1}$) is the contemporaneous (lagged) daily percentage change of the option market's liquidity measure (equal-weighted average of all stocks' liquidity except the stock in question), $X$ is a vector of control variables including the stock's contemporaneous return, the level and percentage change of the firm return squared, and the 30-day implied volatility of the S&P 500 index options, $YearDummy_{j,t}$ is a year-dummy capturing potential time variation in liquidity (as noted by Chordia et al., 2001), and $PSL^{res}_{m,t}$ ($PSL^{res}_{m,t-1}$) is the corresponding contemporaneous (lagged) percentage change of the stock market's liquidity measure, projected on the option market's, i.e., it is the residual from the following regression:

$$PSL_{m,t} = a_0 + a_1 PL_{m,t} + e_t, \tag{2}$$

where $PSL_{m,t}$ is the stock market's liquidity measure.

Unlike CRS (2000), we do not include the market return in (1) since we do not use effective spreads or transaction prices and the potential correlation between spreads and the market return is not a concern; moreover, we only include lagged terms in market liquidity measures since this specification is easy to interpret and our preliminary results indicate that the lead terms are insignificant anyway. The stock's own liquidity measure is used to capture the positive correlation between the liquidities of options and the underlying stock due to hedging demand. Thus, any commonality we find in the options market will be a pure option market phenomenon. We include the orthogonalized stock market liquidity to control for the potential covariation between the option market's liquidity and the stock market's. The stock's return is included to capture its potential influence on options liquidity through channels other than the hedging demand. The stock's return squared and the 30-day implied volatility of the S&P 500 index options capture the stock's instantaneous volatility and investors' assessment of the overall market's volatility. We allow for potential impacts coming from both the volatility level and its changes.

We run the regression in (1) for all stocks and calculate the cross-sectional mean and $t$-value for each coefficient in the Fama and MacBeth (1973) fashion. We also report the percentage of coefficients having the same sign as the average. For brevity, we only report coefficients for the stock's own liquidity measure ($\beta_{1,i}$), the option market's liquidity measure ($\beta_{2,i}$ and $\beta_{2_{lag},i}$), and the stock market's liquidity residual ($\beta_{3,i}$ and $\beta_{3_{lag},i}$). We also report the average adjusted $R^2$ and the statistics for the sum of the contemporaneous and the lagged variables. Table 2 contains the results.[3]

The regression results reveal strong evidence of liquidity commonality in the option market. When the regression is run for all options combined, the $t$-value for the contemporaneous commonality ($\beta_2$) is significant at the 1% level for all liquidity measures and most of the individual coefficients are positive (the lowest percentage of positive coefficients is 67.72% for the $DVOL$ measure). For the bid–ask spread measure, the average coefficient and its $t$-value are 0.863 and 61.90, respectively, and 94.78% of the regression coefficients are positive. By comparison, the corresponding numbers for the stock market from CRS (2000) are 0.791%, 30.09% and 84.26%.

The lagged coefficient ($\beta_{2_{lag}}$) is much smaller than the contemporaneous coefficient ($\beta_2$). For $PBA$, the average lagged coefficient is positive and significant at the 1% level. It is insignificant for the remaining liquidity measures. The sum of the contemporaneous and the lagged coefficients is positive and significant at the 1% level for all liquidity measures.

The evidence is mixed for the covariation between the option market's liquidity and the stock market's. The coefficients for the price impact measures ($AILLIQ$ and $PILLIQ$) have the right sign, but are mostly insignificant; the coefficients for other liquidity measures are mostly negative. For the spread measure $PBA$, the $t$-values are marginal and the negative coefficients are by no means the dominating majority.

Finally, the coefficient for the stock's own liquidity measure is indeed positive, confirming the hedging-demand argument. It is highly significant for the two volume measures. For the price impact measures, the percentage of positive coefficients is actually less than 50%, indicating a positive skew in the distribution of parameter estimates.

For completeness, we perform the analysis separately for call and put options. We use the same specification as in (1) with one modification to the market liquidity definition: For calls, $PL_{m,t}$ ($PL_{m,t-1}$) is the average of call options only and the same applies to puts.

[3]The statistics for $AILLIQ$ and $PILLIQ$ are calculated based on a 1% winsorization at each end of the contemporaneous commonality coefficient $\beta_{2,i}$. This is necessary since some time-series regressions generate extremely large coefficients mainly due to thin trading of certain options.

Table 2
Commonality in option liquidity.

| | *PBA* | *VOL* | *DVOL* | *AILLIQ* | *PILLIQ* |
|---|---|---|---|---|---|
| Panel A: All options | | | | | |
| $\beta_1$ | 0.008 | 1.636 | 2.191 | 0.019 | 0.010 |
| | 7.478* | 65.860* | 44.403* | 3.912* | 1.387 |
| | 55.444 | 95.469 | 93.266 | 39.064 | 40.182 |
| $\beta_2$ | 0.863 | 1.452 | 1.081 | 1.652 | 2.369 |
| | 61.901* | 18.256* | 7.496* | 7.490* | 7.881* |
| | 94.777 | 76.589 | 67.716 | 70.790 | 73.655 |
| $\beta_{2_{lag}}$ | 0.068 | −0.074 | −0.032 | −0.188 | 0.033 |
| | 5.103* | −0.963 | −0.225 | −0.866 | 0.110 |
| | 60.289 | 54.248 | 57.269 | 53.459 | 50.314 |
| $\beta_2+\beta_{2_{lag}}$ | 0.931 | 1.378 | 1.050 | 1.463 | 2.402 |
| | 45.293* | 11.470* | 4.715* | 4.173* | 5.044* |
| | 91.819 | 71.492 | 61.359 | 64.430 | 69.182 |
| $\beta_3$ | −0.033 | −2.099 | −1.776 | 0.702 | 0.619 |
| | −3.876* | −15.412* | −6.949* | 3.449* | 1.922 |
| | 57.772 | 73.946 | 66.960 | 58.910 | 59.399 |
| $\beta_{3_{lag}}$ | −0.012 | 0.053 | −0.269 | −0.134 | −0.058 |
| | −1.410 | 0.399 | −1.082 | −0.672 | −0.182 |
| | 53.807 | 48.458 | 51.668 | 51.852 | 54.158 |
| $\beta_3+\beta_{3_{lag}}$ | −0.044 | −2.046 | −2.044 | 0.568 | 0.561 |
| | −3.235* | −9.970* | −5.198* | 1.647 | 1.043 |
| | 56.073 | 68.408 | 63.373 | 55.625 | 55.765 |
| Adjusted $R^2$ (%) | 1.410 | 7.373 | 6.961 | 1.156 | 0.850 |
| Panel B: Call options | | | | | |
| $\beta_1$ | 0.007 | 1.693 | 2.333 | 0.044 | 0.047 |
| | 5.848* | 67.146* | 47.919* | 3.811* | 2.642* |
| | 53.241 | 94.021 | 92.763 | 42.208 | 42.348 |
| $\beta_2$ | 0.820 | 1.326 | 0.737 | 1.960 | 2.673 |
| | 57.520* | 16.955* | 5.359* | 3.644* | 7.105* |
| | 93.329 | 75.330 | 65.009 | 67.505 | 72.327 |
| $\beta_{2_{lag}}$ | 0.085 | 0.086 | 0.079 | −0.561 | 0.150 |
| | 6.330* | 1.147 | 0.596 | −1.081 | 0.401 |
| | 60.667 | 48.521 | 43.864 | 52.481 | 49.406 |
| $\beta_2+\beta_{2_{lag}}$ | 0.905 | 1.413 | 0.817 | 1.400 | 2.822 |
| | 42.337* | 11.835* | 3.801* | 1.633 | 4.705* |
| | 90.497 | 70.044 | 58.716 | 64.221 | 67.086 |
| $\beta_3$ | −0.016 | −1.611 | −1.008 | 0.850 | 1.422 |
| | −1.608 | −11.365* | −3.812* | 1.333 | 3.243* |
| | 57.143 | 70.673 | 60.919 | 58.281 | 57.512 |
| $\beta_{3_{lag}}$ | −0.003 | −0.084 | 0.122 | −0.146 | −0.075 |
| | −0.346 | −0.618 | 0.490 | −0.235 | −0.179 |
| | 55.192 | 53.052 | 48.081 | 51.642 | 51.572 |
| $\beta_3+\beta_{3_{lag}}$ | −0.019 | −1.695 | −0.887 | 0.704 | 1.347 |
| | −1.204 | −7.883* | −2.206* | 0.657 | 1.865 |
| | 54.500 | 67.464 | 60.101 | 55.276 | 55.835 |
| Adjusted $R^2$ (%) | 1.482 | 7.508 | 7.561 | 1.435 | 0.749 |

