Commonality in Liquidity in the Context of Different Trading Systems: Evidence from an Emerging Market

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ABSTRACT

We offer hitherto unpublished evidence of the impact of different trading systems on commonality in liquidity from an emerging market i.e., The Amman Stock Exchange. We argue that the degree of responsiveness of individual stock's liquidity to changes in market-wide liquidity will vary before and after the automation of a trading system, due to the differences in market structure. In general, the results show different sensitivities in the stock liquidity to changes in market-wide liquidity on both trading systems; the mean coefficient of concurrent market-wide liquidity on an electronic trading system is larger than that on a floor trading system. We also provide evidence on the existence of size effect in commonality. However, regardless of the size pattern revealed in commonality, the liquidity of firms in electronic trading system shows a stronger response to changes in market-wide liquidity. Finally, the results show the existence of commonality within the same industry, which is also stronger after the automation of a trading system. The above results imply that the floor trading system is less vulnerable to the information asymmetry problem.

Keywords: Liquidity, Commonality, Market Microstructure, Information Asymmetry, Floor Trading System, Electronic Trading Systems
JEL Classifications: G10, G18, D47, D82

1. INTRODUCTION

Commonality in liquidity is key issue in financial markets due to the fact it represents a systematic component to which individual stocks' liquidity can be sensitive. Such commonality could be induced by, among other factors, information asymmetry since, at least, some traders will have information that may not be available to others (Chordia et al., 2000). Therefore, differences in market structures in terms of each one's ability to produce and disseminate information are likely to result in differences in commonality levels not only across markets but also across firms. Thus, this paper investigates the existence of commonality in liquidity under two different market structures i.e., floor and electronic trading systems in the same financial market.

Most of the relevant market microstructure research investigates the existence of commonality. Previous evidence shows that commonality exists in quote-driven (Chordia et al., 2000; Huberman and Halka, 2001; and Hasbrouck and Seppi, 2001), order-driven (Brockman and Chung, 2002; Fabre and Frino, 2004; Pukthuanthong-Le and Visaltanachoti 2009; Narayan et al., 2011;

and Tayeh et al., 2015), and options (Syamala et al., 2014) markets in both developed and emerging markets. Notwithstanding the importance of these empirical studies, they focus on investigating the existence of commonality under one design of market structure and overlook the implications of differences in market structures for commonality. One exception is Galariotis and Giouvris (2007), who provide comparative evidence on commonality between order-driven and quote-driven regimes in London Stock Exchange (LSE). We extend this line of research by investigating the impact of different trading systems on commonality in liquidity in an emerging market characterized by relatively low volatility.

Today, most of the financial markets around the world have abandoned the traditional floor trading mechanism and transformed into screen-based electronic trading mechanisms in an attempt to enhance their competitiveness via attracting greater market share. The focus of research that studies the implications of such transformations has been on the effect of market structures on the characteristics of market microstructure including liquidity, volatility and price discovery (Chang et al., 1999; Weber, 1999; Venkataraman, 2001; Theissen, 2002a and Fung et al., 2005).

Relatively, much less focus has been given to studying how the dynamics of financial markets can be affected by the introduction of electronic trading systems. For example, how does individual stock's liquidity compare to the overall market liquidity changes? Therefore, this research examines how individual stock liquidity is associated with market-wide liquidity before and after the automation of the Jordanian Stock Market.

The Jordanian stock market, Amman Stock Exchange (thereafter, ASE), has transferred to an electronic trading system on March 26, 2000. As a result, it is possible to compare between the behavior of stock liquidity before and after the stock has been transferred from floor to electronic trading system, for the same group of stocks and same market participants within the same institutional design feature (i.e., order-execution system)[1]. This enables us, unlike previous research, to establish a direct test for the existence of commonality with no concern about the bias that can result from market-specific unobservable factors (like differences in security exchange regulations and institutional details), and imperfect matching of stocks that is usually encountered when such tests are done in two different stock markets. This helps in the separation of stocks' and traders' characteristics from the effect of different trading systems (Cai et al., 2008). Examples of previous research papers that had this bias include, Huang and Stoll (1996), Venkataraman (2001) and Huang (2004). This study, therefore, is considered as a controlled experiment of floor and electronic trading systems characteristics.

Among the empirical work that has been carried out previously on the ASE before and after the automation of trading system includes: Maghyereh (2005) who finds that the automation of the trading system has no impact on price efficiency, Al-Khouri and Al-Ghazawi (2008) who find a reduction in volatility and an impovement in liquidity, and Iskandrani and Haddad (2012) who find a higher trading volume and negative abonormal return after the adoption of electronic trading system. None of these studies examined the commonality in liquidity of ASE under the floor and electronic trading systems.

Examining this issue on the ASE, one of the emerging markets in the Middle East and North Africa region (henceforth MENA), is stimulated by the following reasons. First, Bekaert et al. (2007) argue that liquidity is more important for emerging markets than developed markets because its effects tend to be stronger in the former. Second, compared with other emerging markets, stock exchanges in the MENA region are considered less developed and are lacking in some institutional features, such as the absence of designated market makers who have a firm obligation to maintain liquidity in the market, and weak information disclosure requirements that could result in an information asymmetric problem (Lagoarde-Segot and Lucey, 2008). Third, ASE is considered a good representative of other markets in the MENA region. Its market capitalization is the largest in the region: It equals 116.80%, 94.25%, 87.05% of gross domestic product for

2010, 2011, and 2012 respectively[2]. Also, ASE is considered the best performer in the region as all its development indicators show a positive variation, and it has the lowest volatility compared with other markets in the MENA region (Lagoarde-Segot and Lucey, 2008; Lagoarde-Segot, 2009; Bino et al., 2016).

