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Commonality in liquidity: Evidence from the Stock Exchange of Thailand ☆

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Abstract

This study examines commonality in liquidity of the Stock Exchange of Thailand (SET) using a limited order book data from 1996 to 2003. Strong evidence is found for market-wide commonality in liquidity, which prevails across several liquidity measurements. Industry-wide commonality is found to be stronger than market-wide commonality in liquidity. However, we do not find a market-wide correlated liquidity supply imbalance. There is evidence that indicates a fall in individual liquidity on Monday and after a day with a positive return.

JEL classification: G23; D82
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1. Introduction

Empirical market microstructure research has recently shifted its focus from the examination of individual securities' liquidity towards analyses of the common determinants of liquidity. Chordia et al. (2000), Hasbrouck and Seppi (2001) and Halka and Huberman (2001) examine common factors in liquidity, looking at New York Stock Exchange (NYSE) stocks, while Brockman and Chung (2002) and Fabre and Frino (2004) focus on the order-driven market,

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looking at the Stock Exchange of Hong Kong (SEHK) and the Australian Stock Exchange (ASX), respectively. These studies report, however, different effects of commonality on liquidity (CML) for the observed markets, suggesting that market structure plays an important role in these differences. Fabre and Frino (2004) find no evidence to support commonality in liquidity on examining the ASX. They attribute the absence of any commonality in liquidity on the ASX to the lower inventory holding cost in the market, with no market maker. On the other hand, Brockman and Chung (2002) report the existence of commonality in liquidity in the HKSE. They explain that individual stocks are directly affected by the common determination of liquidity, due to the absence of the liquidity provider of last resort.

This study examines commonality in liquidity on the Stock Exchange of Thailand (SET), which operates with no market maker. As documented in Comerton-Forde and Rydge (2006), the market microstructure of six of the largest Asia-Pacific exchanges, including the SET, have significant differences in market design in terms of the trading mechanisms, market transparency, order priority rules, or tick sizes. As a result, the inconsistent evidence of the commonality in liquidity in the HKSE and the ASX might be attributed to the variation in the market designs, as argued in Fabre and Frino (2004). The commonality in liquidity has been studied for developed markets but in this paper we aspire to gear attention toward an emerging country, a territory that is unexplored. We study commonality in liquidity in Thailand, one of the emerging countries where our findings will shed light on CML in the other emerging markets. Liquidity is more critical for emerging markets than developed markets (Bekaert et al., 2006) and Thailand is a good example of a market that is very sensitive to a change in liquidity. On December 18, 2006, when the central bank of Thailand implemented a policy of capital control on foreign funds, there was an uproar and the SET index decreased sharply for 15% a day reaching the lowest point since the Asian crisis in 1997.[1,2] Studying CML in such market will help governmental officials or researchers gain insights of the factors that affect the sensitivity of the liquidity market and implement policies that might prevent turmoil from liquidity shocks.

This study contributes to the study of commonality in liquidity in several ways. Firstly, it investigates how the absence of a market marker impacts the commonality in liquidity. An examination of the co-variation of individual stock liquidity and the market liquidity is carried out, as well as a test of market-wide commonality in liquidity, which underlies the basic model employed by Chordia et al. (2000).

Second, to our knowledge there is limited evidence on the nature of liquidity *beyond best bids and offers* in the limit order book and, so far, no evidence on the commonality of liquidity beyond best bids and offers has been reported.[3] Many researchers suggest that liquidity measured by quotes and quantities beyond best prices contains information that is suitable for the study of commonality in liquidity (Domowitz, Hansch and Wang, 2005; Kempf and Mayston, 2006). When investors have large positions to trade, their orders will walk up the book and thus will not only care about liquidity at best prices, but also liquidity beyond best prices. Best quotes are noisy and may not be well-suited for a commonality study. The bid–ask spread and depth at best prices are affected by idiosyncratic risk because the suppliers of liquidity compete intensely for new price priority. Kempf and Mayston (2006) find that the more liquidity measures are extended

[1] http://www.forbes.com/markets/2007/03/01/thailand-investors-capital-markets-equity-cx_jc_0301markets06.html.

[2] http://www.marketwatch.com/news/story/thailand-scraps-some-capital-controls/story.aspx?guid=%7B8C90419A-5249-4AF4-B2CB-8AA28F0C1DEC%7D.

[3] A few exceptions include Kempf and Mayston (2006) and the study of liquidity distribution in the limit order book on the Paris Bourse (Biais et al., 1995), the Stockholm Stock Exchange (Niemeyer and Sandas, 1993), the Saudi Stock Market (Al-Suhaibani and Kryzanowski, 2000) and the Stock Exchange of Thailand (Visaltanachoti et al., 2005).

beyond best prices, the stronger is commonality.[4] This paper adds to the literature by developing two liquidity measures that take advantage of the quotes beyond best prices. To the best of our knowledge, most of the existing literature examines depth and spreads outside quote separately. The price of liquidity is measured by the bid–ask spread while the quantity of liquidity is represented by the depth. Our two new liquidity measures are *average spread* and *proportional average spread*, which take into account both spread and depth at the outside and inside quotes.[5] Specifically, the average spread is computed by taking a difference between depth weighted ask price and depth weighted bid price. The proportional average spread is the average spread divided by the average of depth weighted bid and ask prices.

The reason for the lack of evidence beyond best price is mainly because transaction and limit order book data from non-US exchanges are typically difficult to obtain. The level of liquidity beyond the best quote would affect the price discovery process and the behaviour of traders, which in turn will affect the commonality of liquidity. Parlour (1998) shows that even though all traders have the same set of information, liquidity providers compete against each other for the liquidity payment. At the same time, however, limit order traders are concerned about the risk of being “picked-off” by informed traders. Therefore, a trade-off between the competitions among limit order traders for the best bid–ask quotes and the picked-off risk where limit order traders might trade against better informed traders determines the shape of the limit order book and the dynamics of commonality in liquidity. In this research, we study measures of liquidity from the liquidity at the market and the observed liquidity beyond the market, or the displayed liquidity. We also apply measures that take into account the variability of the level of depths available in each quote. Taken together, we apply more various liquidity proxies than the other studies to ensure that our results are robust.

Third, we investigate commonality in *liquidity supply imbalance* which has not been done in any previous research. Order imbalance is a more powerful determinant of liquidity and stock returns beyond trading volume (Chordia et al., 2002). In the NYSE or NASDAQ, there are specialists or dealers who supply liquidity to traders and actively manage their inventories and order flows. As a result, one would expect dealers to alleviate the liquidity supply shock by being a liquidity lender of last resort. In contrast, the Stock Exchange of Thailand operates under a pure limit order-driven system; therefore, the existence of commonality of liquidity supply imbalance is a particular concern to both traders and regulators.

Finally, most studies use only one year of data (e.g. Chordia et al., 2000; Hasbrouck and Seppi, 2001; Halka and Huberman, 2001; Fabre and Frino, 2004); whereas, we use eight years of data to provide a robust evidence regarding to systematic liquidity. Chordia et al. (2000) point out that the existence of common factors in liquidity may be correlated to the market events and market crashes. Events such as the 1997 East Asian financial crisis may result in individual stock liquidity being influenced by market-wide factors. As a result, we study eight years of limit order book data from 1996 to 2003, in order to investigate the impact of market events including bull, bear, and East Asian periods of financial turbulence on the variation in commonality of liquidity.

Consistent with Chordia et al. (2000), strong evidence of market-wide commonality in liquidity is found, and the effect prevails across all size-sorted stocks, using several liquidity measurements. The common liquidity is found to be robust across bull, bear and financial turmoil periods. The

[4] At beyond best prices, Kempf and Mayston (2006) find that common variation in depth accounts for 20% deeper in the book whereas at best prices, common variations in depth and spread only accounts for roughly 2% and 6% of all liquidity variation.

[5] We thank the referee for suggesting this issue.

overall effect of commonality in liquidity is relatively less than that reported in the New York Stock Exchange (NYSE). The commonality of liquidity beyond the best quotes is also observed. Furthermore, we find that the industry-wide commonality in liquidity is stronger than the market-wide commonality in liquidity for all measures of liquidity except for spread and average spread. Nevertheless, no evidence is found on the existence of the commonality in limit order book imbalance in the SET. In addition, we observe the level of individual stock spreads increases and individual stock depth falls suggesting a decline in liquidity level on Monday. We do not find a significant evidence of a stronger market-wide and industry-wide correlated liquidity on Monday. Moreover, the new tick size rule implemented by the SET increases the percentage change of individual stock spreads but we find no evidence on the impact of new tick size rule and market-wide correlated liquidity. Finally, we find that the lag positive returns significantly increase the percentage change of individual stock spread and decrease the percentage change of individual stock depth. On the other hand, the past negative returns do not have any significant impact on the percentage change of individual stock liquidity. All in all, the Thai market is a good platform to test the commonality in liquidity evidence because liquidity is very important in this market.