Table 2 (*continued*)

| | *PBA* | *VOL* | *DVOL* | *AILLIQ* | *PILLIQ* |
|---|---|---|---|---|---|
| Panel C: Put options | | | | | |
| $\beta_1$ | 0.008 | 1.598 | 2.143 | 0.040 | 0.057 |
| | 4.065* | 49.287* | 38.397* | 0.985 | 1.244 |
| | 52.108 | 87.728 | 86.469 | 39.273 | 39.273 |
| $\beta_2$ | 0.840 | 1.174 | 1.000 | 3.541 | 5.287 |
| | 49.267* | 11.375* | 5.416* | 3.267* | 6.174* |
| | 92.385 | 68.093 | 59.094 | 64.570 | 68.134 |
| $\beta_{2_{lag}}$ | 0.126 | 0.050 | −0.039 | −0.192 | 0.624 |
| | 7.595* | 0.497 | −0.222 | −0.175 | 0.742 |
| | 63.688 | 48.773 | 54.437 | 53.809 | 50.943 |
| $\beta_2+\beta_{2_{lag}}$ | 0.966 | 1.224 | 0.961 | 3.349 | 5.911 |
| | 37.257* | 7.567* | 3.327* | 1.881 | 4.276* |
| | 89.805 | 62.870 | 54.374 | 59.329 | 62.614 |
| $\beta_3$ | −0.021 | −1.932 | −1.536 | 1.674 | −0.238 |
| | −1.324 | −11.410* | −4.962* | 1.556 | −0.260 |
| | 56.073 | 66.834 | 59.597 | 52.341 | 49.266 |
| $\beta_{3_{lag}}$ | −0.014 | 0.253 | 0.719 | 0.223 | −0.866 |
| | −0.905 | 1.527 | 2.394* | 0.212 | −0.980 |
| | 53.933 | 48.710 | 52.108 | 47.939 | 52.341 |
| $\beta_3+\beta_{3_{lag}}$ | −0.035 | −1.679 | −0.817 | 1.896 | −1.105 |
| | −1.359 | −6.324* | −1.680 | 1.049 | −0.719 |
| | 55.066 | 63.059 | 56.514 | 51.363 | 50.105 |
| Adjusted $R^2$ (%) | 1.230 | 4.582 | 3.911 | 1.672 | 1.352 |

This table reports the results for regression (1): $PL_{i,t}=\beta_{0,i}+\beta_{1,i}PSL_{i,t}+\beta_{2,i}PL_{m,t}+\beta_{2_{lag},i}PL_{m,t-1}+\beta_{3,i}PSL^{res}_{m,t}+\beta_{3_{lag},i}PSL^{res}_{m,t-1}+\alpha X+\sum_{j=1}^{8}\gamma_j YearDummy_{j,t}+\varepsilon_{i,t}$. The time-series regression is run separately for each stock and the regression coefficients are averaged across stocks. For brevity, we only report the coefficient and the statistics of the stock's own liquidity measure ($PSL_{i,t}$), the contemporaneous and the lagged variables for the option market liquidity ($PL_{m,t}$ and $PL_{m,t-1}$), and the residual variables for the stock market liquidity ($PSL^{res}_{m,t}$ and $PSL^{res}_{m,t-1}$, which are from regression $PSL_{m,t}=a_0+a_1PL_{m,t}+e_t$). In each time-series regression, the market liquidity is the average liquidity over all stocks other than the stock in question, $X$ is a vector of control variables including the stock's contemporaneous return, the level and percentage change of the stock return squared and the 30-day implied volatility of the S&P 500 index options; *YearDummy* is a year-dummy variable. The triplet for each entry consists of the average coefficient, its $t$-value and the percentage of regression coefficients having the same sign as the average. The adjusted $R^2$ is the average adjusted $R^2$ of all the time-series regressions. The $t$-values indicated by $*$ are significant at the 5% level or higher for two-tail tests.

Panels B and C of Table 2 report the results. It is apparent that commonality also exists separately for both types of options. By and large, as far as commonality is concerned, call options and put options exhibit the same properties. For brevity, in the subsequent analysis, we will combine call and put options whenever warranted.

Before proceeding to other tests, we perform a check of the reliability of the $t$-statistics in Table 2 and in some of the tables to follow. The $t$-statistics are used to infer if the average commonality coefficients are different from zero. For the $t$-tests to be valid, we need to ensure that the error terms from (1) are independent from one another among stocks. Cross-sectional dependence of the error terms would indicate the omission of common variables in the specification. To perform the check, we follow CRS (2000) and do pair-wise, time-series regressions using the error terms. Specifically, we list the stocks by tickers in alphabetical order (to achieve randomization) and regress the error terms of the first stock on those of the second stock, and so on:

$$\varepsilon_{i+1,t} = b_{i,0} + b_{i,1}\varepsilon_{i,t} + \phi_{i,t} \quad (i = 1, 2, \ldots, n-1), \tag{3}$$

where $n$ is the number of stocks that have residuals from (1). This procedure generates $n-1$ pair-wise regressions. Table 3 reports the average of the slope coefficient $b_{i,1}$, the average and the median $t$-values for the slope coefficient. It also reports the percentage of absolute $t$-values that are greater than the critical values at the 10% level (1.645) and the 5% level (1.960).

Very little evidence exists that indicates cross-equation dependence. The slope coefficient and the average $t$-value are both close to zero for all liquidity measures. The percentage of $t$-values larger than the critical levels (1.645 and 1.96, respectively) is very close to what chance would entail: 10% and 5%, respectively.

Table 3
Check for cross-sectional dependence in time-series estimation errors.

| Liquidity measure | Average slope coefficient | Average $t$-value | Median $t$-value | $\|t\|>1.645$ (%) | $\|t\|>1.96$ (%) | Number of pairs |
|---|---|---|---|---|---|---|
| Panel A: Call options | | | | | | |
| *PBA* | 0.001 | 0.033 | 0.017 | 12.154 | 6.126 | 1012 |
| *VOL* | 0.001 | 0.025 | −0.179 | 6.621 | 3.854 | 1012 |
| *DVOL* | 0.000 | 0.000 | −0.153 | 5.632 | 3.854 | 1012 |
| *AILLIQ* | 0.004 | 0.071 | −0.153 | 5.929 | 4.348 | 1012 |
| *PILLIQ* | 0.004 | 0.070 | −0.154 | 5.632 | 4.051 | 1012 |
| Panel B: Put options | | | | | | |
| *PBA* | 0.001 | 0.036 | −0.020 | 12.846 | 8.103 | 1012 |
| *VOL* | 0.002 | 0.018 | −0.175 | 7.510 | 5.138 | 1012 |
| *DVOL* | 0.000 | 0.001 | −0.179 | 7.016 | 4.842 | 1012 |
| *AILLIQ* | 0.000 | 0.029 | −0.142 | 6.719 | 4.941 | 1012 |
| *PILLIQ* | 0.003 | 0.054 | −0.136 | 6.522 | 3.854 | 1012 |
| Panel C: All options | | | | | | |
| *PBA* | 0.000 | −0.010 | −0.013 | 11.265 | 5.435 | 1012 |
| *VOL* | 0.004 | 0.117 | −0.109 | 8.004 | 5.929 | 1012 |
| *DVOL* | 0.005 | 0.097 | −0.116 | 7.510 | 4.743 | 1012 |
| *AILLIQ* | 0.006 | 0.149 | −0.128 | 6.818 | 5.336 | 1012 |
| *PILLIQ* | 0.008 | 0.210 | −0.141 | 7.609 | 4.941 | 1012 |

This table checks for the potential cross-sectional dependence in the estimation errors resulting from the time-series regression (1). For each liquidity measure, we use the available observations to do the pair-wise, time-series regression in (3): $\varepsilon_{i+1,t} = b_{i,0} + b_{i,1}\varepsilon_{i,t} + \phi_{i,t}$ $(i = 1, 2, \ldots, n-1)$. For instance, for the percentage bid–ask spread (*PBA*) measure with call options, there are 1,013 time-series regressions. We randomize the regressions by alphabetically arranging the tickers and regress the time-series regression residuals of stock $i$ on those of stock $i+1$. We thus have 1,012 pair-wise regressions. The slope coefficient and its $t$-value measure the extent of pair-wise dependence. For each liquidity measure, we report the average slope coefficient, the average $t$-value, and the median $t$-value for the slope coefficients. We also report the percentage of absolute $t$-values that are greater than the critical $t$-values at the 10% level (1.645) and the 5% level (1.960) respectively.