The results of this research should be of interest to many market participants. Investors will ask for higher returns on carrying stocks that have higher sensitivity with systematic liquidity i.e., stocks' returns and liquidity are positively related to market-wide liquidity (Pastor and Stambaugh, 2003; Martínez et al., 2005; Acharya and Pedersen, 2005; Sadka, 2006). When making decisions on stock listing, a firm's management must consider which trading system is more convenient to reduce the cost of capital. That is, the trading system in which commonality is a less pervasive exposes firm to lower systematic liquidity risk. Market regulators are also interested in the optimal trading structure, which improves market liquidity and leads to an efficient market. Therefore, empirical evidence on how different trading systems affect commonality in liquidity will ensure which trading system requires further policy procedures and regulations to improve its quality.

Our results provide evidence on the existence of commonality on both trading systems. However, commonality is more pervasive in an electronic trading system. The average coefficient of market-wide liquidity in most regressions on a floor trading system is smaller compared with that on an electronic trading system. We also find, after controlling for market-wide liquidity, that commonality exists within the same industry only in an electronic trading system. Finally, the results show that there is a size effect in the degree of commonality, and the extant of commonality in all size groups varies across different trading systems. Our results imply that the degree of information asymmetry in a floor trading system is lower than that in an electronic trading system, and thus an individual stock's liquidity shows stronger responsiveness to the changes in market-wide and industry-wide liquidity in electronic trading.

In the next section we discuss how different trading systems could affect commonality in liquidity. Section 3 describes the dataset and presents liquidity measures. Empirical results are presented and discussed in section 4. Section 5 concludes.

2. TRADING SYSTEMS AND LIQUIDITY COMMONALITY

The question addressed in this research is whether the change from floor-based to automated trading systems affects commonality in liquidity. According to Chordia et al. (2000), information asymmetry could be a potential source of commonality, to the extent that higher levels of information asymmetry could result in strong co-movements in individual stock liquidity. The level of information asymmetry, however, varies according to the nature of the trading system. O'Hara (2003) argues that specific trading systems may provide more information or better

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1   ASE continued to operate as a pure order-driven market after the automation of its trading system, which offers the advantage to control the possible impact of different execution systems (order-vs. quote-driven systems) on liquidity.

2   World Bank, World Development Indicators Database.

information. Therefore, the level of information asymmetry may vary across floor and electronic trading systems due to their different characteristics. For example, the degree of anonymity of a trading system could be a determinant of the level of information asymmetry. In a non-anonymous floor trading system, Venkataraman (2001) argues that the information asymmetry among traders is not intensive because traders share information on orders flow and fundamental value. Also, floor traders have the chance to observe the trading of market participants and obtain information on why other traders want to trade (Pirrong, 1996). In contrast, the higher degree of anonymity in automated trading prevents an effective transfer of information and thus allows informed traders to exploit their private information, which results in higher levels of information asymmetry (Theissen, 2002b; Fung et al., 2005). Also, the problem of information asymmetry in electronic trading becomes severe in periods of high volatility, during which the knowledge of traders' identity is very important (Kempf and Korn, 1998). Accordingly, commonality in liquidity in electronic trading system is expected to be more persistent (i.e., stronger) compared with that in the floor trading system.

On the other hand, the proponents of electronic trading systems argue that some features of electronic trading systems may result in lower levels of information asymmetry and thus improve market liquidity. For example, orders in automated trading can be submitted and executed efficiently and immediately. This will result in increasing orders flow and makes prices more informative. Furthermore, electronic trading, in contrast to floor trading, is faster in disseminating market information. This will increase market transparency and improve its informational environment, and thus reduce information asymmetry (Pirrong, 1996; Kempf and Korn, 1998; Freund and Pagano, 2000; Theissen, 2002b). Accordingly, an automated trading system is expected to have low commonality in liquidity. No superiority between floor and electronic trading systems can be established regarding the level of information asymmetry. Therefore, which trading system has a stronger or weaker commonality in liquidity is an empirical question that is addressed in this research.

3. DATA

Measuring liquidity for emerging markets, compared with developed markets, is difficult and represents a great challenge. Normally, liquidity measures are computed using intraday data, which is not always available for emerging markets over a relatively long period of time. Given the paucity of detailed transaction data, daily data for all companies are obtained from ASE for the period from 01 January, 1993 to 19 June, 2007. This sample period covers the trading on both floor and electronic trading systems which is further divided into two sub-periods to allow for the investigation of commonality under different trading systems. The first sub-period represents the floor trading system, which ranges from 01 January, 1993 to 25 March, 2000. The second sub-period ranges from 26 March, 2000 to 19 June, 2007, which covers the electronic trading system phase. The dataset is retrieved from three files (closing prices file, trading data file and historical indices file), which include daily stocks' closing price,

trading volume, and the daily market index of ASE[3]. The data of the number of shares outstanding for the period from 01 January, 1999 to the end of the sample period is obtained from the research department of ASE, while the rest of data before 01 January, 1999 is hand-collected from the company's guide published by ASE. To ensure its reliability, the data has been checked for errors such as the existence of multiple codes for the same company, the repetition of the same data entry, and errors in date entry (error in day, month or year). Chordia et al. (2000) and Fabre and Frino (2004) argue that infrequently traded stocks will not provide reliable information. Therefore, this study applies the same trading frequency filter that is employed by Pukthuanthong-Le and Visaltanachoti (2009) and Tayeh et al. (2015). To be included in the sample, each stock must have traded at least for 20 trading days in each year during the sample period. Furthermore, to avoid the problem of imperfect matching of stocks, following Jain (2005), the same set of stocks listed on ASE before and after the automation has been used in the analysis. After applying these criteria, the sample consists of 206 stocks; 103 stocks in each trading system.