2. Market structure and data

2.1. Market structure

Due to the development and improvement in information technology and financial market deregulation, order-driven market structures and the electronic limit order book have become a popular trading platform in recent years. Many new equity and derivative markets adopt order-driven systems and some of more mature exchanges are initiating, or developing the order-driven structure. It is important to distinguish between order-driven and quote-driven market structures, because market structure determines how orders are transformed into trades and how this transformation affects liquidity. In an order-driven market, no designated market maker has an obligation to provide liquidity to the market.[6] Traders and investors submit a limit order book to buy and sell shares. How such a submission provision of liquidity responds to market-wide liquidity movement is the focus of the current study.

Brockman and Chung (2002) argue that order-driven systems are more vulnerable to commonality because no liquidity provider of last resort is obliged to maintain a balance of liquidity in the market. Due to the absence of such an obligation, traders have the right to withdraw their liquidity provision orders during market-wide liquidity shocks. Brockman and Chung (2002) also argue that, if order imbalance is more easily diffused due to the existence of multiple liquidity providers, commonality may be less pervasive. In contrast to order-driven markets, quote-driven markets rely on designated market makers to provide liquidity by continuously quoting bid and ask prices until they are willing to trade. Our study examines the measurement and analysis of commonalty in *order-driven* market structures.

2.2. Data

Transactions and limit order book data for the Stock Exchange of Thailand are obtained from the Securities Industry Research Centre of Asia-Pacific (SIRCA) over eight-year period from

[6] It is well known for order-driven markets everywhere that, even when there is no official market maker, some individuals will become de facto market makers. We thank Richard Roll for this comment.

Table 1
Definition of liquidity variable

Liquidity variable	Symbol	Definition	Units
Panel A: Measurements of liquidity at the outside quote			
Spread	SPR	$P_{A,1}-P_{B,1}$	Baht
Proportional spread	PSPR	$(P_{A,1}-P_{B,1})/[(P_{A,1}+P_{B,1})/2]$	None
Depth	DEP	$D_{A,1}+D_{B,1}$	Shares
Imbalance of depth	IBD	$(D_{A,1}-D_{B,1})/(D_{A,1}+D_{B,1})$	None
Slope of outside quote	SLOPE	$\text{Log}(P_{A,1}/P_{B,1})/(\text{Log } D_{A,1}+\text{Log } D_{B,1})$	None
Panel B: Measurements of depths at the outside and inside quotes			
Displayed depth	DDEP	$\sum_{i=1}^{3}(D_{A,i}+D_{B,i})$	Shares
Imbalance of displayed depth	IBDD	$\sum_{i=1}^{3}(D_{A,i}-D_{B,i})/\sum_{i=1}^{3}(D_{A,i}+D_{B,i})$	None
Ratio of outside depth	RATIO	$(D_{A,1}+D_{B,1})/\sum_{i=1}^{3}(D_{A,i}+D_{B,i})$	None
Panel C: Measurements of average spreads that include depths at the outside and inside quotes			
Average spread	ASPR	$\overline{P}_A-\overline{P}_B$	Baht
Proportional average spread	PASPR	$(\overline{P}_A-\overline{P}_B)/[(\overline{P}_A+\overline{P}_B)/2]$	None

This table presents the definition of the liquidity variables used in this study. A and B present ask and bid, respectively. P denotes price, and D denotes depths at bid or ask. The distinguished subscripts indicate: 1 = bid or ask at the outside quote; 2 = second best quote; and 3 = third best quote. $\overline{P}_A=\frac{P_{A,1}D_{A,1}+P_{A,2}D_{A,2}+P_{A,3}D_{A,3}}{D_{A,1}+D_{A,2}+D_{A,3}}$, $\overline{P}_B=\frac{P_{B,1}D_{B,1}+P_{B,2}D_{B,2}+P_{B,3}D_{B,3}}{D_{B,1}+D_{B,2}+D_{B,3}}$. Note that 1 indicates the outside quote where 2 and 3 represent the inside quote. Panel A shows the calculation of liquidity measurements at the best quote. Panel B describes the formula used to compute the measurements of displayed liquidity beyond the best quote. Panel C presents the definition of average spreads that take into account the depth at outside and inside quotes.

1996 to 2003. The data includes all transactions which have trade and order records entered into the Automatic System for the Stock Exchange of Thailand (ASSET). Trade and order records include bid (ask) prices and volume corresponded to price, at a time stamp accurate to 100 s throughout the trading day, which consists of a morning session from 10:00 to 12:30 and an afternoon session from 14:30 to 16:30. The records also include the first best according to price priority and a sequenced chronological order of trades and orders accessed through ASSET. This guarantees precise matches of first, second and third buy and sell orders in the queue.

According to Chordia et al. (2000) and Fabre and Frino (2004), infrequently traded stocks cannot provide reliable information. Therefore, this study applies the following stock selection criteria. To be included, a stock has to be present in each year during the sample period of January 3, 1996 to October 31, 2003. Each selected stock must have at least 160 active trading days over the sample period and at least five transactions on those trading days. These criteria ensure that each stock with active and fluid liquidity during the observed years is included. After applying these criteria, 418 stocks were selected from 538 available stocks, during 1,868 trading days across 1996 to 2003 sample period.[7]

For every transaction, in each stock, on each trading day, ten different liquidity measures are computed. The basic measures of liquidity are drawn from the best quotes, which include spread, proportional spread, depth, average spread, proportional average spread, depth imbalance, and

[7] Our results are robust to the 112 firms sample comprising of the stocks that have at least 20 active trading days within one year and at least ten transactions per day on those trading days.

slope of outside quote. The slope of outside quote combines both best bid and ask prices and volumes, viewed as a summary measure of the quoted liquidity supply curve. An average spread and proportional average spread are better indicators of liquidity level for illiquid securities.[8] The measurements of liquidity beyond the best quotes are displayed depth, displayed depth imbalance, and the ratio of depth to displayed depth. Table 1 gives the symbol and definition of each liquidity variable. Only transactions which occurred during the two ASSET trading sessions, morning (10:00–12:30) and afternoon (14:30–16:30), are included in the analysis. Those trades generated by the pre-opening and closing call market and off-hours trading were excluded, as they are not a part of the continuous transaction. According to Chordia et al. (2000), the sample of transaction-level data for each stock, on each day, is averaged across all trades in that stock for the day. This smoothes out intraday patterns and reduces the data to a daily time series for each stock, with up to 252 observations.

Table 2 reports cross-sectional statistics for the time series means of the liquidity variables. Panel A presents the descriptive statistics for market-wide liquidity measures used in this study. There is right skewness in the cross-section of the average spreads and depths, as the mean value is larger than the medians except for imbalance of depth where the mean equals the median. This result is consistent with Chordia et al. (2000) and Fabre and Frino (2004). The average quoted spread is approximately 2.36 Thai Baht, and the average proportional spread is 8.12%. The average spread is 3.58 Thai Baht whereas proportional average spread is 12.34%. As expected, both average spread and proportional average spread are higher than the spread and proportional spread because they take into account the depth outside the inside quote. Compared to Australian Stock Exchange (ASX) stocks and New York Stock Exchange (NYSE) stocks, the percentage bid–ask spreads on the SET are significantly higher than both markets. Chordia et al. (2000) document the proportional spread of 1.60% across 1169 stocks in year 1992. Fabre and Frino (2004) report the proportional spread of 3.91% across 660 stocks in year 2000. In contrast, the proportional spread of our sample from 1996 to 2003 show over two times larger than those on the ASX (8.12% compared to 3.91%) and more than five times larger than those on the NYSE (8.12% compared to 1.60%). The high proportional spread in our sample is driven by the Asian financial crisis in Thailand that occurred during year 1997 and overshadowed the Thai's financial markets over the next three years. The proportional spreads in year 1998–2000 are 17.42%, 13.10% and 11.40% respectively. On the other hand, the proportional spreads in year 2001–2004 fell to 7.93%, 5.28% and 4.60% respectively. The substantial time variation of proportional spreads suggests that the financial crisis had a strong impact on the level of liquidity in the market. The question regarding whether financial crisis would determine the commonality of liquidity will be addressed in Section 3.5 where the commonality of liquidity are examined year-by-year.

Additionally, the measure of depth also shows that liquidity in the SET is weak. The quantity of orders at best bid and ask is low, and there is a big difference in the volume between the depth and the displayed depth. As a result, there is a small proportion of depth in the total display depth (35%). Order imbalance of depth on the best bid and ask has positive means and medians, and the quoted orders on best bid and ask can be considered to be buyer-initiated. Order imbalance on displayed depth on the total of the bids and asks has, however, negative means and median. As a consequence, the total quoted orders on total bids and asks can be viewed as being seller-initiated. Intuition suggests that liquidity is influenced by inventory concerns, caused by an imbalance between buyer and seller-initiated trades. The quoted slope is the slope of the line that connects the bid and ask prices and the quantity pairs. A flatter line indicates that more liquidity is available

[8] We thank the referee for this suggestion.