## 2.2. Commonality with size- and volatility-effects

When sorting the commonality coefficients into quintiles by firm size, CRS (2000) found a strong size-effect: Large firms exhibit a much stronger commonality than smaller firms and the relationship is monotonic. CRS (2000) offered some conjectures as to the potential reasons for the size-effect but did not pursue the issue further. To shed some light on this issue for the options market, we use two metrics to do the sorting: the firm size and the implied volatility. To assign a size for each firm/stock, we use the number of shares outstanding from CRSP and the daily stock prices to obtain the daily size measures; we then average them over the entire sample and take this average as the firm size. To assign a stock to an implied volatility quintile, we use the average implied volatility over the entire sample to do the sorting. Once the quintiles are in place, we calculate the statistics in exactly the same way as we did in Table 2 except that they are now quintile specific. We also perform a *t*-test on the equality of commonality coefficients between the two extreme quintiles and this is done for both the contemporaneous coefficient and the sum of the contemporaneous and the lagged coefficients. Table 4 reports the results.[4]

When stratified by the implied volatility, the volume-based measures do not exhibit statistically significant differences among quintiles, but the spread and price impact measures do. Specifically, high volatility groups have a much stronger commonality and the relationship is monotonic for *PBA* and *AILLIQ*. The results are largely as expected since, no matter whether the underlying driving force behind liquidity is inventory risk or information asymmetry (an issue we will delineate later in the paper), a higher volatility will intensify the impact of either factor within each framework.

When stratified by size, all liquidity measures exhibit a statistically significant size-effect, albeit non-monotonic. For the spread measure and the two price impact measures, smaller firms have a stronger commonality, contrary to what CRS (2000) found, and the difference between the two extreme quintiles is statistically significant either for the contemporaneous and/or the summed coefficient. The volume-based liquidity measures exhibit a reverse pattern: Larger firms have a stronger commonality, especially for the contemporaneous coefficient. Insofar as size and volume are positively related, the trading volume of larger firms should co-move more with the market's when commonality is present. Thus the stronger volume commonality for larger firms is not surprising. More intriguing is the size-effect associated with the spread and price-impact measures. Before offering insights into the size-effect per se, we need to reconcile our results with the findings in CRS (2000). Since the only common measure used in CRS (2000) and our study is the proportional bid–ask spread, we will only focus on this measure in the remainder of the discussions.

To begin with, we first investigated whether there is a similar size-effect for the stocks in our sample, and the answer turned out to be yes: Smaller stocks have a stronger commonality and the difference between the two extreme quintiles is statistically

[4]In Table 3, we already ruled out the potential cross-sectional dependence among the error terms from (1) for the entire sample. It is possible that the cross-sectional dependence exists within a subset of the sample such as a particular size quintile or an implied-volatility quintile. To verify this, we repeat the checks for each quintile/liquidity measure. The results are consistent with those in Table 3 in that no interdependence is found within any quintile. The *t*-values in Table 4 are therefore reliable. The table containing the results for the error-dependence checking is omitted for brevity but is available upon request.

Table 4
Size and volatility effects in commonality.

| | | Size quintiles | | | | | t-Test | Implied volatility quintiles | | | | | t-Test |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Smallest | 2 | 3 | 4 | Largest | (L vs. S) | Lowest | 2 | 3 | 4 | Highest | (H vs. L) |
| *PBA* | $\beta_2$ | 0.938 | 0.881 | 0.820 | 0.824 | 0.850 | | 0.685 | 0.842 | 0.876 | 0.930 | 0.978 | |
| | | 23.938* | 25.611* | 24.964* | 31.844* | 42.908* | 2.151* | 19.687* | 26.804* | 28.284* | 30.082* | 35.963* | −6.858* |
| | $\beta_2+\beta_{2_{lag}}$ | 1.007 | 0.929 | 0.906 | 0.929 | 0.877 | | 0.668 | 0.926 | 0.971 | 1.035 | 1.041 | |
| | | 17.771* | 18.206* | 18.535* | 24.075* | 29.911* | 2.290* | 12.752* | 20.010* | 21.556* | 22.948* | 26.057* | −6.403* |
| *VOL* | $\beta_2$ | 0.772 | 1.644 | 1.890 | 1.476 | 1.436 | | 1.269 | 1.469 | 1.662 | 1.491 | 1.356 | |
| | | 4.740* | 10.170* | 8.183* | 8.305* | 10.394* | −2.651* | 5.861* | 8.415* | 8.319* | 9.751* | 10.320* | −0.297 |
| | $\beta_2+\beta_{2_{lag}}$ | 0.994 | 1.703 | 1.600 | 1.246 | 1.244 | | 1.123 | 1.652 | 1.612 | 1.313 | 1.169 | |
| | | 4.027* | 6.940* | 4.620* | 4.653* | 5.950* | −0.682 | 3.459* | 6.260* | 5.345* | 5.622* | 5.872* | −0.122 |
| *DVOL* | $\beta_2$ | 0.148 | 1.371 | 1.332 | 0.956 | 1.508 | | 1.202 | 1.263 | 1.316 | 0.867 | 0.751 | |
| | | 0.607 | 5.313* | 3.925* | 2.213* | 5.598* | −3.615* | 2.268* | 4.682* | 4.506* | 3.874* | 4.183* | 0.753 |
| | $\beta_2+\beta_{2_{lag}}$ | 0.547 | 1.597 | 1.092 | 0.667 | 1.175 | | 1.060 | 1.135 | 1.547 | 0.903 | 0.577 | |
| | | 1.447 | 3.996* | 2.097* | 0.994 | 2.898* | −1.290 | 1.303 | 2.718* | 3.416* | 2.591* | 2.067* | 0.757 |
| *AILLIQ* | $\beta_2$ | 1.935 | 1.841 | 1.630 | 2.124 | 0.980 | | 0.670 | 1.627 | 1.844 | 1.854 | 2.199 | |
| | | 2.814* | 3.935* | 0.637 | 6.218* | 3.613* | 1.383 | 1.576 | 3.976* | 3.913* | 3.939* | 3.102* | −2.655* |
| | $\beta_2+\beta_{2_{lag}}$ | 1.766 | 2.336 | 0.373 | 1.992 | 0.380 | | −0.055 | 1.141 | 1.964 | 2.374 | 1.913 | |
| | | 1.611 | 3.139* | 0.092 | 3.646* | 0.881 | 1.995* | −0.080 | 1.749 | 2.636* | 3.171* | 1.711 | −2.600* |
| *PILLIQ* | $\beta_2$ | 2.655 | 2.317 | 1.742 | 3.174 | 1.810 | | 1.888 | 2.397 | 2.504 | 2.778 | 2.351 | |
| | | 3.804* | 3.210* | 1.682 | 4.131* | 5.008* | 1.200 | 2.334* | 2.702* | 2.979* | 5.032* | 5.577* | −1.164 |
| | $\beta_2+\beta_{2_{lag}}$ | 2.960 | 2.811 | 2.545 | 2.024 | 1.381 | | 0.719 | 2.977 | 3.586 | 3.254 | 2.891 | |
| | | 2.686* | 2.464* | 1.566 | 1.658 | 2.412* | 1.975* | 0.557 | 2.123* | 2.667* | 3.722* | 4.422* | −2.367* |

This table reports the quintile version of Panel A in Table 2. Specifically, after performing the commonality regression in (1) for each stock, we group the results either by the firm size or by the average implied volatility. The firm size is based on the number of shares outstanding and the daily stock prices. We average the firm size over the sample period and use this average to form size quintiles. Similarly, the average of implied volatilities of all maturities and moneyness over the entire sample is used to form the implied volatility quintiles. The regression coefficients are then averaged within each quintile. For brevity, we only report the coefficient and the *t*-value of the contemporaneous and the lagged commonality variables for each liquidity measure. We also report the *t*-values for the test of equality between the contemporaneous coefficients of the smallest and the largest firms (S vs. L: small versus large). Similar *t*-values are also reported for tests between the lowest and the highest implied volatility quintiles (L vs. H: low versus high). The *t*-values indicated by $*$ are significant at the 5% level or higher for two-tail tests.

significant, again contrary to what CRS (2000) found. We then performed the commonality regression and quintile partition year by year for both stocks and options. Interestingly, the observed size-effect for options is basically consistent across years; for stocks, however, the size-effect is consistent with CRS (2000) for the first four years in the data (1996, 1997, 1998, and 1999) but turns the other way for the remainder of the sample years (2000 through 2004). Therefore it follows that the later years in the sample dominate the overall results for stocks. CRS (2000) used one-year data for 1992, a few years prior to the beginning of our sample. Thus it appears that there was a structural change around 1999–2000 as far as size-effect in commonality is concerned.[5] We will leave this issue for future research. The important finding for us is that the size-effect is consistent for options across years.

Why do small firms exhibit a stronger commonality in option spreads? Simply put, smaller firms are more susceptible to inventory risk and information asymmetry. As a result, whenever there is a common movement in the marketplace, the spreads of smaller firms' options tend to co-move more since they respond more to the underlying forces. A full investigation of the liquidity characteristics versus firm size will be carried out in Section 3.1.[6]

### 2.3. Commonality at the portfolio level

The results so far reveal a strong commonality in all liquidity measures. Recalling from Table 2, the coefficient for the contemporaneous covariation is significant at the 1% level for all liquidity measures. The explanatory power is quite low, though. When all options are combined, the highest adjusted $R^2$ is 7.37% for *VOL* (volume) and the lowest is merely 0.85% for *PILLIQ*. The highest and lowest adjusted $R^2$ in CRS (2000) is 1.7% and 1%, respectively. There are two potential reasons for the low explanatory power: the omission of important systematic factors in (1) and/or a significant amount of idiosyncratic liquidity variation. Our error-dependence check in Table 3 largely rules out the omission of systematic factors. To confirm that the low explanatory power is indeed due to the idiosyncratic time-variation in liquidity of individual options, we perform regression analysis at the portfolio level, as in CRS (2000).