3.1. Liquidity Measures and Summary Statistics
For each stock included in the sample, the following daily liquidity measures are calculated, which are commonly employed in the literature of market microstructure.

3.1.1. First, illiquidity ratio[4]
A rough measure of price impact was computed by Amihud (2002), which captures the daily stock prices' response that is associated to one dollar of trading value. That is, it measures the impact of order flow on stock prices, which follows Kyle's (1985) price impact measure. Goyenko et al. (2009) find that Amihud's illiquidity ratio does measure price impact very well. Illiquidity ratio is defined as follows:

$$ILLIQ_{i,t} = \frac{|r_{i,t}|}{Tvalue_{i,t}}$$

(1)

Where, $ILLIQ_{i,t}$ is the illiquidity ratio for stock i at day t, $r_{i,t}$ is the stock return on day t and $Tvalue_{i,t}$ is the stock trading value (i.e., currency volume in Jordanian dinar) on day t. This ratio is calculated over all positive-currency volume days, as the ratio is undefined for zero-volume days.

3.1.2. Second, turnover ratio
Second, turnover ratio is one of the most commonly used measures of liquidity in the literature of market microstructure. It is relatively easy to construct using low frequency data and it has intuitive appeal (Datar et al., 1998). It is defined as follows:

$$TOV_{i,t} = \frac{Volume_{i,t}}{Number\ of\ shares\ outstanding_{i,t}}$$

(2)

Where, $TOV_{i,t}$ is the turnover ratio for stock i at day t, $Volume_{i,t}$ is the stock's number of shares traded in day t.

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3   These data files are available on the website of ASE.
4   Illiquidity ratio is interchangeable with price impact.

3.1.3. Third, effective spread (i.e., Roll measure)

Roll (1984) proposes a measure of implied effective spread based on the serial co-variance of the change in daily stock prices. Roll shows that the effective spread is calculated as follows:

$$ES_{i,t} = 2\sqrt{-cov(\Delta P_{i,t}, \Delta P_{i,t-1})} \qquad (3)$$

Where, $ES_{i,t}$ is the effective spread for stock i at day t, P_t and P_{t-1} are the observed price on day t and $t-1$ respectively.

3.1.4. Fourth, modified effective spread

One problem of Roll measure is that it will be meaningless when the sample serial co-variance is positive; Equation (3) will be undefined. Therefore, following Goyenko et al. (2009) we use the modified version of Roll measure, which substitutes the positive serial co-variance with a default numerical value of zero. The modified version of Roll measure is estimated as follows:

$$MES_{i,t} = \begin{cases} 2\sqrt{-cov\left(\Delta P_{i,t}, \Delta P_{i,t-1}\right)} \; when \, cov\left(\Delta P_t, \Delta P_{t-1}\right) < 0 \\ 0 \qquad when \, cov\left(\Delta P_t, \Delta P_{t-1}\right) \geq 0 \end{cases} \qquad (4)$$

Where, $MES_{i,t}$ is modified effective spread for stock i at day t.

Table 1 reports the descriptive statistics of liquidity measures for the two sub-sample periods related to before and after the automation of the trading system. Panel A presents pooled time-series cross-sectional averages of the level of liquidity variables. All variables, except turnover ratio on the floor trading system, show right skewness as the sample means are larger than the median. This is consistent with other previous studies such as Chordia et al. (2000), Fabre and Frino (2004), Pukthuanthong-Le and Visaltanachoti (2009) and Tayeh et al. (2015). After the automation of the trading system, the average turnover ratio and the modified effective spread increase, while the mean of illiquidity ratio and effective spread decrease. In contrast to Tayeh et al. (2015), who examined commonality for ASE using a longer sample period that represents the electronic trading phase,

our results report higher (lower) values of illiquidity ratio and turnover ratio (effective spread and modified effective spread). Panel B displays the correlation coefficients among liquidity measures on both trading systems. The correlations reported for ASE among liquidity measures on both trading systems are either weak or almost non-existent, which is consistent with correlations values between liquidity measures reported by Fabre and Frino (2004) for the Australian Stock Exchange and by Pukthuanthong-Le and Visaltanachoti (2009) for the Thailand Stock Exchange.

4. EMPIRICAL EVIDENCE ON COMMONALITY IN LIQUIDITY

This section reports the estimation of the variations of individual stock liquidity with market-wide liquidity, and reports the estimation of individual stock liquidity variations with market-wide and industry-wide liquidity on both floor and electronic trading systems.