Table 2
Summary statistics

Panel A: Cross-sectional statistics for time series means

	Mean	Median	Standard deviation	Maximum	Minimum
SPR	2.36	1.22	4.28	56.98	0.02
PSPR	8.12%	7.23%	5.02%	23.75%	0.76%
ASPR	3.58	1.95	6.80	107.61	0.05
PASPR	12.34%	11.50%	5.97%	29.16%	2.34%
DEP	94,855	20,426	209,590	1,972,400	1007
DDEP	369,020	70,701	864,420	9,298,000	2135
RATIO	35.22%	34.82%	8.61%	58.22%	19.98%
IBD	2.54%	2.55%	7.64%	26.98%	−42.21%
IBDD	−2.34%	−2.54%	11.27%	34.11%	−45.73%
SLOPE	0.0054	0.0046	0.0036	0.0182	0.0003

Panel B: Cross-sectional means of time series correlations between liquidity variable pairs for an individual stock

	SPR	PSPR	ASPR	PASPR	DEP	DDEP	RATIO	IBD	IBDD
PSPR	0.21								
ASPR	0.98	0.13							
PASPR	0.17	0.98	0.10						
DEP	−0.18	−0.35	−0.16	−0.31					
DDEP	−0.18	−0.37	−0.15	−0.33	0.98				
RATIO	0.33	0.88	0.23	0.82	−0.42	−0.43			
IBD	0.06	0.28	0.04	0.26	−0.05	−0.05	0.36		
IBDD	0.19	0.21	0.17	0.17	−0.04	−0.03	0.33	0.91	
SLOPE	0.33	0.98	0.24	0.93	−0.38	−0.39	0.90	0.29	0.25

This table reports the cross-sectional statistics computed from individual stock. Each variable is calculated for every transaction during the years from 1996 to 2003. During this eight-year period, there were 1868 trading days. 418 stocks were selected from the total of 538 Thailand's stocks. The stock selection was based on two criteria; first, the selected stock must have at least 160 active trading days over the sample period; second, there were at least five transactions on one individual trading day. The intraday observations are averaged within each day to obtain a sample of 1868 trading days. Panel A calculates the mean, median, standard deviation, maximum and minimum for each variable. Panel B shows the correlations between liquidity variable pairs.

at the best quote. According to Hasbrouck and Seppi (2001), the slope of the SET is much steeper than that of the Dow stocks (0.0054 compared to 0.00043). In summary, the SET offers less liquidity than the NYSE, or the ASX.

Table 2 Panel B reports correlations among the eight liquidity variables. The order imbalances on the displayed depth and on the depth are uncorrelated with depth and display depth, as they are virtually zero. There is, however, a different correlation degree between the other six variables. Similar to Fabre and Frino (2004), the negative correlations between the bid–ask spread and the depth for the NYSE stocks are stronger than those for the ASX and the SET stocks. Chordia et al. (2002) show that the correlation between quoted spread and depth is −0.396 for 1169 NYSE stocks in 1992. Fabre and Frino (2004) find that such correlation is −0.054 for 660 ASX stocks in 2000. In our sample, the correlation between spread and depth is −0.18 for 418 stocks from 1996–2003. These findings could be driven by the differences between the trading mechanisms of the automatic centralized trading systems and the specialists. The active role played by the specialists to control the bid–ask spreads and depths on the NYSE results in the stronger correlation between the spread and depth compared to the markets without dedicated liquidity suppliers such as the SET.

3. Empirical evidence

3.1. Evidence of common liquidity

A similar market model approach to that proposed by Chordia et al. (2000) is used for our initial estimates of liquidity commonality. The model is as follows:

$$\mathrm{DL}_{i,t} = \alpha + \beta_1 \mathrm{DL}_{M,t} + \beta_2 \mathrm{DL}_{M,t-1} + \beta_3 \mathrm{DL}_{M,t+1} + \varepsilon_{i,t} \quad (1)$$

where $\mathrm{DL}_{i,t}$ is the daily percentage change in liquidity variable L (ten variables are measured in this study) for stock i from trading day $t-1$ to $t+1$ and $\mathrm{DL}_{M,t}$ is the concurrent change in a market-wide equally weighted change in a cross-sectional average of the same liquidity variable. Other variables are also included in the regressions. The one period lead and lag of the market average liquidity variable ($\mathrm{DL}_{M,t+1}$ and $\mathrm{DL}_{M,t-1}$) are included in order to allow for non-contemporaneous adjustments in liquidity caused by thin trading. In addition, concurrent, lead and lag equally weighted market returns are included in order to remove any spurious dependence represented by the relationship between returns and liquidity measures. The concurrent daily percentage change in the individual stock squared return is also included as a proxy for price change volatility, which may influence liquidity variables. Aggregated independent variables exclude related dependent variable values, thus when computing the market liquidity variable DL_M, stock j is excluded to remove a potential constraint on the cross-sectional mean coefficient to achieve unity. The standard errors in the commonality regressions tend to be understated because of cross-correlations in the residual. The ideal solution is to apply SUR instead of OLS regression; nevertheless, SUR is not applicable because of the large size of the cross-sections. To address this problem, we follow footnote 8 of Chordia et al. (2000) by applying adjusted t-stat, which is the OLS t-stat divided by $\sqrt{1+(N-1)\rho}$ where N is the number of regressions and ρ is the common cross-correlation of residuals from 418 regressions. The average residual cross-correlation across 418 regressions or the average of the 87,153 pair-wise residual correlations serve as a proxy for ρ. We apply this adjusted t-stat for all regressions in this paper.[9]

Table 3 reports the regression results, which provide evidence of commonality in liquidity. For the spread, the average coefficient on the concurrent market liquidity variable is 0.450, with an associated t-statistic of 38.86. Approximately 99% of these individual coefficients from the 418 time series regressions are positive and 25% are positively significant at the 5% level. These empirical results provide evidence of the existence of commonality in liquidity in an order-driven market structure. In addition, our smaller coefficient estimates, compared with Chordia et al.'s (2000) quoted mean spread of 0.690 suggest that commonality has relatively less effect on spread for the SET sample.

For proportional spread, the mean coefficient of the concurrent market liquidity variable is 0.841, with an associated t-statistic of 48.23. All individual coefficients are positive and 72% of them are significant at the 5% level. In contrast to the spreads, our proportional spread coefficient is larger than that reported in Chordia et al.'s (2000) study (0.791). This suggests that commonality has a relatively greater effect on the proportional spreads of the sample after controlling for the overall level of the trading prices.

Furthermore, the concurrent market-wide commonality in liquidity exists for the two liquidity measures that take the variability of the level of depths available in each quote into account. For

[9] Our results are robust when we apply Newey-West HAC t-statistics to adjust for heteroscedasticity and autocorrelation.

Table 3
Market-wide commonality in liquidity

	Concurrent				Lag				Lead				Sum		Adj-R^2 (%)	
	Mean	*t*-stats	% (+)	% (+) s	Mean	*t*-stats	% (+)	% (+) s	Mean	*t*-stats	% (+)	% (+) s	Mean	*t*-stats	Mean	Median
SPR	0.450	38.86	99	25	0.018	2.11	54	0	−0.025	−3.36	33	0	0.443	24.05	1.52	1.21
PSPR	0.841	48.23	100	72	0.007	0.68	44	1	−0.015	−1.64	41	0	0.834	32.96	2.49	2.12
ASPR	0.326	31.62	97	17	0.016	2.37	57	0	−0.013	−1.89	43	0	0.330	21.12	1.39	0.94
PASPR	0.732	36.53	99	59	0.025	2.54	51	0	−0.024	−2.12	42	0	0.732	25.36	2.69	2.26
DDEP	0.311	19.38	88	35	0.013	1.74	50	1	0.011	1.45	51	1	0.335	15.63	1.32	0.42
DEP	0.414	26.07	97	46	0.010	1.71	53	0	0.005	0.85	49	0	0.428	22.07	2.83	1.24
RATIO	0.858	31.62	97	66	0.024	0.92	51	10	0.019	0.80	51	9	0.901	16.95	0.55	0.40
IBDD	0.005	1.99	54	3	0.005	1.87	51	5	0.004	1.43	52	5	0.013	2.80	0.04	−0.04
IBD	0.002	0.71	52	2	0.002	0.81	53	2	0.001	0.49	53	4	0.006	1.21	0.02	−0.04
SLOPE	0.800	46.62	100	65	0.008	0.76	46	1	−0.013	−1.55	39	0	0.795	31.49	2.43	2.04

This table presents the market-wide commonality in liquidity using the following multiple regressions:

$$\mathrm{DL}_{i,t} = \alpha + \beta_1 \mathrm{DL}_{M,t} + \beta_2 \mathrm{DL}_{M,t-1} + \beta_3 \mathrm{DL}_{M,t+1} + \varepsilon_{i,t}$$

For each stock, daily percentage changes in liquidity variables for the individual stock, $\mathrm{DL}_{i,t}=L_{i,t}/L_{i,t-1}-1$, are regressed in time series on the percentage change of an equally weighted cross-sectional average of the liquidity variable for all stocks excluding stock i (the 'market'), $\mathrm{DL}_{M,t}$, in the sample. During the period from 1996 to 2003, there were 1868 trading days and 418 stocks were tested. Cross-sectional mean of time series slope coefficients are reported with the corresponding *t*-statistics. '%(+)' reports the proportion of positive coefficients, while '%(+)s' presents the percentage which the adjusted *t*-statistics is significant at the 5% critical level. The adjusted *t*-stat reflects the cross-correlation in the individual stock regression residuals. Following footnote 8 of Chordia et al. (2000), the adjusted *t*-stat is the OLS *t*-stat divided by $\sqrt{1+(N-1)\rho}$ where N is the number of regressions and ρ is the common cross-correlation of residuals from 418 regressions. ρ is proxied by the average residual cross-correlation across 418 regressions or the average of the 87,153 pair-wise residual correlations. Note that the Chordia et al. (2000)'s formula contains a typographical error in the form of an extraneous digit, 2. (see footnote 6 of Chordia et al., 2005). Sum=Concurrent+Lag+Lead coefficients. The results for the coefficients are reported for the concurrent

average spread, the average coefficient of the concurrent market liquidity is 0.326 with *t*-statistic of 31.62. 97% of coefficients from 418 time regressions are positive and 17% of these coefficients are significant at 5% critical value. For proportional average spread, the mean coefficient of the concurrent market liquidity is 0.732 with *t*-statistics of 36.53. 99% and 59% of the coefficients are positive and significant at 5% critical level, respectively.