Based on the findings in the previous section, we construct size and implied volatility portfolios. The quintile construction follows exactly the same procedure as before. The time-series regression in (1) is then run for each measure and quintile with the following modifications: (1) the market liquidity of each quintile is the liquidity average over all options other than those in the current quintile; (2) all other control variables are calculated at the quintile level; and (3) to allow for potential error correlations among quintiles, for each liquidity measure, we run a set of five seemingly unrelated regressions (SUR) by matching daily observations. Results are in Table 5. For brevity, we only report the contemporaneous and the lagged coefficients for the market liquidity variable.

[5]Brockman et al. (2009), using intra-day data from October 1, 2002 to June 30, 2004, for 47 exchanges around the world, also found a stronger commonality for smaller firms.

[6]Our overall findings about the size-effect and the implied-volalitility-effect are consistent with Acharya and Pedersen (2005), who found that smaller stocks and more volatile stocks have more commonality in liquidity and Hameed et al. (2006), who found that smaller firms and firms with a higher volatility react more to (negative) market movements.

Table 5
Commonality in liquidity for option portfolios.

| | | Size quintiles | | | | | | Implied volatility quintiles | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Smallest | 2 | 3 | 4 | Largest | System-wide $R^2$ (%) | Lowest | 2 | 3 | 4 | Highest | System-wide $R^2$ (%) |
| *PBA* | $\beta_2$ | 0.903 | 0.847 | 0.775 | 0.806 | 0.715 | 79.41 | 0.629 | 0.785 | 0.829 | 0.929 | 0.991 | 81.35 |
| | | 29.469* | 33.448* | 33.544* | 43.351* | 43.146* | | 31.823* | 42.823* | 43.238* | 42.850* | 37.421* | |
| | $\beta_{2_{lag}}$ | 0.078 | 0.076 | 0.115 | 0.092 | 0.028 | | 0.017 | 0.078 | 0.082 | 0.055 | 0.098 | |
| | | 2.561* | 3.033* | 5.059* | 5.045* | 1.738 | | 0.894 | 4.311* | 4.353* | 2.592* | 3.746* | |
| *VOL* | $\beta_2$ | 0.362 | 0.428 | 0.360 | 0.408 | 0.463 | 72.86 | 0.329 | 0.499 | 0.587 | 0.430 | 0.452 | 77.45 |
| | | 11.114* | 13.287* | 12.525* | 14.753* | 21.084* | | 14.061* | 20.914* | 21.865* | 15.938* | 16.037* | |
| | $\beta_{2_{lag}}$ | 0.045 | 0.051 | 0.014 | 0.016 | 0.045 | | 0.030 | 0.004 | 0.036 | 0.036 | 0.036 | |
| | | 1.581 | 1.928 | 0.680 | 0.923 | 3.160* | | 1.670 | 0.247 | 1.942 | 1.970* | 1.554 | |
| *DVOL* | $\beta_2$ | 0.224 | 0.273 | 0.141 | 0.154 | 0.270 | 58.67 | 0.218 | 0.240 | 0.322 | 0.247 | 0.232 | 61.48 |
| | | 6.221* | 7.671* | 4.312* | 5.041* | 10.958* | | 7.263* | 8.081* | 11.256* | 8.347* | 7.016* | |
| | $\beta_{2_{lag}}$ | 0.052 | 0.051 | −0.009 | −0.010 | 0.051 | | 0.031 | −0.001 | 0.008 | 0.042 | −0.008 | |
| | | 1.644 | 1.801 | −0.402 | −0.537 | 3.204* | | 1.358 | −0.049 | 0.449 | 1.990* | −0.289 | |
| *AILLIQ* | $\beta_2$ | 0.550 | 0.518 | 0.493 | 0.418 | 0.433 | 20.34 | 0.374 | 0.497 | 0.466 | 0.635 | 0.546 | 20.30 |
| | | 11.308* | 12.669* | 13.057* | 12.984* | 16.148* | | 12.390* | 15.667* | 12.636* | 15.536* | 10.765* | |
| | $\beta_{2_{lag}}$ | 0.114 | 0.180 | 0.079 | 0.042 | 0.061 | | 0.048 | 0.089 | 0.094 | 0.130 | 0.142 | |
| | | 2.515* | 4.690* | 2.294* | 1.395 | 2.441* | | 1.678 | 2.974* | 2.924* | 3.416* | 2.988* | |
| *PILLIQ* | $\beta_2$ | 0.657 | 0.555 | 0.488 | 0.503 | 0.483 | 20.32 | 0.450 | 0.520 | 0.548 | 0.666 | 0.677 | 22.86 |
| | | 14.596* | 14.021* | 13.203* | 15.678* | 17.941* | | 15.187* | 17.252* | 16.558* | 18.442* | 14.347* | |
| | $\beta_{2_{lag}}$ | 0.095 | 0.112 | 0.102 | 0.094 | 0.094 | | 0.077 | 0.120 | 0.112 | 0.100 | 0.153 | |
| | | 2.184* | 2.982* | 2.921* | 3.109* | 3.656* | | 2.702* | 4.120* | 3.648* | 2.866* | 3.359* | |

This table reports the results for option portfolios from regression (1):

$$PL_{i,t} = \beta_{0,i} + \beta_{1,i}PSL_{i,t} + \beta_{2,i}PL_{m,t} + \beta_{2_{lag},i}PL_{m,t-1} + \beta_{3,i}PSL^{res}_{m,t} + \beta_{3_{lag},i}PSL^{res}_{m,t-1} + \alpha X + \sum_{j=1}^{8}\gamma_j YearDummy_{j,t} + \varepsilon_{i,t}.$$

Portfolios are formed based on either the firm size or the implied volatility of the stock. The firm size is based on the number of shares outstanding and the daily stock prices. We average the firm size over the sample period and use this average to form size portfolios. Similarly, the average of implied volatilities of all maturities and moneyness over the entire sample is used to form the implied volatility quintiles. The above regression is run for quintile portfolios as a set of seemingly unrelated regressions (SUR) in order to account for the error correlations across the quintiles. The market liquidity is calculated using all stocks/options excluding the ones in the quintile. For brevity, we only report the coefficient and the $t$-value of the contemporaneous and the lagged variables for the option market liquidity ($PL_{m,t}$ and $PL_{m,t-1}$). We also report the system-wide $R^2$. The $t$-values indicated by $*$ are significant at the 5% level or higher for two-tail tests. Please refer to the text or Table 2 for variable definitions in (1).

Aside from the fact that the $t$-value for the contemporaneous market liquidity is highly significant for all cases, the adjusted $R^2$ improves tremendously for all liquidity measures, confirming the highly idiosyncratic nature of individual option liquidity. The percentage bid–ask measure sees the biggest improvement, going from 1.41% in Table 2 to 79.41% (by size quintiles) or 81.35% (by implied volatility quintiles). The volume measures also see significant improvement. At the portfolio level, the two price impact measures are the least effective.[7] The lagged coefficient is either positive with modest significance or not statistically different from zero, indicating that the few negative lagged coefficients in Table 2 do not reflect market-wide phenomena.

The idiosyncratic nature of options liquidity is also reflected in a simple comparison between the commonalities of the options market and the corresponding stock market. In this comparison, we run the "market model" regression in (1) for the two markets separately at the stock level as in Table 2, except that, for options we omit the stock's own liquidity measure ($PSL_{i,t}$) and the two residual terms ($PSL^{res}_{m,t}$ and $PSL^{res}_{m,t-1}$) and for stocks we replace $PL_{m,t}$ and $PL_{m,t-1}$ by $PSL_{m,t}$ and $PSL_{m,t-1}$. In other words, we make sure that the two regressions have exactly the same structure. It turns out that the stock market has a stronger commonality than the option market in terms of both statistical significance/explanatory power ($t$-value/$R^2$) and the magnitude of the commonality coefficient.[8] As shown in the next section, as an underlying driving force of liquidity in the option market, information asymmetry plays a much more prominent role than inventory risk. By definition, inventory risk tends to be affected by market-wide factors, while information events tend to be firm-specific. Therefore, the dominance of information asymmetry would lead to a relatively larger idiosyncratic component in the variation of options' liquidity or, equivalently, a lower commonality.

## 3. Other characteristics of the option market liquidity

Our analyses so far confirm the liquidity commonality in the options market. We now turn to the general characteristics of the option market's liquidity. We first investigate the underlying driving forces of illiquidity: the inventory risk and information asymmetry. We then study how the general market movements affect the market-wide liquidity.