4.1. Market-wide Commonality in Liquidity

To investigate the co-movements in liquidity on floor and electronic trading systems and to what extent these co-movements could vary across trading systems, the market model proposed by Chordia et al. (2000) is estimated before and after the automation of the trading system. Specifically, the following time-series regression is estimated for each stock in the two sub-periods:

$$DLiq_{i,t} = \alpha_i + \beta_{i1} DLiq_{M,t} + XB + \varepsilon_{i,t} \qquad (5)$$

Where, $DLiq_{i,t}$ is the daily proportional change in the liquidity variable for stock i on day t and $DLiq_{M,t}$ is the concurrent proportional change in market-wide liquidity, which is measured as equally-weighted, cross-sectional average of liquidity for all stocks in the sample traded in day t. According to Chordia et al. (2000), stock i is excluded from the calculation of market-wide liquidity to avoid the constraint on the cross-sectional mean of coefficients to exact unity. X is a vector of control variables which includes one period lag and lead of the market liquidity, which are included to capture any lagged and leaded adjustments in

Table 1: Descriptive statistics

	Panel A: Cross-sectional statistics for time series means									
Liquidity	**Mean**		**Median**		**Standard deviation**		**Minimum**		**Maximum**	
measure	**Floor**	**Electronic**	**Floor**	**Electronic**	**Floor**	**Electronic**	**Floor**	**Electronic**	**Floor**	**Electronic**
ILLIQ	0.029	0.025	0.012	0.010	0.058	0.033	0.000	0.000	0.390	0.173
TOV	0.001	0.003	0.001	0.002	0.001	0.002	0.000	0.000	0.008	0.010
ES	0.041	0.039	0.017	0.021	0.155	0.111	0.003	0.002	1.537	1.129
MES	0.016	0.019	0.009	0.012	0.035	0.042	0.002	0.001	0.304	0.416
	Panel B: Cross-sectional means of time series correlations between liquidity variable pairs for an individual stock									
	Floor				**Electronic**					
	ILLIQ	*TOV*	*ES*			*ILLIQ*	*TOV*	*ES*		
TOV	−0.182				*TOV*	−0.164				
ES	−0.028	0.116			*ES*	−0.062	0.167			
MES	−0.021	0.019	1.000		*MES*	−0.012	−0.024	1.000		

This table provides the summary statistics, which are cross-sectional statistics calculated from individual stock time-series means, during the two sub-sample periods, during the floor trading period (Floor) and the electronic trading period (Electronic). The acronyms *ILLIQ*, *TOV*, *ES*, and *MES* denote, respectively, the Amihud's (2002) illiquidity ratio, the turnover ratio, the Roll (1984) measure of the effective spread, and the modified version of Roll (1984) measure

commonality that result from thin trading; concurrent, lag and lead market returns, which are used to control for any spurious dependence that may result from the relationship between return and liquidity; and the concurrent change in the squared stock return, as a proxy for stock volatility, which is included as it may affect stock liquidity. To estimate Equation (5), we use the generalized method of moment estimation method, with Newey-West standard error correction to adjust for heteroscedasticity and auto-correlation.

Table 2 reports the estimates of regression Equation (5). As Chordia et al. (2000), we are interested in the significance of the mean coefficient of concurrent market-wide liquidity to look for evidence on the existence of commonality. The results show that commonality is present on both trading systems; all means of market-wide betas are statistically significant at 5% level or better on both floor and electronic trading systems, except those of illiquidity ratio regression. In turnover ratio, the estimated coefficient of market-wide liquidity on a floor trading system is greater than that on an electronic trading system by more than 3 times. It is 2.17 before automation compared with 6.69 after the automation. Also, approximately 76% of these coefficients are positive and 21% are significantly positive on a floor trading system compared with 83% positive and 31% positive and significant at the 5% level on an electronic trading system. This indicates that co-movement in individual stock liquidity is

more pervasive after automation, which implies that the level of information asymmetry on an electronic trading system is higher and represent a major concern to market participants than on a floor trading system.

The results of effective spread and modified effective spread provide evidence on commonality, respectively, on an electronic trading system and for both trading systems, but it is not as strong as in the case of turnover ratio measure. That is, the mean coefficient of concurrent market-wide liquidity in effective spread regression is statistically significant only on an electronic trading system; it is 0.036 with an associated t-statistic of 3.24. About 67.96% of these coefficients are positive; more than 15% of these coefficients are positive and significant. In addition, the mean coefficient of concurrent market-wide liquidity in modified effective spread on an electronic trading system is slightly larger than that on a floor trading system; it is 0.093 compared with 0.091. Further, the percentage of positive and significant coefficients on an electronic trading system is 24.27 compared with 13.59 on a floor trading system. These results also indicate that commonality in liquidity after the automation of a trading system is stronger than that before the automation. This is consistent with our argument that commonality in liquidity could vary across trading systems because of expected different levels of information asymmetry, which, in this case, is higher on an electronic trading system. These results also confirm the notion of Chordia et al. (2000)