Considering the depth variables, the regression results also provide strong evidence for commonality. The change in the percentage displayed depth displays an average value of 0.311, with an associated *t*-statistic of 19.38. Approximately 88% of these individual coefficients are positive and 35% exceed the 5% one-tail critical value. For depth, the coefficient shows a value of 0.414. Approximately 97% of the coefficients are positive and 46% of all coefficients are significant at 5%. Consistent with the spread measures, the depth coefficients are smaller than those reported for the NYSE (i.e., 1.373). Concerning the variables of order imbalance, imbalance of displayed depth and depth, average coefficients of the concurrent market liquidity variables are very low (0.0005 and 0.0002), with associated *t*-statistics of 1.99 and 0.71, respectively. It should be noted that commonality exists only for imbalance of displayed depth but the result is very weak with 10% critical value. Nevertheless, the slope variable (a combination of the spread and depth) displays significant responses to concurrent movements of the market, where 100% of the coefficients of the slope are positive and 65% of the coefficients are significant at the 5% level. Taken together, all liquidity measures except for imbalance of depth have significant *concurrent* coefficients implying that the market-wide commonality in liquidity exists for all liquidity measures. Moreover, the liquidity of Thai stocks seems to respond significantly to the market-wide liquidity *across time* as the sum of concurrent, lead, and lag coefficients for all liquidity measures except for imbalance of depth are highly significant.

As a result, the initial evidence is consistent with previous studies, which find commonality to be an important feature of the liquidity provision existing in the SET. In aggregate, the evidence also shows that the commonality effect in the SET is relatively less than that of the NYSE. This evidence suggests that, in order-driven markets, there is no obligation on the market makers to maintain an orderly market. Therefore, the market makers are free to exit or have low barriers to enter into the market. The imbalances are more easily diffused across multiple liquidity providers and demanders; therefore, commonality is less pervasive in order-driven markets. Additionally, special market makers in an order-driven market do not provide the common adjustment in the liquidity provision; thus, commonality in liquidity in an order-driven market is less than that in quote-driven markets.

3.2. Industry-wide commonality in liquidity

We examine the effect of industry liquidity on individual liquidity proxies while controlling for the effect of market liquidity. As pointed out by Chordia et al. (2000), the technology breakthrough or occasional occurrences of asymmetric information could have an impact on many firms in the same sector resulting in the co-variation in liquidity of firms in the same industry. In addition, institutional investors and informed traders who concentrate themselves in a specific sector could contribute significantly on the industry-wide commonality in liquidity. To examine the industry-wide correlated liquidity, we estimate the following regression:

$$\mathrm{DL}_{i,t} = \alpha + \beta_1 \mathrm{DL}_{M,t} + \beta_2 \mathrm{DL}_{M,t-1} + \beta_3 \mathrm{DL}_{M,t+1} + \lambda_1 \mathrm{DL}_{\mathrm{Ind},t} + \lambda_2 \mathrm{DL}_{\mathrm{Ind},t-1} + \lambda_3 \mathrm{DL}_{\mathrm{Ind},t+1} + \varepsilon_{i,t} \tag{2}$$

where $\mathrm{DL}_{i,t}$ is the percentage change of an individual liquidity, $\mathrm{DL}_{M,t}$ and $\mathrm{DL}_{\mathrm{Ind},t}$ are equally weighted cross-sectional average of the liquidity variable for all stocks (the 'market') and the corresponding industry liquidity of the stock. We classify all stocks into 10 industries including basic materials, consumer goods, consumer services, financials, health care, industrials, energy, technology, telecommunication, and utilities based on the Datastream level 3 industry classifications.

The results in Table 4 show that change in concurrent industry-wide liquidity can explain any individual liquidity proxies and in all cases. The explanatory power of change in concurrent industry-wide liquidity dominates the explanatory power of change in concurrent market-wide liquidity except for the cases of spread and average spread. Moreover, the effect of industry-wide CML is stronger for aggregated periods indicated by the sum of industry-wide concurrent, lead, and lag coefficients than the effect of market-wide CML. In other words, the existence of commonality within the same industry emerges whereas commonality within the same market decreases in magnitude and significance level. For instance, in case of spread and proportional spread, after including the industry-wide CML, the concurrent market-wide CML falls significantly from 0.450 and 0.841 (see Table 3) to 0.345 and 0.139 respectively. The magnitudes of concurrent industry-wide CML after controlling for market-wide CML are positive and highly significant at 0.177 and 0.712 for spread and proportional spread, respectively. The results are robust across other liquidity measures. We do not perform the analysis of industry-wide correlated limit order book imbalance because as shown in Table 3 there is no evidence of market-wide commonality in limit order book imbalance.

Table 4
Industry-wide and market-wide commonality in liquidity

		Concurrent				Lag				Lead				Sum		Adj-R^2 (%)	
		Mean	t-stats	%(+)	%(+)s	Mean	t-stats	%(+)	%(+)s	Mean	t-stats	%(+)	%(+)s	Mean	t-stats	Mean	Median
SPR	M	0.345	18.89	89	5	0.004	0.35	46	0	−0.007	−0.70	43	0	0.341	12.02	3.00	1.65
	I	0.177	10.08	73	11	0.013	1.66	53	0	−0.015	−2.17	47	0	0.175	7.90		
PSPR	M	0.139	4.22	59	8	−0.010	−0.52	47	1	−0.009	−0.48	49	0	0.120	2.50	4.45	3.05
	I	0.712	24.37	92	38	0.016	1.01	53	0	−0.005	−0.28	46	0	0.723	16.60		
ASPR	M	0.265	15.82	85	8	−0.003	−0.35	50	0	−0.002	−0.18	51	0	0.260	11.23	3.43	1.71
	I	0.199	10.60	75	15	0.019	3.10	54	0	−0.003	−0.48	51	0	0.215	10.12		
PASPR	M	0.154	5.17	60	12	0.037	2.13	51	1	0.016	0.91	50	2	0.207	4.75	5.17	3.94
	I	0.697	25.91	90	51	0.004	0.28	49	0	−0.009	−0.62	48	1	0.692	17.22		
DDEP	M	0.125	11.25	74	13	0.024	2.60	54	1	0.018	2.07	55	1	0.167	9.43	3.22	0.81
	I	0.235	15.03	82	30	−0.012	−2.04	41	0	−0.005	−0.88	46	0	0.217	12.18		
DEP	M	0.190	16.75	84	14	0.003	0.34	49	0	0.005	0.54	48	0	0.198	10.92	5.16	2.08
	I	0.280	16.93	90	30	0.006	0.81	51	0	0.002	0.36	46	0	0.288	14.21		
RATIO	M	−0.201	−5.39	35	6	0.077	2.16	54	12	0.013	0.38	51	9	−0.110	−1.46	2.79	1.74
	I	1.061	43.63	98	83	−0.050	−2.10	47	11	0.005	0.20	54	8	1.015	20.38		
SLOPE	M	0.003	1.07	53	4	0.007	2.29	53	5	−0.001	−0.45	49	3	0.009	1.60	0.02	−0.04
	I	0.010	3.89	60	7	0.001	0.34	53	2	0.001	0.47	51	4	0.012	2.70		