### 3.1. Option liquidity: inventory risk and information asymmetry

In this section, we attempt to uncover the fundamental factors that influence the option market's liquidity: the inventory risk and information asymmetry. CRS (2000) argued that the broad market activity would influence the inventory risk while the extent of information asymmetry will be reflected in the individual trading activities. A higher trading volume would reduce the risk of order imbalance and the market-maker would face a lower inventory risk as a result. In this sense, we expect the liquidity to improve when more options are being traded. On the other hand, the trading pattern of specific

[7] The weak performance of the price impact measures could be due to several reasons, the obvious of which is their model-specific nature. Recall that, when calculating these measures, we use the option's delta and the stock price to adjust the change in the option price, a procedure that is not only model-specific, but is also affected by the potential nonsynchronous nature of option and stock prices.

[8] Details of the comparison are omitted for brevity but are available upon request.

options may reflect the extent of information asymmetry on the stock. For instance, some authors (e.g., Barclay and Warner, 1993) suggest that informed traders may hide the information by executing frequent, smaller orders. If so, market-makers would increase the spread in response. Thus, we expect the bid–ask spread to be positively related to the number of trades within a day. CRS (2000) used the average dollar size of a transaction and the total number of trades in a stock as proxies to capture this type of information asymmetry.

In this paper, we use each stock's total option trading volume and open interest to proxy the inventory risk.[9] While the use of trading volume is motivated by the argument of CRS (2000), the idea behind using open interest is that an increase in open interest will increase the chance of order imbalance as well as the inventory level, both of which will lead to a higher inventory risk.

As for proxies for information asymmetry, we have neither the average trade size nor the total number of trades in options. Instead, we use the total number of distinct options (across maturity and moneyness) being traded per day to approximate the number of trades or trading frequency. This proxy is based on the thinking that when informed traders break their orders, they spread them over options with different strike prices and maturities. To ensure the robustness of our results, we develop another proxy for information asymmetry: the volume-weighted average time in days elapsed between two trades. To calculate this measure for each day, we first find out, for a particular option, how many days have elapsed between this trade and the previous trade; we then use today's volumes to calculate a weighted average over all options being traded today. This time-measure of information is motivated by the model of Easley and O'Hara (1992). Building on the intuition that non-trading itself could bear information signals (e.g., Diamond and Verrecchia, 1987), Easley and O'Hara (1992) extended the framework of Glosten and Milgrom (1985) and Kyle (1985) by allowing the information events to be uncertain. In their model, traders infer information from trades as well as the absence of trades and, as a result, the intervals between trades may convey information. Their model predicts that spreads will decrease as the time between trades increases.

Since the bulk of the liquidity literature on inventory risk and information asymmetry focuses on the bid–ask spread, we only perform the analysis for the proportional spread measure, $PBA$. The following multivariate regression summarizes the potential relationship between the bid–ask spread and the proxies and control variables:

$$\begin{aligned} PPBA_{i,t} = {} & \beta_{0,i} + \beta_{1,i}PSPBA_{i,t} + \beta_{2,i}PT_{i,t} + \beta_{3,i}PTE_{i,t} + \beta_{4,i}POI_{i,t} \\ & + \beta_{5,i}PV_{i,t} + \beta_{5_{lag},i}PV_{i,t-1} + \beta_{6,i}PSV^{res}_{i,t} + \beta_{6_{lag},i}PSV^{res}_{i,t-1} \\ & + \alpha X + \sum_{j=1}^{8}\gamma_j YearDummy_{j,t} + \varepsilon_{i,t}, \end{aligned} \tag{4}$$

where as before, $P$ stands for daily percentage change, $SPBA_{i,t}$ is the stock's own percentage bid–ask spread, $T_{i,t}$ is the number of distinct options written on stock $i$ being traded on day $t$, $TE_{i,t}$ is the average time in days elapsed between two trades, $OI_{i,t}$ is

[9]Although not reported here, the results are similar when the aggregate trading volume in the options market is used as a proxy for inventory risk. We use the stock-level option trading volume for sharper results.

the total open interest of options for stock $i$ on day $t$, $V_{i,t}$ ($V_{i,t-1}$) is the contemporaneous (lagged) trading volume of all options written on stock $i$, $X$ is a vector of control variables including the stock's return, the level and percentage change of the stock return squared, and the 30-day implied volatility of the S&P 500 index options, $YearDummy_{j,t}$ is a year-dummy and $PSV_{i,t}^{res}$ is the residual from the following regression (in the same spirit as (2)):

$$PSV_{i,t} = a_0 + a_1 PV_{i,t} + e_t, \tag{5}$$

where $PSV_{i,t}$ is the percentage change of trading volume of the underlying stock.

As in (1), we first run the time-series regression for each stock and then average the regression coefficients. Since the trading volume variables ($PV_{i,t}$, $PV_{i,t-1}$, $PSV_{i,t}^{res}$, and $PSV_{i,t-1}^{res}$) are highly correlated with the number of distinct options ($PT_{i,t}$) and the open interest variable ($POI_{i,t}$), we run two versions of (4) to avoid multi-collinearity. In the first version, we drop the volume variables; in the second version, we add back the volume variables but drop the number of distinct options and the open interest variables.[10]

According to the theories discussed above, we expect $\beta_{1,i}>0$, $\beta_{2,i}>0$, $\beta_{3,i}<0$, $\beta_{4,i}>0$, and $\beta_{5,i}<0$. As shown in the first two columns of Table 6, the average coefficients for the stock's own spread ($\beta_1$), the distinct number of options ($\beta_2$), days elapsed between trades ($\beta_3$), and open interest ($\beta_4$) all have the expected sign and their *t*-values are highly significant, confirming the role of information asymmetry ($\beta_2$ and $\beta_3$) and inventory risk ($\beta_4$). The coefficients of the stock volume residuals ($\beta_6$ and $\beta_{6_{lag}}$) are negative and significant, seemingly confirming the inventory-risk theory. However, we should not draw conclusions about inventory risk from these coefficients since a higher trading volume in stocks cannot directly help balance orders in the option market. One way to understand the result is via the hedging argument proposed by Cho and Engle (1999). According to their model, irrespective of how liquid the option market is, as long as the market-makers can hedge their option positions through the underlying stocks, the spread on options should be minimal. In this sense, controlling for other factors, a higher trading volume in the stock will facilitate hedging and hence reduce the spread in options. This is exactly what we observe.

The regression result for the option-volume variable is surprising: The coefficient is positive for both the contemporaneous and the lagged variables and the *t*-values are highly significant. Here, an increase in trading volume is associated with widening spreads, contrary to what the inventory-risk theory predicts. To be sure that our results are not due to sample selection, we modified (4) by putting the stock's own spread on the left and deleting the trading frequency, days elapsed between trades, open interest, and the residual terms and ran it for the stocks in our sample. We did obtain a significant, *negative* coefficient for the volume variable. Therefore, the positive relation between the percentage changes in the spread and the trading volume appears to reflect a phenomenon specific to the option market.

[10]To ensure that the *t*-values are reliable, a check for potential cross-sectional error dependence similar to Table 3 is performed for each version of the regressions. Similar to the results in Table 3 for the *PBA* measure, the average slope coefficient is close to zero and the percentage of significant *t*-values is slightly higher than, but nonetheless close to, what chance would entail. The dependence-checking results are omitted for brevity and are available upon request.

Table 6
Inventory risk, information asymmetry, and spreads.

| | Regression 1 | Regression 2 | Regression 2 | | Regression 2 | |
|---|---|---|---|---|---|---|
| | | | Small firms | Large firms | Low volume | High volume |
| $\beta_1$ | 0.0068 | 0.0065 | 0.0070 | 0.0059 | 0.0060 | 0.0105 |
| | 7.6675* | 7.1956* | 4.8044* | 5.5349* | 5.0653* | 4.1230* |
| $\beta_2$ | 0.0479 | | | | | |
| | 42.5027* | | | | | |
| $\beta_3$ | −0.0155 | −0.0115 | −0.0136 | −0.0093 | −0.0148 | −0.0071 |
| | −25.5384* | −19.0044* | −14.1546* | −12.6883* | −20.3747* | −5.3264* |
| $\beta_4$ | 0.0069 | | | | | |
| | 17.2946* | | | | | |
| $\beta_5$ | | 0.0035 | 0.0048 | 0.0023 | 0.0164 | 0.0018 |
| | | 22.6763* | 17.4868* | 15.2458* | 33.0581* | 8.5465* |
| $\beta_{5_{lag}}$ | | 0.0005 | 0.0001 | 0.0008 | 0.0009 | 0.0003 |
| | | 3.2008* | 0.4581 | 5.5939* | 3.4680* | 0.9731 |
| $\beta_5+\beta_{5_{lag}}$ | | 0.0040 | 0.0049 | 0.0031 | 0.0173 | 0.0021 |
| | | 17.5034* | 12.2751* | 13.8526* | 29.0627* | 4.9200* |
| $\beta_6$ | | −0.0046 | −0.0022 | −0.0071 | −0.0072 | −0.0053 |
| | | −3.8261* | −1.2492 | −4.3038* | −3.9800* | −2.5784* |
| $\beta_{6_{lag}}$ | | −0.0035 | −0.0027 | −0.0047 | −0.0052 | −0.0013 |
| | | −3.3657* | −1.7804 | −3.1630* | −3.3891* | −0.6614 |
| $\beta_6+\beta_{6_{lag}}$ | | −0.0081 | −0.0049 | −0.0118 | −0.0124 | −0.0067 |
| | | −4.5661* | −1.8983 | −4.7363* | −4.6492* | −2.0809* |
| Adjusted $R^2$ (%) | 1.93 | 1.04 | 1.15 | 0.92 | 1.44 | 1.98 |