Table 2: Market-wide commonality in liquidity

Independent Variables	DILLIQ		DTOV		DES		DMES	
	Floor	Electronic	Floor	Electronic	Floor	Electronic	Floor	Electronic
Concurrent	−0.162	0.017	0.336	1.017	0.054	0.036	0.091	0.093
t-statistics	−0.65	0.38	2.17	6.69	1.51	3.24	2.53	5.78
P value	0.516	0.705	0.033	0.000	0.135	0.002	0.013	0.000
%Pos	45.63	57.28	75.73	82.52	64.08	67.96	63.11	83.50
%Pos&Sig	1.94	3.88	21.36	31.07	5.83	15.53	13.59	24.27
Lag	0.173	−0.031	−0.013	0.312	0.016	−0.002	0.014	−0.037
t-statistics	0.84	−0.93	−0.12	1.93	0.64	−0.17	0.88	−2.28
P value	0.402	0.353	0.903	0.056	0.527	0.867	0.380	0.025
%Pos	45.63	29.13	57.28	56.31	54.37	41.75	54.37	43.69
%Pos&Sig	1.94	5.83	2.91	3.88	8.74	7.77	10.68	6.80
Lead	−0.096	−0.029	−0.114	0.227	0.043	−0.012	0.022	−0.035
t-statistics	−0.92	−0.70	−0.97	2.20	1.43	−0.78	0.90	−1.58
P value	0.357	0.487	0.334	0.030	0.155	0.439	0.370	0.118
%Pos	35.92	18.45	50.49	59.22	47.57	39.81	57.28	47.57
%Pos&Sig	1.94	1.94	3.88	3.88	8.74	7.77	8.74	6.80
Sum								
Mean	−0.086	−0.043	0.210	1.556	0.113	0.022	0.127	0.021
t-statistics	−0.37	−0.44	0.66	5.03	1.87	1.16	2.09	0.65
P value	0.715	0.659	0.514	0.000	0.064	0.249	0.039	0.519
Median	−0.116	0.040	0.432	1.188	0.048	0.008	0.074	0.043
P value	0.325	0.167	0.001	0.000	0.010	0.431	0.002	0.237
Adjusted-R²								
Mean	0.080	0.087	0.019	0.008	−0.005	0.009	0.010	0.013
Median	0.041	0.056	0.004	0.003	−0.005	0.001	0.003	0.008

This table presents the results of examining the market-wide commonality in liquidity through the time-series regression of daily proportional changes in the liquidity measures of individual stock on the proportional changes in market liquidity (Equation 5), during the two sub-sample periods; the floor trading period (Floor) and the electronic trading period (Electronic). Market liquidity is the equally-weighted average of the liquidity measures for all stocks in the sample that represent the market on trading day t. In every regression, the market averages do not include the dependent variable stock. Liquidity measures ILLIQ, TOV, ES, and MES are as defined in Table 1. "D" preceding the acronyms of liquidity variable e.g., DILLIQ, denotes the proportional change in the variables; for example, the liquidity measure Li, $DLi_t = (Li_t/Li_{t-1})−1$. The estimated time-series slope coefficients are averaged in a cross-sectional fashion and reported with their corresponding t-statistics for concurrent (same), lag (previous), and lead (next trading day) market liquidity. %Pos gives the percentage of positive coefficient. %Pos&Sig presents the proportion of positive slope coefficients with t-statistics>+1.645 at 5% critical level using the one-tailed test. Sum is the summation of the coefficients of concurrent, lag and lead market liquidity with the t-statistic and P value is the sign test for the null hypothesis: Sum median equals to 0. The coefficients of concurrent, lag, and lead market return variables and the proportional change in individual stock squared return (i.e., a measure for return volatility for individual firm), are not reported

that asymmetries in market-wide information could result in commonality in liquidity.

Although our study is the first that addresses the issue of the impact of different trading systems on commonality in liquidity, its results are consistent with previous studies. However, the results show that commonality in ASE stocks is weaker than that for a quote-driven market. The percentage of positive and significant concurrent coefficients, regardless of the liquidity measures used, ranges from 5.83% to 31.07% which is smaller than 59.78% to 86.75% reported by Galariotis and Giouvris (2007) for LSE stocks (i.e., FTSE 100). This is consistent with the argument that the free-entry aspect of order-driven markets reduces the effect of market-wide liquidity on individual stock liquidity, and thus results in less pervasiveness of commonality in liquidity (Brockman and Chung, 2002). Furthermore, compared with other order-driven markets, the commonality in liquidity in ASE is weaker (stronger) than that for the Hong Kong Stock Exchange and Thailand Stock Exchange (the Australian Stock Exchange) as reported by Brockman and Chung (2002), Pukthuanthong-Le and Visaltanachoti (2009) and Fabre and Frino (2004) respectively.

Moreover, except for the coefficient of the lagged and leading market liquidity in turnover ratio and lagged market liquidity in modified effective spread regressions on an electronic trading system, the majority of other estimated coefficients of lag and lead market-wide liquidity are statistically insignificant. This is consistent with the findings of Fabre and Frino (2004), Galariotis and Giouvris (2007), and Tayeh et al. (2015) but inconsistent with the results of Chordia et al. (2000). The insignificance of the estimated coefficients of lagged and leading market liquidity indicates that liquidity of individual stock is rapidly adjusted to the changes in leading and lagged market liquidity, which implies the absence of asynchronous adjustments in stock liquidity caused by thin trading in the ASE. However, the significant coefficients of both lagged and leading market liquidity in turnover ratio regression in an electronic trading system, compared with insignificant coefficients in a floor trading system, may imply that the rapid adjustments in an individual stock's liquidity to lagged and leading changes in market liquidity is due to the lower information asymmetry in a floor trading system that may result from the advantage of sharing information in a floor trading system. In addition, the sum of all market liquidity coefficients is significant in turnover ratio (effective spread and modified effective spread) regression on both trading systems (floor trading system). The P values of the sign test are less than 1% significant level. This implicates a significant joint effect of contemporaneous, lag and lead market liquidity on an individual stock's liquidity.