This table presents the results of the industry-wide commonality in liquidity using the following multiple regressions:

$$DL_{i,t} = \alpha + \beta_1 DL_{M,t} + \beta_2 DL_{M,t-1} + \beta_3 DL_{M,t+1} + \lambda_1 DL_{\mathrm{Ind},t} + \lambda_2 DL_{\mathrm{Ind},t-1} + \lambda_3 DL_{\mathrm{Ind},t+1} + \varepsilon_{i,t}$$

where $DL_{i,t}=L_{i,t}/L_{i,t-1}-1$ is the percentage change of an individual liquidity, $DL_{M,t}$ and $DL_{\mathrm{Ind},t}$ are equally weighted cross-sectional average of the liquidity variable for all stocks excluding stock i (the 'market') and the corresponding industry liquidity excluding stock i. M and I denote for market and industry, respectively. We classify all stocks into 10 industries including basic materials, consumer goods, consumer services, financials, health care, industrials, energy, technology, telecommunication, and utilities based on the Datastream level 3 industry classification. '%(+)' reports the proportion of positive coefficients, while '%(+)s' presents the percentage which the adjusted t-statistics is significant at the 5% critical level. The adjusted t-stat reflects the cross-correlation in the individual stock regression residuals. Following footnote 8 of Chordia et al. (2000), the adjusted t-stat is the OLS t-stat divided by $\sqrt{1+(N-1)\rho}$ where N is the number of regressions and ρ is the common cross-correlation of residuals from 418 regressions. ρ is proxied by the average residual cross-correlation across 418 regressions or the average of the 87,153 pair-wise residual correlations. Note that the Chordia et al. (2000)'s formula contains a typographical error in the form of an extraneous digit, 2. (see footnote 6 of Chordia et al., 2005). Sum = Concurrent + Lag + Lead coefficients. The results for the coefficients are reported for the concurrent variables ($DL_{M,t}$), the day before or lag ($DL_{M,t-1}$) and the day after or lead ($DL_{M,t+1}$).

3.3. Commonality in liquidity and size effect

Chordia et al. (2000) and Fabre and Frino (2004) also report existence of a size effect in the degree of commonality in liquidity, using the same regression shown in Table 3. According to Chordia et al. (2000), the bid–ask spreads of large firms tend to have a greater response to market-wide changes. They find, however, no size effect for depth. This suggests that specialists revise bid–ask spreads to a greater extent for larger stocks than for smaller stocks. They also argue that this result may be driven by a greater prevalence of institutional herd trading in larger stocks. In both studies, the sample is partitioned into quintiles by market capitalization. The coefficients in all quintiles are statistically significant and gradually increase with firm size in the findings of Chordia et al.'s (2000) study. Nevertheless, Fabre and Frino (2004) produce different results, whereby only the largest quintile exhibits statistically significant commonality in liquidity for all liquidity variables. Brockman and Chung (2002) find, however, that the middle third quintile has the highest sensitivity to commonality, while large firms are less susceptible to market-wide changes in liquidity than are medium firms.

Table 5 explicitly demonstrates the size effect on the coefficient of the market-wide average liquidity variable. Unlike the studies which partition their samples into quintiles, in this study the samples were sorted and partitioned into three groups (small, medium and large) based on the total assets of each company. As a result, these groupings of small, medium and large size contain 139, 140 and 139 stocks, respectively. Apparently, all three size groupings of all liquidity measures exhibit significant commonality in liquidity in both concurrent and aggregated times. Consistent with Chordia et al. (2000), this study's results show that large firms have relatively large market-wide coefficients when liquidity is measured in terms of average spread, depth, and displayed depth. The largest size grouping is the most sensitive to changes in market-wide depth. By revising the number of shares in which they are ready to trade, investors trading in large firms' stocks respond to changes in market-wide liquidity. However, in contrast to Chordia et al. (2000) but consistent with Brockman and Chung (2002) the slope of outside quote and the proportional average spread of the medium (small) size group tend to have the strongest response to concurrent (sum) market-wide movement. Sum stands for the aggregated time of concurrent, lag, and lead times. In contrast, the ratio of depth to displayed depth for small (medium) size group has the strongest response to concurrent (sum) market-wide movement. For proportional spread, the smallest size grouping is the most sensitive to changes in market-wide liquidity. For spread, the large and medium size groups are the most sensitive to changes in concurrent market-wide liquidity with average coefficients of 0.464 and 0.465, respectively whereas the large size group responds the most to the sum market-wide liquidity with the mean coefficient of 0.470.

Our evidence shows that the large size grouping is the most sensitive to changes in market-wide depth and average spread. Chordia et al. (2000) speculate that the herding behavior of institutional investors causes high commonality in liquidity of large firms compared to the other firm-size groups. We speculate in the same way as Chordia et al. (2000) that this can be explained by the preference of large and liquid stocks by foreign institutional investors. In Thailand, there are Main Board trading where Thai investors trade and Alien Board trading where foreign investors trade. Bailey et al. (2006) show there is a significant difference of the fraction of trading value for foreigners in both Main Board and Alien Board between large market cap and small market cap. There is significantly larger fraction of foreigners trading large market cap shares than the fraction of foreigners trading small market cap shares in both Alien and Main Boards (Table 2 in their paper). The information-processing advantage of foreign investors is particularly valuable for assessing large firm, liquid firms, and firms that are extensively studied by foreign investors

Table 5
Market-wide commonality in liquidity by size

		Concurrent				Lag				Lead				Sum		Adj-R^2 (%)	
		Mean	*t*-stats	%(+)	%(+)s	Mean	*t*-stats	%(+)	%(+)s	Mean	*t*-stats	%(+)	%(+)s	Mean	*t*-stats	Mean	Median
	L	0.464	24.86	99	34	0.034	2.31	57	0	−0.028	−2.32	30	0	0.470	14.89	1.52	1.41
SPR	M	0.465	20.94	99	27	0.014	0.98	55	1	−0.032	−2.51	32	0	0.447	13.64	1.64	1.32
	S	0.422	22.14	99	14	0.006	0.41	52	0	−0.015	−1.09	36	0	0.414	13.14	1.41	0.96
	L	0.817	27.34	100	72	−0.005	−0.25	43	1	−0.038	−2.66	35	0	0.775	18.61	2.37	2.16
PSPR	M	0.852	29.47	100	75	0.016	0.87	48	1	−0.026	−1.72	37	0	0.842	19.60	2.52	2.10
	S	0.853	26.84	99	68	0.010	0.57	41	1	0.019	1.13	50	0	0.883	19.03	2.58	1.93
	L	0.368	20.69	97	25	0.021	1.67	61	0	−0.013	−1.04	44	0	0.376	13.77	1.73	1.46
ASPR	M	0.346	18.30	98	14	0.011	0.82	55	0	−0.017	−1.45	41	0	0.340	11.77	1.35	0.91
	S	0.266	16.87	96	11	0.018	1.71	54	0	−0.008	−0.76	44	0	0.275	11.29	1.10	0.69
	L	0.691	19.11	99	59	−0.007	−0.41	38	1	−0.038	−2.13	34	1	0.646	13.64	2.62	2.38
PASPR	M	0.772	23.34	99	67	0.032	1.97	55	0	−0.044	−2.11	42	1	0.759	15.09	2.83	2.30
	S	0.731	21.09	99	52	0.048	2.77	60	0	0.008	0.41	50	1	0.788	15.28	2.64	2.06
	L	0.436	13.66	91	54	0.013	0.89	44	1	−0.017	−1.50	43	3	0.431	10.32	2.03	1.07
DDEP	M	0.295	11.19	87	38	0.015	1.13	55	1	0.041	3.06	57	3	0.351	9.33	1.28	0.43
	S	0.205	9.83	85	14	0.011	1.01	49	0	0.008	0.63	52	3	0.225	7.71	0.67	0.18
	L	0.540	17.59	98	62	0.005	0.48	47	0	−0.012	−1.30	45	0	0.533	14.63	4.13	3.20
DEP	M	0.395	14.24	96	45	0.017	1.85	54	0	0.018	1.93	49	0	0.431	12.54	2.71	1.04
	S	0.308	15.84	97	33	0.007	0.71	57	0	0.007	0.77	52	0	0.323	11.80	1.68	0.82
	L	0.812	17.13	99	66	−0.005	−0.14	47	7	0.030	0.76	53	28	0.836	9.77	0.40	0.30
RATIO	M	0.865	20.55	98	69	0.066	1.65	53	13	0.006	0.14	47	28	0.936	11.52	0.56	0.46
	S	0.898	17.58	94	64	0.010	0.19	53	11	0.021	0.49	54	28	0.929	8.67	0.68	0.46
	L	0.785	27.04	100	69	0.004	0.19	46	1	−0.030	−2.12	31	0	0.760	17.65	2.34	1.98
SLOPE	M	0.811	28.57	100	68	0.011	0.65	51	1	−0.019	−1.18	40	0	0.804	18.67	2.41	2.14
	S	0.804	25.32	100	57	0.009	0.50	41	1	0.007	0.49	45	0	0.820	18.17	2.53	1.99

This table presents the market-wide commonality in liquidity when the sample is separated into three groups, according to the total asset of each stock. The regression model is similar to the one presented in Table 3. Small, medium and large size covers 139, 140 and 139 stocks, respectively. L, M, and S denote for large, medium, and small stocks. For each stock, daily percentage changes in liquidity variables for the individual stock are regressed in time series on the percentage change of an equally weighted cross-sectional average of the liquidity variable for all stocks excluding stock *i* in the sample. During the period from 1996 to 2003, there were 1868 trading days and 418 stocks were tested. Cross-sectional mean of time series slope coefficients are reported with the corresponding *t*-statistics. '%(+)' reports the proportion of positive coefficients, while '%(+)s' presents the percentage which the adjusted *t*-statistics is significant at the 5% critical level. The adjusted *t*-stat reflects the cross-correlation in the individual stock regression residuals. Following footnote 8 of Chordia et al. (2000), the adjusted *t*-stat is the OLS *t*-stat divided by $\sqrt{1+(N-1)\rho}$ where N is the number of regressions and ρ is the common cross-correlation of residuals from 418 regressions. ρ is proxied by the average residual cross-correlation across 418 regressions or the average of the 87,153 pair-wise residual correlations. Note that the Chordia et al. (2000)'s formula contains a typographical error in the form of an extraneous digit, 2. (see footnote 6 of Chordia et al., 2005). Sum = Concurrent + Lag + Lead coefficients. The results for the coefficients are reported for the concurrent variables ($DL_{M,t}$), the day before or lag ($DL_{M,t-1}$) and the day after or lead ($DL_{M,t+1}$).