This table reports the results from two versions of regression (4):

$$PPBA_{i,t}=\beta_{0,i}+\beta_{1,i}PSPBA_{i,t}+\beta_{2,i}PT_{i,t}+\beta_{3,i}PTE_{i,t}+\beta_{4,i}POI_{i,t}+\beta_{5,i}PV_{i,t}+\beta_{5_{lag},i}PV_{i,t-1}$$
$$+\beta_{6,i}PSV_{i,t}^{res}+\beta_{6_{lag},i}PSV_{i,t-1}^{res}+\alpha X+\sum\nolimits_{j=1}^{8}\gamma_j\,YearDummy_{j,t}+\varepsilon_{i,t},$$

where the percentage change of the option's proportional spread ($PPBA_{i,t}$) is regressed on the percentage changes of (1) the underlying stock's proportional spread ($PSPBA_{i,t}$), (2) the number of distinct options ($PT_{i,t}$), (3) the average time elapsed between two trades ($PTE_{i,t}$), (4) the total daily open interest ($POI_{i,t}$), (5) the contemporaneous and lagged option trading volume ($PV_{i,t}$ and $PV_{i,t-1}$) and (6) the contemporaneous and lagged stock trading volume projected to the option trading volume ($PSV_{i,t}^{res}$ and $PSV_{i,t-1}^{res}$, which are from regression $PSV_{i,t}=a_0+a_1PV_{i,t}+e_t$). Refer to the text or Table 2 for the definition of the vector of control variables $X$ and the dummy variables. The regression coefficients are averaged across all stocks. We also report the sum of the contemporaneous and lagged coefficients and its statistics. Each entry consists of the average coefficient and its $t$-value. The adjusted $R^2$ is the average adjusted $R^2$ of all the time-series regressions. In Regression 1 we drop the volume variables, and in Regression 2 we drop the distinct number of options and the open interest variables. For Regression 2, we further split the sample according to firm size and trading volume. The $t$-values indicated by $*$ are significant at the 5% level or higher for two-tail tests.

Although intended to proxy inventory risk, the option volume variable may indeed reveal the informational role of options. Many authors (e.g., Black, 1975; Easley et al., 1998) have argued and demonstrated that informed traders may choose to trade options due to their leverage benefit. Pan and Poteshman (2006) corroborated the previous findings and showed that option trading volumes can predict future stock prices. If informed traders use the option market to realize the information value as argued by these authors, then it is logical that market-makers react to volume changes. To be more precise, an increase in trading volume suggests the arrival of new information (Easley and O'Hara, 1992) and the market-makers would then widen the spread to protect themselves against potential losses. Some authors (e.g., Diamond and Verrecchia, 1991; Easley et al., 2002) have argued and empirically shown that information asymmetry is more severe for small firms. If the information asymmetry is indeed more pronounced with small firms *and* informed traders use options to realize the information value, then for smaller firms we should see a bigger coefficient for the volume variable. To verify this, we perform sub-sample analyses by firm size. The results in the two middle columns of Table 6 confirm our prediction. The average coefficient for the contemporaneous volume variable ($\beta_5$) of small firms is more than twice that of large firms. The other information asymmetry variable, the days elapsed between two trades, also confirms the stronger role of information in affecting the spreads for smaller firms. The *t*-values for the test that the coefficient of smaller firms is larger than that of larger firms (in magnitude) are 2.605, 5.444, and 3.326, respectively, for $\beta_3$, $\beta_5$, and $\beta_5 + \beta_{5_{lag}}$.

For the two inventory risk proxies, the option volume variable turns out to convey information asymmetry while the open interest variable has the smallest *t*-value relative to information asymmetry proxies in Regression 1. These two observations indicate a stronger role of information asymmetry in determining the spreads. To offer some additional support to this conclusion, we now explore further the dynamics between the spread and the volume. In the framework of Easley and O'Hara (1992), both the current level and the history of volumes play a role in determining the spread. Specifically, a higher volume leads to a higher probability of new information and hence a wider spread; a streak of low volumes followed by a spike also indicates the likely arrival of new information, which causes the market-maker to widen spreads. In a model that links accounting disclosures to information asymmetry, liquidity, and trading volume, Kim and Verrechia (1994) also showed that an increase in trading volume may actually be accompanied by widening bid–ask spreads due to intensified information asymmetry. Similar findings were also reported by Lee et al. (1993). The above insights imply that the informational effect (i.e., *changes* in volume) on spreads would be more severe on low-volume days. The reasoning is as follows. When the overall volume is already high (which could be driven by non-informational events such as directional trading), the *incremental* impact on spreads of a further increase in volume is likely to be small; besides, the increase in volume could be driven by the same non-informational event, which should not have major impacts on spreads. In contrast, when the overall volume is low (which indicates the absence of new information), a sudden increase is most likely due to the arrival of new information, which would bring about a bigger impact on the spreads.

To confirm the above prediction, we run another two sets of Regression 2, one for low-volume days and the other for high-volume days. To partition the sample according to volume, we first calculate the daily average volume for each stock within each calendar year; we then subtract this average from the daily volume to obtain a deviation; and finally we use this deviation to assign a particular day's observation to either the "low-volume" sample or the "high-volume" sample, depending on if the deviation is negative or positive. The last two columns of Table 6 contain the results. Our predictions are confirmed with overwhelming statistical significance. For the two information asymmetry variables ($\beta_3$ and $\beta_5$), the *t*-values are much larger in magnitude on low-volume days than on high-volume days. The $t$-values for the test that the coefficient on low-volume days is larger than that of high-volume days (in magnitude) are 4.432, 20.367, and 17.799, respectively, for $\beta_3$, $\beta_5$, and $\beta_5+\beta_{5_{lag}}$.

Taken together, the results in Table 6 clearly suggest that, compared with inventory risk, information asymmetry plays a much more important role in influencing the option market's liquidity. Our results are consistent with the notion that informed traders tend to trade in the option market and, to the extent that market-makers infer information contents from volumes, an increase in volume actually brings about the widening of bid–ask spreads.[11]

### 3.2. *Market-wide liquidity versus market movements*

Several studies relate market-wide liquidity to the direction of market movements. Chordia et al. (2001) found that the aggregate market spread responds asymmetrically to up and down market movements. The percentage spread declines modestly in up markets and increases significantly in down markets. They attributed this phenomenon to market-makers' increased aversion to inventory risk in down markets. Other authors (e.g., Amihud, 2002) have also found a link between market return and market illiquidity.

Motivated by these findings, we would like to see (1) whether the option market's liquidity also responds asymmetrically to upward and downward market movements and (2) whether calls and puts behave differently when liquidity reacts to market movements. For completeness, we also examine the corresponding stock market's liquidity. In their analysis of market liquidity for stocks, aside from market-direction variables, Chordia et al. (2001) also included some macroeconomic variables to capture the impact of economy-wide information on liquidity. Since our focus is on options and on the impact of market movements, we run a simplified version of the regression. Specifically, for stocks, we run the following regression:

$$PSL_{m,t}=\beta_0+\beta_1^+R_{m,t}^+ +\beta_1^-R_{m,t}^- +\beta_2^+R_{m5,t}^+ +\beta_2^-R_{m5,t}^- +\beta_3R_{m,t}^2 +\beta_4\sigma_{m5,t}+\sum_{j=1}^{8}\gamma_j\,YearDummy_{j,t}+\varepsilon_{i,t}, \tag{6}$$

where $PSL_{m,t}$ is the daily percentage change of the market liquidity (equal-weighted average of individual stocks' liquidity), $R_{m,t}^+$ ($R_{m,t}^-$) is the daily return of the value-weighted CRSP composite index when the return is positive (negative) and zero otherwise, $R_{5m,t}^+$ ($R_{5m,t}^-$) is the five-day counterpart of $R_{m,t}^+$ ($R_{m,t}^-$), and $\sigma_{m5,t}$ is the market standard deviation in the past five trading days. The market return squared ($R_{m,t}^2$) measures the instantaneous volatility, while the year-dummy variables capture the potential time-variation in liquidity

[11] Information events such as earnings announcements may intensify the response of spreads to asymmetric information. We re-ran (4) by adding dummy variables that are the product of the information proxy and the dummy for the earnings announcement period ranging from 5 to 10 days, either before or after the announcement day. We did not obtain significantly positive coefficients for the dummy variables regardless if the event period is before or after the quarterly earnings announcement. This may be due to the lack of power: There are only four announcements a year and many stocks do not have options for the entire sample period. Nevertheless, as in Amin and Lee (1997), we did find higher volumes a few days prior to earnings announcements and widening spreads shortly after the announcements.

changes. The setup in (6) is motivated by the inventory argument (Chordia et al., 2001) and the market volatility variables allow for potential impacts of volatility on the market-wide inventory risk.