Finally, the results show that the explanatory power of the individual regression is very low. This is consistent with average adjusted R^2 reported by Chordia et al. (2000), Brockman and Chung (2002), Tayeh et al. (2015) and others, but inconsistent with those reported by Coughenour and Saad (2004). This could be due to the existence of a large noise component and/or other effects on the construction of daily changes of an individual stock's liquidity, or due to different aggregation periods as argued by Chordia et al. (2000) and Coughenour and Saad (2004).

4.2. Firm Size and Commonality in Liquidity

In order to investigate the effect of a firm's size on the co-movement of liquidity, the sample of each floor trading system and electronic trading system is sorted and divided into three groups (small, medium and large) by a firm's market capitalization at the beginning to each sample period. The regression Equation (5) is estimated for each group and its results are reported in Table 3. With the exception of the results of price impact regression, the results of other regressions not only show the existence of the size effect in commonality in liquidity, but also show that size effect varies across trading systems.

More specifically, the results show that there is an inverted U-shape in commonality across size groups for turnover ratio on both floor and electronic trading systems, although the average coefficient of concurrent market-wide liquidity for small size group on a floor trading system is statistically insignificant. This means that the liquidity of medium size firms has the strongest response to the changes in market-wide liquidity, which means that the traders revise the number of shares traded of medium size firms when there is a systematic change in liquidity. These results are consistent with those of Tayeh et al. (2015) and Brockman and Chung (2002), but inconsistent with results of Chordia et al. (2000), Fabre and Frino (2004) and Pukthuanthong-Le and Visaltanachoti (2009), who find, for some liquidity measures, that commonality is stronger for large firms. Furthermore, after the automation of a trading system, the individual stock's liquidity in all size groups of turnover ratio, regardless of the statistical significance of the coefficients, shows a higher degree of responsiveness to the changes in market-wide liquidity compared with that for all size groups before the automation. The mean coefficient of concurrent market-wide liquidity in all size groups on an electronic trading system is larger than that on a floor trading system. This implies that the level of information asymmetry on an electronic trading system may be higher than that on a floor trading system and thus stocks under this trading mechanism show stronger commonality, regardless of their size.

Although the results of effective spread regression provide no evidence on size effect in a floor trading system, they show that only medium and large size groups in electronic trading systems exhibit commonality in liquidity, where the largest group is the most sensitive to the changes in market-wide liquidity. In contrast, Tayeh et al. (2015) finds that commonality is stronger in small size groups. This may be due to the different sample periods used in the analysis, as changing in commonality is time dependent (Galariotis and Giouvris, 2007).

Further, in contrast to Brockman and Chung (2002), who find an inverted U-shape pattern in the commonality of spread measures, the evidence in this study shows a U-shape pattern in the degree of responsiveness of modified effective spread to the changes in market-wide liquidity on both trading systems. The firms in a medium size group have the lowest sensitivity to concurrent market-wide movements compared with both small and large firms. This contrasts with the results of Tayeh et al. (2015), which show that commonality is stronger in a large size group. However, the liquidity of individual firms in large and medium (small) size

Table 3: Market-wide commonality in liquidity by size

Liquidity Regression	Number of firms	Concurrent Mean	t-statistics	Lag Mean	t-statistics	Lead Mean	t-statistics	Sum Mean	t-statistics	Median	P value	Adjusted-R² Mean	Median
DILLIQ													
Floor													
Small	34	−0.615	−0.90	0.526	0.89	−0.139	−0.53	−0.228	−0.44	−0.177	0.864	0.118	0.041
Medium	35	0.104	0.37	−0.120	−0.86	−0.010	−0.08	−0.026	−0.06	−0.129	0.500	0.051	0.039
Large	34	0.017	0.11	0.120	0.89	−0.142	−1.24	−0.005	−0.02	−0.097	0.608	0.073	0.052
Electronic													
Small	34	0.110	1.87*	−0.025	−0.50	0.052	0.95	0.137	1.65*	0.046	0.392	0.119	0.079
Medium	35	−0.001	−0.01	−0.008	−0.16	−0.011	−0.45	−0.020	−0.23	−0.022	1.000	0.074	0.046
Large	34	−0.057	−0.59	−0.062	−0.85	−0.128	−1.18	−0.247	−0.92	0.046	0.121	0.068	0.052
DTOV													
Floor													
Small	34	0.033	0.08	−0.001	0.00	−0.332	−1.31	−0.299	−0.36	0.383	0.058	0.030	0.011
Medium	35	0.649	3.64***	−0.033	−0.30	0.182	1.01	0.799	2.3**	0.429	0.090	0.023	0.006
Large	34	0.318	1.86*	−0.004	−0.03	−0.200	−1.25	0.113	0.35	0.443	0.058	0.004	0.002
Electronic													
Small	34	0.679	2.63**	0.284	1.05	0.224	1.22	1.188	2.33**	1.055	0.024	0.010	−0.001
Medium	35	1.234	5.65***	0.121	0.72	0.235	1.36	1.590	3.96***	1.163	0.001	0.009	0.005
Large	34	1.131	3.7***	0.536	1.44	0.221	1.20	1.888	2.79***	1.350	0.000	0.004	0.002
DES													
Floor													
Small	34	0.024	0.39	−0.052	−1.20	0.107	1.80*	0.079	0.70	0.057	0.392	−0.008	−0.008
Medium	35	0.119	1.39	0.086	1.50	0.031	0.48	0.235	1.72*	0.072	0.090	−0.001	0.000
Large	34	0.018	1.04	0.012	0.99	−0.009	−0.58	0.021	0.76	0.040	0.121	−0.006	−0.005
Electronic													
Small	34	0.029	1.23	0.043	1.7*	−0.028	−0.76	0.044	1.11	0.031	0.121	0.014	0.000
Medium	35	0.034	2.27**	−0.024	−1.42	−0.030	−1.55	−0.019	−0.83	−0.035	0.736	0.005	0.005
Large	34	0.044	2.43**	−0.024	−1.96*	0.022	1.05	0.042	1.25	0.006	0.864	0.008	−0.001
DMES													
Floor													
Small	34	0.181	1.99*	−0.008	−0.26	0.050	1.04	0.223	1.64	0.136	0.009	0.003	0.004
Medium	35	0.032	0.58	0.040	1.50	0.021	0.39	0.092	0.80	0.038	0.311	0.016	−0.003
Large	34	0.061	3.37***	0.010	0.39	−0.004	−0.24	0.068	1.53	0.070	0.121	0.009	0.006
Electronic													
Small	34	0.123	3.03***	−0.037	−0.94	−0.063	−1.02	0.023	0.27	0.102	0.392	0.024	0.017
Medium	35	0.073	3.53**	−0.060	−2.92***	−0.018	−0.88	−0.005	−0.15	−0.024	1.000	0.009	0.005
Large	34	0.082	5.15***	−0.014	−0.64	−0.023	−1.65*	0.045	1.32	0.054	0.230	0.008	0.006