(Bailey and Jagtiani, 1994; Hirshleifer, 1988; Allen and Gale, 1994). Generally depths and spread of large firms have greater response to market-wide change in depths and spread.

In aggregate, the empirical evidence confirms the existence of commonality in liquidity across all three size groupings. It is also noted that the percentage of firms with positive and significant coefficients is very high for all three size groupings. The market-wide correlated liquidity is higher for large firms when liquidity is measured by spread, average spread, depth and displayed depth. When liquidity is measured as proportional spread and ratio, liquidity in small firms have the strongest response to market-wide movement. We suspect that the minimum price variation or the minimum tick size might partially resolve this issue. In the Stock Exchange of Thailand, large firms are likely to have high stock price and also large minimum tick size. As a result, large firms face the tick size binding much more frequently than the group of medium and small firms i.e., their spreads are always equal to the minimum tick size; therefore, there is no sensitivity to market-wide movements in spreads. To test this statement, we compute the ratio of the bid–ask spread to minimum tick size based on closing price on each day across three size groupings. Then we calculate the median of this ratio for each grouping. The cross-sectional average ratio for small firm group is 5.74, the medium group is 6.48, and the large group is 3.88. This result indicates that large firm group has tick size binding much more frequently than the other groups. Nevertheless we admit that the ratio of spread to minimum price variation is simply an ad-hoc measurement. The formal test on the role of tick size, commonality in liquidity, and firm size is beyond the scope of this study.

3.4. Weekly seasonality and performance impact on commonality in liquidity

So far we find evidence that supports the existence of market-wide and industry-wide commonality in liquidity. This section aims to examine the weekly seasonality and performance impact on market-wide or industry-wide commonality in liquidity. Admati and Pfleiderer (1989) and Foster and Viswanathan (1990) provide theoretical and empirical evidence confirming that liquidity may display predictable patterns though time, but they neither specify which days of the week involve high or low liquidity nor do they discuss the weekly seasonality of commonality in liquidity. To test the relationship between liquidity and trading activity, four day-of-the-week dummies representing Monday, Tuesday, Wednesday and Thursday are presented. The Friday dummy is excluded to remove any potential constraints on the mean coefficient achieving exact unity. The day-of-the-week measure is included based on the notion that trading activity may display systematic seasonal patterns.

Tick size is an important feature which could affect liquidity (Chordia et al., 2001); therefore, the new tick size rule should affect liquidity. The SET has effectively applied the tick size from November 5, 2001, onwards. Under the old tick size rule, there were seven price ranges that defined the minimum tick size, from a lowest tick of 0.1 baht to a highest tick of 6 baht. For securities with prices below 10 baht, the minimum tick size could be very large relative to the price. For securities priced less than 1 baht, their prices were allowed to fluctuate within a range of $\pm$100%. In general, the minimum tick size was more than 0.5% but less than 1% of the price. The use of various minimum tick sizes suggests that SET attempts to control the variation of the relative tick sizes across price ranges. This argument was strengthened when SET decided to implement a new minimum tick size rule on November 5, 2001. The relative tick sizes under the new rule have less variation than those under the old rule.

Furthermore, market performance is another determinant of liquidity change. Chordia et al. (2001) argue that the direction of stock market movements could have asymmetrical effects on liquidity. Liquidity should rise in the bull market and fall during the bear market so variables which separate market movements into the bull and bear markets are included. The regression model below allows us to analyse whether the effect of changes in market-wide liquidity on an individual liquidity is caused by weekly seasonality, tick size effect, or stock performance.

$$\begin{aligned}\mathrm{DL}_{i,t} = {} & \varphi + \beta_1\mathrm{DL}_{M,t} + \beta_2\mathrm{DL}_{M,t-1} + \beta_3\mathrm{DL}_{M,t+1} + \lambda_1\mathrm{DL}_{\mathrm{Ind},t} + \lambda_2\mathrm{DL}_{\mathrm{Ind},t-1} \\ & + \lambda_3\mathrm{DL}_{\mathrm{Ind},t+1} + \omega_1\mathrm{Mon} + \omega_2\mathrm{Tue} + \omega_3\mathrm{Wed} + \omega_4\mathrm{Thu} + \alpha_1\mathrm{DL}_{M,t}{}^*\mathrm{Mon} \\ & + \alpha_2\mathrm{DL}_{M,t}{}^*\mathrm{Tue} + \alpha_3\mathrm{DL}_{M,t}{}^*\mathrm{Wed} + \alpha_4\mathrm{DL}_{M,t}{}^*\mathrm{Thu} + \rho_1\mathrm{DL}_{\mathrm{Ind},t}{}^*\mathrm{Mon} \\ & + \rho_2\mathrm{DL}_{\mathrm{Ind},t}{}^*\mathrm{Tue} + \rho_3\mathrm{DL}_{\mathrm{Ind},t}{}^*\mathrm{Wed} + \rho_4\mathrm{DL}_{\mathrm{Ind},t}{}^*\mathrm{Thu} + \tau_1\mathrm{Ntick} \\ & + \tau_2\mathrm{DL}_{M,t}{}^*\mathrm{Ntick} + \tau_3\mathrm{DL}_{\mathrm{Ind},t}{}^*\mathrm{Ntick} + \pi_1|\,\mathrm{Max}\,(0,R_{t-1})| \\ & + \pi_2|\,\mathrm{Min}\,(0,R_{t-1})| + \varepsilon_{i,t}\end{aligned} \tag{3}$$

where $\mathrm{DL}_{i,t}$ is the percentage change of an individual liquidity. $\mathrm{DL}_{M,t}$, $\mathrm{DL}_{M,t-1}$, $\mathrm{DL}_{M,t+1}$ and $\mathrm{DL}_{\mathrm{Ind},t}$, $\mathrm{DL}_{\mathrm{Ind},t-1}$, $\mathrm{DL}_{\mathrm{Ind},t+1}$ are the concurrent, lag and lead coefficients of $\mathrm{DL}_{M,t}$ and $\mathrm{DL}_{\mathrm{Ind},t}$ which are the equally weighted cross-sectional average of the liquidity variable for all stocks (the 'market') and the corresponding industry liquidity of the stock. Cross-sectional mean of time series slope coefficients are reported and the corresponding *t*-statistics are presented in Table 6. Liquidity variables are spread (SPR), proportional spread (PSPR), average spread (ASPR), proportional average spread (PASPR), depth (DEP), displayed depth (DDEP), ratio of depth to displayed depth (RATIO), and slope of outside quote (SLOPE). The day-of-the-week dummy variables are Monday, Tuesday, Wednesday, and Thursday. NTick is equal to one for dates after November 5, 2001, when the SET implemented the new tick size rule. $|\mathrm{Max}(0,R_{t-1})|$ and $|\mathrm{Min}(0,R_{t-1})|$ coefficients capture the impact of lag positive and negative returns. We add product regressors into the regression model to capture the interaction between industry-wide, market-wide liquidity, and weekly seasonality.

The results in Table 6 show that for all liquidity measures industry- and market-wide commonalities represented by $\mathrm{DL}_{M,t}$ and $\mathrm{DL}_{\mathrm{Ind},t}$ are positive and highly significant after controlling for weekly seasonality and performance effect. Consistent with the results in Table 4, industry-wide commonality dominates market-wide commonality for all liquidity measures except for spread and average spread where the coefficient of $\mathrm{DL}_{M,t}$ is greater than that of $\mathrm{DL}_{\mathrm{Ind},t}$. All spread measures significantly increase except for market and displayed depths that fall on Monday compared to Friday. Unlike the statistical increase in bid–ask spread on Monday, a fall in depth is statistically insignificant. Our findings suggest that the level of liquidity decreases on Monday compared to Friday. This evidence is consistent with the study by Foster and Viswanathan (1990), who discuss whether the trading break over the weekend produces a stronger adverse selection problem on Mondays. They find that trading volume is lower, and trading costs are higher, on Mondays than on other days.