For options, we run a pooled version of (6) for calls and puts. Specifically, we calculate the market liquidity separately for calls and puts and further dichotomize the market movement variables ($R^+_{m,t}$, $R^-_{m,t}$, $R^+_{5m,t}$ and $R^-_{5m,t}$). For instance, the term $\beta^+_1 R^+_{m,t}$ is split into $\beta^+_{1,call} R^{+,call}_{m,t}$ and $\beta^+_{1,put} R^{+,put}_{m,t}$, where $R^{+,put}_{m,t}$ takes the value of zero when the observation is for calls and so on. Since the dependent variable measures the change of the market-wide liquidity, the error terms in (6) are likely to be autocorrelated. The Durbin–Watson statistics from the OLS estimation of (6) are significantly different from 2, confirming the autocorrelation in the error term. To combat this problem, we estimate (6) via generalized least squares using the Yule–Walker method by allowing for three lags in the error term. Table 7 contains the results.[12]

We first examine the results for stocks. To begin with, the negative sign of $\beta^+_1$ for the spread measure *PBA* is consistent with the findings of Chordia et al. (2001) and Hameed et al. (2006). However, our $\beta^-_1$ is positive, albeit insignificant. One possible explanation is that our *PBA* is calculated using the average intra-day bid and ask quotes over the last 5 min of trading each day, while the spread in the above two studies is averaged over all intra-day quotes during the day. This perhaps also partly explains why our adjusted $R^2$ is close to zero. We should therefore treat our results for *PBA* with caution. Nonetheless, our results for the volume measures (*VOL* and *DVOL*) are consistent with those in Chordia et al. (2001): The overall volume goes up when the market moves in either direction contemporaneously (measured by $R^+_{m,t}$ and $R^-_{m,t}$), and it goes down when the market moves in either direction in the recent past—over the past five trading days (measured by $R^+_{5m,t}$ and $R^-_{5m,t}$). The price impact (*AILLIQ* and *PILLIQ*) becomes larger as long as the market moves in either direction contemporaneously; the reverse is true for market movements over the last five trading days. There is clear evidence of reversal in the liquidity's response to market movements.

The results for options are quite interesting. For the spread measure *PBA*, the option market liquidity does respond asymmetrically to upward and downward market movements. For calls, $\beta^+_1$ and $\beta^-_1$ are both negative, indicating that the spread decreases in up markets and increases in down markets; for puts, $\beta^+_1$ has no significance but $\beta^-_1$ is positive with a significant *t*-value, indicating that the spread remains unchanged in up markets but decreases in down markets. Such asymmetrical responses are not found with other liquidity measures.

More intriguing is the difference in response of call and put options to the *same* market movement, observed with all liquidity measures except for *PILLIQ*. This striking feature is reflected by the boxed coefficients and *t*-values in Table 7. Let us take *PBA* as an illustration. In up markets, the percentage spread for calls decreases while that for puts decreases slightly and the response of call options' spread is much stronger as reflected in both the size of the coefficient $\beta^+_1$ and its *t*-value. In down markets, the reverse is true.

[12]For some liquidity measures, incorporating one or two lags in the error term is sufficient. We use three lags across the board for consistency. Moreover, an alternative regression for options was also run in which the five-day historical volatility was replaced by the 30-day average implied volatility of the S&P 500 index options. Results are similar. The results are also robust to alternative specifications of the market index: either the equal-weighted CRSP index or the S&P 500 index.

Table 7
Market-wide liquidity versus market movements.

| | *PBA* | | | *VOL* | | | *DVOL* | | | *AILLIQ* | | | *PILLIQ* | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Stock | Call | Put | Stock | Call | Put | Stock | Call | Put | Stock | Call | Put | Stock | Call | Put |
| $\beta_1$ | −6.345 | −2.300 | −0.028 | 4.376 | 15.706 | 2.989 | 5.141 | 17.233 | −0.877 | 9.044 | −6.131 | −0.516 | 7.275 | −1.469 | −2.626 |
| | −1.781 | −6.182* | −0.076 | 3.982* | 12.479* | 2.374* | 4.579* | 12.769* | −0.650 | 6.026* | −5.641* | −0.475 | 4.809* | −1.133 | −2.024* |
| $\beta_1^-$ | 5.178 | −0.833 | 0.958 | −5.126 | −0.764 | −9.066 | −4.122 | 1.371 | −10.777 | −13.999 | −0.265 | 5.399 | −13.345 | 4.476 | 2.524 |
| | 1.437 | −2.214* | 2.549* | −4.669* | −0.601 | −7.155* | −3.676* | 1.011 | −7.959* | −9.331* | −0.242 | 4.941* | −8.839* | 3.420* | 1.933 |
| $\beta_2$ | −0.257 | 0.076 | −0.294 | −0.509 | −1.555 | 0.430 | −0.506 | −1.713 | 1.153 | −0.810 | −1.407 | −1.661 | −0.948 | −2.057 | −1.093 |
| | −0.298 | 0.731 | −2.868* | −2.312* | −4.731* | 1.321 | −2.260* | −4.998* | 3.381* | −2.665* | −5.054* | −6.018* | −3.148* | −6.051* | −3.248* |
| $\beta_2^-$ | 0.246 | 0.347 | 0.167 | 0.721 | 0.343 | 0.943 | 0.805 | 0.099 | 1.156 | 2.036 | 2.029 | 1.567 | 1.681 | 0.865 | 1.894 |
| | 0.278 | 3.217* | 1.576 | 3.114* | 1.000 | 2.778* | 3.420* | 0.275 | 3.217* | 6.394* | 6.962* | 5.431* | 5.318* | 2.437* | 5.404* |
| $R^2$ (%) | 0.52 | 6.90 | | 4.90 | 14.90 | | 5.06 | 18.66 | | 20.91 | 8.93 | | 17.89 | 2.80 | |

Similar observations also apply to *VOL*, *DVOL*, and *AILLIQ* and the contrast is even more striking: Not only are the coefficients drastically different for calls and puts corresponding to the same market movement, the response is also completely one-sided in that calls only respond to upward movements while puts only to downward movements. The results are also internally consistent among different liquidity measures. In up markets, the contract volume (*VOL*) and dollar volume (*DVOL*) increase for calls, reflecting more active trading; the percentage spread (*PBA*) and the price impact (*AILLIQ*) decrease for calls, again reflecting a better liquidity. The same phenomenon is observed with put options in down markets.

Clearly, call options are more active and more liquid in up markets while put options are more liquid in down markets. Numerous studies (e.g., the most recent one by Lakonishok et al., 2007) have found that call options generally dominate put options in both open interest and trading volume. Supplementing this finding, we show a directional feature of the trading pattern for calls and puts.

Equally interesting are the higher $R^2$ and the much larger and more significant coefficients ($\beta_1^+$ and $\beta_1^-$) for the option volume measures (*VOL* and *DVOL*) compared with their stock counterparts. Our previous results demonstrate that informed traders use options to realize their information value. The results in Table 7 seem to indicate that options are also favored when investors trade in response to general market movements.

Finally, we see a general reversal in liquidity responses to market movements when we extend the horizon to five trading days, broadly consistent with what Chordia et al. (2001) observed for the stock market. In a recently rising market ($R_{m5,t}^+$), call options tend to see a decreasing volume and an increasing spread while put options experience the reverse; in a recently falling market ($R_{m5,t}^-$), call options tend to see a slightly increasing volume and a narrowing spread. One potential explanation is as follows. Take the recently rising market as an example. When the market sees an initial upward movement ($R_{m,t}^+$), both the speculative and the hedging related demands go up, leading to a higher volume and reduced spread (market-makers profit from a higher volume by ‘‘discounting the spread’’). As the upward trend continues, market-makers exhaust their inventories and start charging a higher spread for compensation, which in turn leads to declining volumes. Regardless of the intertemporal dynamics of liquidity, our results demonstrate convincingly that call and put options respond to the same market movement in opposite ways.

## 4. Conclusion

Liquidity and its impact on asset prices have become a major focus in the academic literature. Most studies focus on liquidity properties for individual securities in isolation. Recently, some studies have emerged that examine the covariation or commonality in liquidity in the stock market. Arguably, identifying and understanding liquidity covariation is the first step toward building an asset pricing model encompassing liquidity risk. In this sense, there exists a large gap in the literature on option market liquidity, for there are no studies that examine the liquidity commonality for options. The current paper is the first step towards filling this gap in the literature by examining commonality and other liquidity characteristics for the option market.