This table presents the results of examining market-wide commonality in liquidity (Equation 5) after the sample is divided into three groups according to the market capitalization of each firm at the beginning of each sub-sample period; the floor trading period (Floor) and the electronic trading period (Electronic). Market liquidity is the equally-weighted average of the liquidity measures for all stocks in the sample that represent the market on trading day *t*. In every regression, the market averages do not include the dependent variable stock. Liquidity measures *ILLIQ, TOV, ES,* and *MES* are as defined in Table 1. "D" preceding the acronyms of liquidity variable e.g., *DILLIQ*, denotes the proportional change in the variables; for example, the liquidity measure Li, $DLi_t = (Li_t/Li_{t-1})−1$. The estimated time-series slope coefficients are averaged in a cross-sectional fashion and reported with their corresponding t-statistics for concurrent (same), lag (previous), and lead (next trading day) market liquidity. Sum is the summation of the coefficients of concurrent, lag and lead market liquidity with the t-statistic and P value is the sign test for the null hypothesis: Sum median equals to 0. The coefficients of concurrent, lag, and lead market return variables and the proportional change in individual stock squared return (i.e., a measure for return volatility for individual firm), are not reported. *,**,***Indicate significance at 10%, 5% and 1%, respectively

groups on an electronic (floor) trading system is more sensitive to systematic changes in liquidity than that for the same groups on a floor (electronic) trading system. The average coefficient of concurrent market-wide liquidity is 0.082 and 0.073 (0.123) for large and medium (small) groups on an electronic (floor) trading system, respectively, is larger (smaller) than 0.061 and 0032 (0.181) on a floor (electronic) trading system. All in all, the results provide evidence that confirms the existence of the commonality across all size groups, and the extent of commonality is different across different trading systems, possibly due to the different level of information asymmetry before and after the automation of the trading system.

4.3. Industry-wide Commonality in Liquidity
To investigate the effect of industry-wide liquidity on an individual stock's liquidity before and after the automation of trading systems, while controlling for market liquidity, we estimate the following regression model:

$$DLiq_{i,t} = \alpha_i + \beta_{i1}DLiq_{M,t} + \gamma_{i1}DLiq_{i,t} + XB + \varepsilon_{i,t} \qquad (6)$$

Where, $DLiq_{i,t}$ is the concurrent proportional change in industry-wide liquidity, which is the equally-weighted, cross-sectional average of liquidity for all stocks in the industry that are traded in day *t*, excluding stock *i*. All other variables are the same as defined in model (5).

The results of market-wide and industry-wide commonality are reported in Table 4. Although the industrial component exerts a significant impact on an individual firm's liquidity on the electronic trading system, the results do not support the existence of industry-wide commonality on the floor trading system. Except for price