We find that the market CML is higher on Monday than on the other days. An increase in the market CML could be related to the fact that investors could not observe an equilibrium price due to non-trading resulting in a higher adverse selection cost on Monday and that leads to an increase of common market behaviour on liquidity measures. However, the results are not positively significant for all liquidity measures. In contrast to the evidence of the market CML, the evidence of the industry CML is inconclusive. We find mixed evidence on the change of industry CML on Monday.

NTick appears positively significant for the percentage change of individual stock spread, proportional spread, average spread, proportional average spread, displayed depth, and slope. New tick size rules also increases market-wide CML for proportional spread, proportional average

Table 6
Weekly seasonality and performance effects on commonality in liquidity

Variable	SPR	PSPR	ASPR	PASPR	DDEP	DEP	RATIO	SLOPE
Constant	0.130*	0.118*	0.064*	0.061*	0.183*	0.123*	0.133*	0.134*
$DL_{M,t}$	0.298*	0.037	0.233*	0.042	0.081*	0.111*	−0.202	0.100*
$DL_{M,t-1}$	0.011	0.036*	0.016	0.057*	0.036*	0.013	0.030	0.023
$DL_{M,t+1}$	0.011	0.031	0.013	0.055*	0.021*	0.003	−0.025	0.025
$DL_{Ind,t}$	0.228*	0.676*	0.225*	0.695*	0.167*	0.272*	0.885*	0.649*
$DL_{Ind,t-1}$	0.016*	0.019	0.013	0.007	−0.017	0.007	−0.024	0.008
$DL_{Ind,t+1}$	−0.003	−0.018	−0.001	−0.014	−0.009	0.003	0.016	−0.021
Mon	0.044*	0.025*	0.032*	0.023*	−0.039	−0.033	0.009*	0.039*
Tue	−0.009	−0.007	−0.008	−0.004	0.009	0.017*	0.001	−0.006
Wed	0.002	−0.002	−0.003	0.004	0.003	−0.003	0.007	0.001
Thu	0.003	0.004	−0.005	0.005	−0.002	0.002	0.007	0.008
$DL_{M,t}$*Mon	0.093*	0.049	−0.002	0.011	0.033	0.088*	−0.032	0.099*
$DL_{M,t}$*Tue	−0.142	−0.165	−0.096	−0.126	0.035	0.067*	−0.114	−0.160
$DL_{M,t}$*Wed	0.024	0.111*	−0.052	0.156*	0.004	0.032	−0.109	0.177*
$DL_{M,t}$*Thu	0.059	0.119*	0.029	0.094*	−0.009	0.039	0.068	0.168*
$DL_{Ind,t}$*Mon	−0.020	−0.087	0.024	−0.059	0.003	−0.036	−0.016	−0.101
$DL_{Ind,t}$*Tue	−0.002	−0.041	−0.021	−0.059	−0.035	−0.061	−0.002	−0.078
$DL_{Ind,t}$*Wed	−0.022	−0.040	0.007	−0.085	0.001	−0.060	0.020	−0.087
$DL_{Ind,t}$*Thu	−0.011	−0.051	0.012	−0.021	−0.025	−0.035	0.020	−0.027
NTick	0.033*	0.030*	0.021*	0.022*	0.032*	0.018	−0.002	0.028*
$DL_{M,t}$*NTick	−0.066	0.214*	−0.049	0.208*	0.005	−0.003	0.005	0.255*
$DL_{Ind,t}$*NTick	−0.014	−0.126	0.045*	−0.028	0.066*	0.012	0.012	−0.165
$\lvert Max(0,R_{t-1})\rvert$	0.496*	0.518*	0.455*	0.430*	−0.347	−0.189	−0.236	0.566*
$\lvert Min(0,R_{t-1})\rvert$	−0.196	−0.257	−0.295	−0.314	0.152*	0.377*	−0.149	−0.253

This table presents the existence of commonality in liquidity, given the control variables of weekly seasonal, tick size, and stock performance using the following multiple regressions:

$$DL_{i,t} = \varphi + \beta_1 DL_{M,t} + \beta_2 DL_{M,t-1} + \beta_3 DL_{M,t+1} + \lambda_1 DL_{Ind,t} + \lambda_2 DL_{Ind,t-1} + \lambda_3 DL_{Ind,t+1} + \omega_1 Mon + \omega_2 Tue + \omega_3 Wed + \omega_4 Thu + \alpha_1 DL_{M,t}{*}Mon + \alpha_2 DL_{M,t}{*}Tue + \alpha_3 DL_{M,t}{*}Wed + \alpha_4 DL_{M,t}{*}Thu + \rho_1 DL_{Ind,t}{*}Mon + \rho_2 DL_{Ind,t}{*}Tue + \rho_3 DL_{Ind,t}{*}Wed + \rho_4 DL_{Ind,t}{*}Thu + \tau_1 Ntick + \tau_2 DL_{M,t}{*}Ntick + \tau_3 DL_{Ind,t}{*}Ntick + \pi_1 \lvert \mathrm{Max}(0, R_{t-1})\rvert + \pi_2 \lvert \mathrm{Min}(0, R_{t-1})\rvert + \varepsilon_{i,t}$$

$DL_{i,t}$ is the percentage change of an individual liquidity. $DL_{M,t}$, $DL_{M,t-1}$, $DL_{M,t+1}$ and $DL_{Ind,t}$, $DL_{Ind,t-1}$, $DL_{Ind,t+1}$ are the concurrent, lag and lead coefficients of $DL_{M,t}$ and $DL_{Ind,t}$ which are the equally weighted cross-sectional average of the liquidity variable for all stocks (the 'market') and the corresponding industry liquidity of the stock. During the period from January 1996 to October 2003, there were 1868 trading days and 418 stocks were tested. Cross-sectional mean of time series slope coefficients are reported and the corresponding t-statistics are presented. The asterisk sign (*) indicates statistical significance at the 5% level. Liquidity variables are spread (SPR), proportional spread (PSPR), average spread (ASPR), proportional average spread (PASPR), depth (DEP), displayed depth (DDEP), ratio of depth to displayed depth (RATIO), and slope of outside quote (SLOPE). The results for the coefficients reported on the concurrent variables are denoted by "t". The day-of-the-week dummy variables are Monday, Tuesday, Wednesday, and Thursday. NTick is equal to one for dates after November 5, 2001, when the SET implemented the new tick size rule. $\lvert Max(0,R_{t-1})\rvert$ and $\lvert Min(0,R_{t-1})\rvert$ coefficients capture the impact of lag positive and negative returns, respectively.

spread, and slope of outside quote, and industry-wide CML for average spread and displayed depth.

Finally, the lag positive returns are shown to significantly increase the percentage change of all spread measures but decrease the percentage change of depth measures. In contrast, following the stock declines, the percentage change of individual stock depth and displayed depth increases significantly whereas that of individual stock spreads insignificantly declines. A positive