Using data from Ivy DB’s OptionMetrics covering the period from January 1, 1996 to December 31, 2004, we establish convincing evidence of liquidity commonality in the options market for a variety of liquidity measures. The commonality remains after removing the impacts of the underlying stock market and other liquidity determinants such as volatility. Liquidity commonality in options is stronger with smaller firms and more volatile stocks, indicating the existence of a size-effect and a volatility-effect.

Aside from commonality, this study also uncovers several important features of the option market liquidity. To begin with, information asymmetry plays a far more important role than inventory risk as a fundamental driving force of liquidity. Besides the larger $t$-values for the information asymmetry proxies in the regression analysis, an important piece of supporting evidence is the *positive* relation between the changes in bid–ask spread and volume, contrary to the negative relation observed with stocks. Our results support the previous finding that informed traders may choose to trade in the option market (Black, 1975; Easley et al., 1998; Pan and Poteshman, 2006). The results also support the notion that volumes also convey information and market-makers tend to protect themselves by widening the spread upon seeing an increase in the trading volume (Easley and O'Hara, 1992; Kim and Verrechia, 1994).

Another feature is the linkage between the options' market-wide liquidity and the movements of the overall underlying stock market. There are two interesting findings in this regard. First, the option market liquidity responds asymmetrically to upward and downward market movements. For instance, call options' liquidity improves in up markets and deteriorates in down markets. Second, the liquidity of call and put options behaves differently during the same market movement, with call options' liquidity mostly responding to upward movements, while put options' mostly responding to downward movements. Therefore, options are not only favored as informational trading tools, but they are also used as directional trading tools.

This study serves as a first step toward understanding the overall property of the option market liquidity. It opens up several avenues for future research. One natural extension would be a cross-sectional study concerning the pricing of liquidity risk in options. Another area would be the in-depth examination of potential structures in options liquidity, especially with respect to moneyness and maturity buckets.

## Acknowledgments

We thank Viral Acharya, Long Chen, Aparna Gupta, Madhu Kalimipalli, Raymond Kan, Lukasz Pomorski, Andriy Shkilko, Dragon Tang, Chris Veld, Qing Wang and seminar/conference participants at the National Central University (Taiwan), National Chiao Tung University (Taiwan), National Taiwan University, University of Waterloo, University of Windsor, the 2007 Northern Finance Association meeting, the 2008 Financial Management Association meeting and the 2008 Midwest Finance Associate meeting for useful comments. We thank especially an anonymous referee and the Editor, Avanidhar Subrahmanyam for their constructive comments and suggestions. We also thank Siu Kai Choy for his able research assistance. Both authors gratefully acknowledge the financial support from the Social Sciences and Humanities Research Council of Canada.

## References

Acharya, V., Pedersen, L., 2005. Asset pricing with liquidity risk. Journal of Financial Economics 77, 375–410.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets 5, 31–56.

Amin, K., Lee, C., 1997. Option trading, price discovery, and earnings news dissemination. Contemporary Accounting Research 14 (2), 153–192.
Barclay, M., Warner, J., 1993. Stealth trading and volatility: which trades move prices?. Journal of Financial Economics 34, 281–306.
Black, F., 1975. Fact and fantasy in use of options. Financial Analyst Journal 31 (4), 36–72.
Brenner, M., Eldor, R., Hauser, S., 2001. The price of options illiquidity. Journal of Finance 56 (2), 789–805.
Brockman, P., Chung, D., 2002. Commonality in liquidity: evidence from an order-driven market structure. Journal of Financial Research 25 (4), 521–539.
Brockman, P., Chung, D., Pérignon, C., 2009. Commonality in liquidity: a global perspective. Journal of Financial and Quantitative Analysis 44 (3), forthcoming.
Cho, Y., Engle, R., 1999. Modeling the impacts of market activity on bid–ask spreads in the option market. NBER working paper.
Chordia, T., Roll, R., Subrahmanyam, A., 2000. Commonality in liquidity. Journal of Financial Economics 56, 3–28.
Chordia, T., Roll, R., Subrahmanyam, A., 2001. Market liquidity and trading activity. Journal of Finance 56 (2), 501–530.
Coughenour, J., Saad, M., 2004. Common market makers and commonality in liquidity. Journal of Financial Economics 73 (1), 37–69.
Çetin, U., Jarrow, R., Protter, P., 2004. Liquidity risk and arbitrage pricing theory. Finance and Stochastic 8, 311–341.
Çetin, U., Jarrow, R., Protter, P., Warachka, M., 2006. Pricing options in an extended Black Scholes economy with illiquidity: theory and empirical evidence. Review of Financial Studies 19 (2), 493–529.
Deuskar, P., Gupta, A., Subrahmanyam, M., 2008. Liquidity effect in OTC options markets: premium or discount? Working paper, New York University.
Diamond, D., Verrecchia, R., 1987. Constraints on short-selling and asset price adjustment to private information. Journal of Financial Economics 18 (2), 277–311.
Diamond, D., Verrecchia, R., 1991. Disclosure, liquidity, and the cost of capital. Journal of Finance 46 (4), 1325–1359.
Domowitz, I., Hansch, O., Wang, X., 2005. Liquidity commonality and return co-movement. Journal of Financial Markets 8, 351–376.
Easley, D., O'Hara, M., 1992. Time and the process of security price adjustment. Journal of Finance 47 (2), 577–605.
Easley, D., O'Hara, M., Srinivas, P., 1998. Option volume and stock prices: evidence on where informed traders trade. Journal of Finance 53 (2), 431–465.
Easley, D., Hvidkjaer, S., O'Hara, M., 2002. Is information risk a determinant of asset returns?. Journal of Finance 57 (5), 2185–2221.
Fabre, J., Frino, A., 2004. Commonality in liquidity: evidence from the Australian stock exchange. Accounting and Finance 44, 357–368.
Fama, E., MacBeth, J., 1973. Risk, return, and equilibrium: empirical tests. Journal of Political Economy 81, 607–636.
Glosten, L., Milgrom, P., 1985. Bid, ask, and transaction prices in a special market with heterogeneously informed traders. Journal of Financial Economics 14 (1), 71–100.
Hameed, A., Kang, W., Viswanathan, S., 2006. Stock market decline and liquidity. Working paper, National University of Singapore and Duke University.
Hasbrouck, J., Seppi, D., 2001. Common factors in prices, order flows, and liquidity. Journal of Financial Economics 59, 383–411.
Hasbrouck, J., 2006. Trading costs and returns for US equities: estimating effective costs from daily data. Working paper, New York University.
Huberman, G., Halka, D., 2001. Systematic liquidity. Journal of Financial Research 24 (2), 161–178.
Jarrow, R., Protter, P., 2007. Liquidity risk and option pricing theory. In: Birge, J., Linetsky, V. (Eds.), Handbook of Financial Engineering, Elsevier Publishers.
Kalodera, I., Schlag, C., 2004. An empirical analysis of the relation between option market liquidity and stock market activity. Working paper, Goethe University, Germany.
Kim, O., Verrechia, R., 1994. Market liquidity and volume around earnings announcements. Journal of Accounting and Economics 17 (1–2), 41–67.
Korajczyk, R., Sadka, R., 2008. Pricing the commonality across alternative measures of liquidity. Journal of Financial Economics 87 (1), 45–72.

Kyle, A.P., 1985. Continuous auctions and insider trading. Econometrica 6, 1315–1335.
Lakonishok, J., Lee, I., Pearson, N., Poteshman, A., 2007. Option market activity. Review of Financial Studies 20 (3), 813–857.
Lee, C., Mucklow, B., Ready, M., 1993. Spreads, depths, and the impact of earnings information: an intraday analysis. Review of Financial Studies 6 (2), 345–374.
Mayhew, S., Sarin, A., Shastri, K., 1999. What drives option liquidity? Working paper, University of Pittsburgh.
Pástor, L., Stambaugh, R., 2003. Liquidity risk and expected stock returns. Journal of Political Economy 111 (3), 642–685.
Pan, J., Poteshman, A., 2006. The information in option volume for future stock prices. Review of Financial Studies 19 (3), 871–908.
Sadka, R., 2006. Momentum and post-earnings-announcement drift anomalies: the role of liquidity risk. Journal of Financial Economics 80 (2), 309–349.
Spiegel, M., Wang, X., 2005. Cross-sectional variation in stock returns: Liquidity and idiosyncratic risk. Working paper, Yale School of Management.
Tang, D., Yan, H., 2008. Liquidity and credit default swap spreads. Working paper, University of Hong Kong.
Vijh, A., 1990. Liquidity of the CBOE equity options. Journal of Finance 55 (3), 1157–1179.
Zheng, X., Zhang, Z., 2006. Commonality in liquidity in emerging markets: evidence from the Chinese stock market. Working paper, University of Durham.