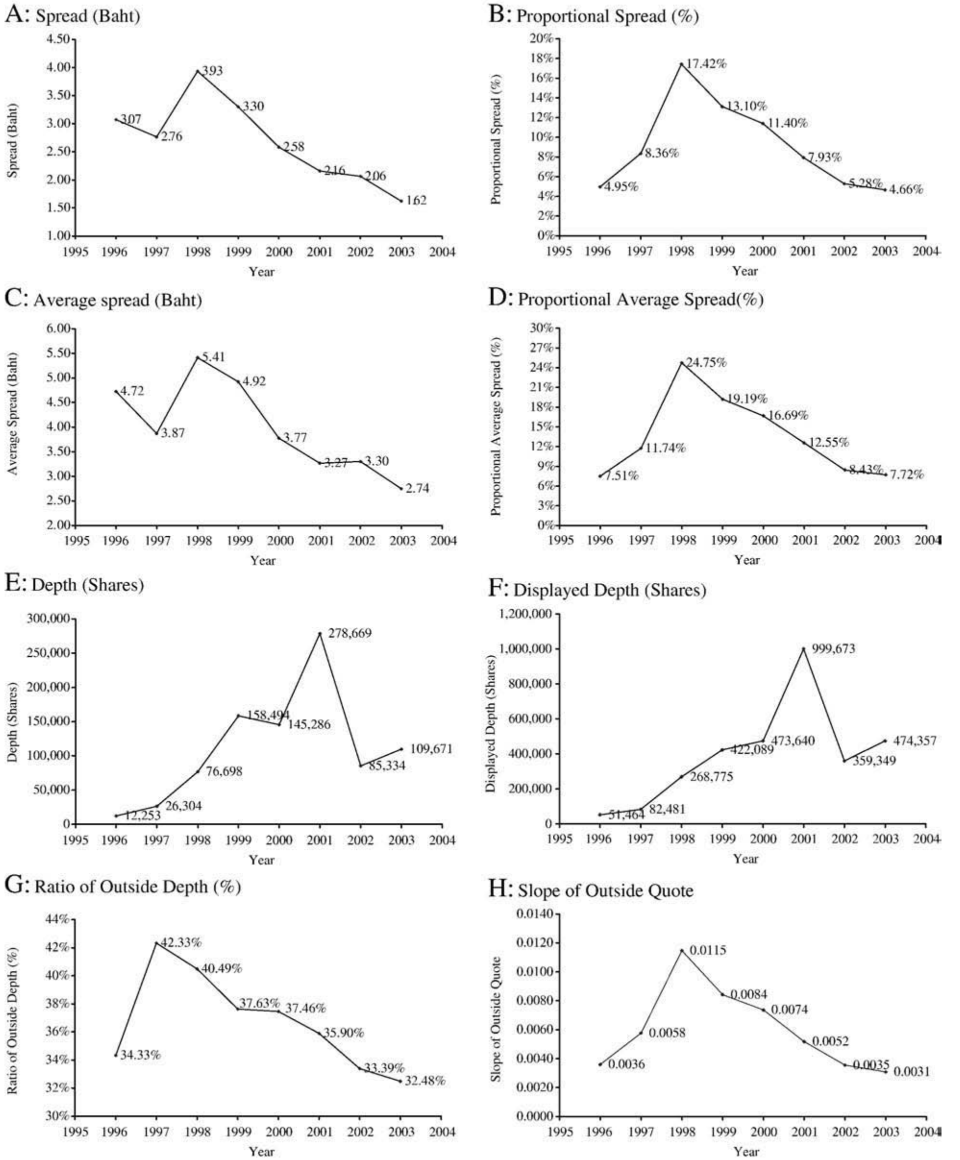

Fig. 1. Time variation of liquidity measurements. This figure shows the time variation of liquidity measurements of inside and outside quotes from 1996 to 2003.

relationship between past return and spread is consistent Foster and Viswanathan's (1993) argument that liquidity traders delay their trades if they believe that the informed trader is particularly well-informed. As such, liquidity traders would wait and learn from the trades that occur. After liquidity traders learn about positive returns on a particular stock yesterday, they are concerned that such returns are driven by informed traders. Thus, liquidity traders widen spread to compensate for an information asymmetry.

3.5. Year-by-year commonality in liquidity

The studies of the previous sections focus on the overall eight-year analysis. The following sections concentrate on the change in year-by-year liquidity. Fig. 1A presents the descriptive statistics for market-wide bid–ask spread measurement for each year from 1996 to 2003. As the figure shows, the spread exhibits very high values from 1996 to 1998, and the average value for these three years is 3.25 Thai Baht, with 0.565 Thai Baht difference compared with the eight-year average value of 2.685 Thai Baht. From 2000, the values of the bid–ask spread remain stable. Fig. 1B illustrates the descriptive statistics for the market-wide proportional spread measure of each year from 1996 to 2003. As shown in Fig. 1B, from 1996 through 1998 there is a dramatically increasing trend. In 1998, the proportional spread reaches a peak, which is followed by the significant decrease. From 2002, the change in the proportional spread is smooth and stable.

Fig. 1C and D illustrates the trends in average spread and proportional average spread, which have patterns similar to the trends of spread and proportional spread, respectively.

Fig. 1E and F displays the trend in the depth and displayed depth over the eight years examined. Clearly, the lowest trading volume occurs in 1996. There is a smooth increase in the depth from 1996 to 2001. During 2001 there is a sharp increase to the peak, followed by a sharp decrease during 2002. The time series pattern of displayed depth is consistent with the trend in the depth. Fig. 1G shows the time series of the ratio between depth and displayed depth. The ratio reached a high of 42.33% in 1997, and decrease during the period from 1998 to 2003. The slope of best quote in limit order book is shown in Fig. 1H. The best quoted slope during the financial crisis period (1998–1999) was significantly higher than that in other periods, which reflects the relatively low level and the higher cost of liquidity. In summary, the peaks in the market-wide bid–ask spread occur in 1998.

The 1997 East Asian financial crisis might be the underlying cause of these peak and troughs. This event led to high market illiquidity. In consequence, the spreads exhibited are very high,

Table 7
Time variation of commonality in liquidity

	1996		1997		1998		1999		2000		2001		2002		2003	
	Mean	% (+)	Mean	% (+)	Mean	% (+)	Mean	% (+)	Mean	% (+)	Mean	% (+)	Mean	% (+)	Mean	% (+)
SPR	0.671	80	0.492	73	0.275	71	0.443	78	0.290	68	0.763	83	0.558	73	0.580	81
PSPR	0.978	87	0.817	82	0.748	78	1.137	84	0.668	76	1.224	93	1.247	86	1.067	90
ASPR	0.170	64	0.557	81	0.327	75	0.134	66	0.331	79	0.611	84	0.358	72	0.618	81
PASPR	1.015	87	0.874	82	0.849	80	0.240	67	0.707	85	1.262	90	1.104	87	1.114	89
DDEP	0.286	69	0.126	59	0.138	61	0.263	64	0.388	71	0.549	77	0.405	71	0.375	69
DEP	0.419	78	0.218	64	0.254	69	0.395	76	0.513	78	0.643	83	0.480	77	0.472	79
RATIO	0.839	63	0.979	70	0.936	69	0.877	68	0.790	67	0.964	64	0.894	68	0.959	70
SLOPE	0.947	88	0.755	81	0.767	79	1.169	87	0.645	78	1.305	93	1.341	88	1.080	91

This table compares the market-wide commonality in liquidity from 1996 to 2003 using the following multiple regressions:

$$\mathrm{DL}_{i,t} = \alpha + \beta_1 \mathrm{DL}_{M,t} + \beta_2 \mathrm{DL}_{M,t-1} + \beta_3 \mathrm{DL}_{M,t+1} \varepsilon_{i,t}$$

For each stock, daily percentage changes in liquidity variables for the individual stock, $\mathrm{DL}_{i,t}=L_{i,t}/L_{i,t-1}-1$, are regressed in time series on the percentage change of an equally weighted cross-sectional average of the liquidity variable for all stocks excluding stock i (the 'market'), $\mathrm{DL}_{M,t}$, in the sample. During the period from 1996 to 2003, there were 1868 trading days and 418 stocks were tested. The sum of cross-sectional mean of time series slope coefficients is reported, $\beta_1+\beta_2+\beta_3$, Sum=Concurrent+Lag+Lead coefficients. '%(+)' reports the proportion of positive coefficients.

while the depths are very low, during this period. From the perspective of commonality, Brockman and Chung (2002) argue that the financial crisis may have led to individual liquidity being strongly influenced by market-wide factors. The empirical evidence shown in Table 7 does not strongly support this notion, however, through a magnitude comparison of the summed concurrent, lead, and lag market-wide commonality coefficients for eight liquidity measures across all eight years. Chordia et al. (2001) state that liquidity levels could vary with market trends and that the determinations of day-to-day changes in liquidity are probably the same in most environments (i.e., market crash), though their explanatory power might very well fluctuate. In fact, we exclude the period of financial crisis in year 1997 from the analysis of market commonality and industry commonality. Our results remain intact with those including the period of financial crisis and the market and industry commonalities are still evident during financial crisis period.[10]

4. Conclusions

Commonality in liquidity may be caused by several factors. Generally, price swings may lead to a market-wide trading activity response. According to Fernando (2003), common determinations in liquidity imply that liquidity shocks are systematically transmitted across investors or securities, causing broad market effects. Liquidity co-movement can be divided into common and idiosyncratic components. Common liquidity shocks have a significant influence on price volatility, but they do not provide a demand for liquidity, or give rise to any commonality in trading volume. Milgrom and Stokey (1982) argue that systematic liquidity shocks will not result in trading, even when the market is liquid. In contrast, the demand for, and volume of, liquidity increases as a result of idiosyncratic liquidity shocks, and an investor can diversify the risk through trading. Chordia et al. (2000) contend that trading volume variation is likely to respond to co-movement in the optimal level of inventory, which in turn induces co-movement in individual spread, depth and other measures of liquidity. Moreover, the risk of inventory based on volatility may include a market component, which could induce common pressure on inventories, or across market-wide sectors. In other words, if the inventory volatilities are correlated to individual assets, then liquidity could display similar co-movements.

Previous studies of the commonality of liquidity typically span short time periods. In contrast to the extant literature, this study examines liquidity for a comprehensive sample of SET stocks over an eight-year period. The empirical results are based on 418 stocks from SET from Jan 3, 1996 to Oct 31, 2003. The results show strong evidence of market-wide commonalty in liquidity for SET stocks. The effect of commonality in liquidity is generally less than that reported in the NYSE. It is found that commonality in spreads and depths is important across all size-based portfolios, although spread-related individual liquidity is generally more susceptible to market-wide liquidity for firms in the small size range, and depth-related commonality is relatively more pronounced for firms in the larger size range. Furthermore, it is found that the common liquidity beyond the best quote measured in terms of the displayed depth and the ratio of outside depth does exist, but no evidence is found to support the existence of the common order imbalance.

In addition to confirming the existence of commonality, this paper provides some suggestive evidence about the determinants of commonality. It is found that commonality in liquidity is influenced by several factors, based on a price formation model. Some explanatory variables are

[10] For the sake of brevity, we do not report the results here but they are available upon request.

nominated as being possible determinants, including indicator variables for the day-of-the-week, tick size, and stock returns.

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