Table 4: Market-wide and industry-wide commonality in liquidity

Independent variables	ILLIQ				DTOV				DES				DMES			
	Floor		Electronic		Floor		Electronic		Floor		Electronic		Floor		Electronic	
	MKT	IND	MKT	IND	MKT	IND	MKT	IND	MKT	IND	MKT	IND	MKT	IND	MKT	IND
Concurrent	0.136	−0.470	−0.016	0.021	0.293	0.032	0.829	0.181	−0.109	0.075	0.029	0.056	0.128	0.013	0.095	0.082
t-statistics	0.66	−0.92	−0.36	1.63	1.87	0.53	4.62	1.82	−1.15	0.99	2.68	3.08	1.91	0.47	5.83	2.71
P value	0.513	0.357	0.717	0.105	0.065	0.601	0.000	0.072	0.253	0.323	0.009	0.003	0.059	0.642	0.000	0.008
%Pos	46.53	43.56	54.37	45.63	71.84	54.37	71.84	64.08	63.73	49.02	66.99	62.14	64.08	59.22	77.67	65.05
%Pos&Sig	3.96	4.95	4.85	5.83	13.59	6.80	19.42	9.71	9.80	9.80	10.68	11.65	9.71	7.77	21.36	27.18
Lag	1.875	−1.213	−0.010	−0.010	−0.197	0.185	0.279	0.044	−0.047	0.062	−0.008	0.001	0.052	−0.007	−0.048	−0.021
t-statistics	1.03	−1.06	−0.24	−0.96	−1.38	1.73	1.33	0.49	−1.31	1.16	−0.54	0.10	1.71	−0.35	−2.77	−1.12
P value	0.305	0.290	0.807	0.339	0.170	0.087	0.185	0.627	0.193	0.247	0.591	0.923	0.090	0.730	0.007	0.265
%Pos	52.48	33.66	51.46	39.81	48.54	44.66	54.37	46.60	48.04	53.92	37.86	57.28	53.40	51.46	39.81	51.46
%Pos&Sig	4.95	3.96	5.83	2.91	1.94	2.91	4.85	1.94	5.88	11.76	6.80	5.83	11.65	11.65	5.83	8.74
Lead	−0.547	0.435	−0.049	−0.001	−0.065	−0.011	0.177	0.056	0.046	0.017	−0.020	−0.029	0.016	0.031	−0.026	−0.056
t-statistics	−1.07	0.91	−1.11	−0.12	−0.52	−0.13	1.14	0.51	0.66	0.34	−0.93	−1.06	0.59	0.95	−1.11	−2.85
P value	0.289	0.363	0.269	0.905	0.606	0.901	0.255	0.611	0.510	0.735	0.357	0.290	0.554	0.345	0.268	0.005
%Pos	40.59	33.66	43.69	30.10	49.51	39.81	47.57	50.49	50.00	45.10	40.78	44.66	62.14	48.54	52.43	35.92
%Pos&Sig	2.97	1.98	4.85	2.91	5.83	1.94	6.80	4.85	10.78	6.86	3.88	4.85	5.83	9.71	6.80	0.97
Sum																
Mean	1.464	−1.249	−0.075	0.010	0.031	0.206	1.285	0.281	−0.110	0.154	0.001	0.028	0.196	0.037	0.021	0.004
t-statistics	0.97	−1.06	−0.75	0.44	0.09	1.28	3.32	1.37	−0.71	1.08	0.06	0.74	2.27	0.81	0.63	0.08
P value	0.333	0.290	0.458	0.661	0.929	0.204	0.001	0.175	0.477	0.285	0.951	0.462	0.025	0.420	0.533	0.939
Median	−0.191	−0.013	0.015	−0.003	0.330	−0.010	0.913	0.132	0.026	0.006	0.005	0.048	0.087	0.006	0.034	0.019
P value	0.163	0.111	0.431	0.010	0.076	0.844	0.000	0.018	0.092	0.276	0.844	0.030	0.018	0.694	0.030	0.076
Adjusted-R²																
Mean	0.087		0.093		0.018		0.011		0.004		0.013		−0.023		0.017	
Median	0.043		0.062		0.005		0.004		−0.005		0.003		0.002		0.015	

This table presents the results of examining both market-wide and industry-wide commonality in liquidity (Equation 6). During the two sub-sample periods, the floor trading period (Floor) and the electronic trading period (Electronic). Market liquidity (Industry liquidity) is the equally-weighted average of the liquidity measures for all stocks in the sample that represent the market (all stocks in an industry) on trading day t. In every regression, the market and industry averages do not include the dependent variable stock. Liquidity measures *ILLIQ, TOV, ES,* and *MES* are as defined in Table 1. "D" preceding the acronyms of liquidity variable e.g., *DILLIQ*, denotes the proportional change in the variables; for example, the liquidity measure Li, $DLi_t = (Li_t / Li_{t-1}) - 1$. The estimated time-series slope coefficients are averaged in a cross-sectional fashion and reported with their corresponding t-statistics for concurrent (same), Lag (previous), and Lead (next trading day) market liquidity. %Pos gives the percentage of positive coefficient. %Pos&Sig presents the proportion of positive slope coefficients with t-statistics>+1.645 at 5% critical level using the one-tailed test. Sum is the summation of the coefficients of concurrent, lag and lead market liquidity with the t-statistic and P value is the sign test for the null hypothesis: Sum median equals to 0. The coefficients of concurrent, lag, and lead market return variables and the proportional change in individual stock squared return (i.e., a measure for return volatility for individual firm), are not reported.

impact, all liquidity measures in an electronic trading system are influenced by both market-wide and industry-wide liquidity. The coefficient of concurrent market and industry liquidity are statistically significant at 10% and 1% level of significance. Moreover, the combined concurrent, lag, and lead effect of industry-wide liquidity (i.e., sum coefficient) in all regressions is positive and statistically significant only on an electronic trading system. Consequently, the exclusive existence of an industry-wide component in an electronic trading system compared with a floor trading system implies that the information asymmetry within a particular industry increases in the former. In floor trading system, in contrast, the degree of information asymmetry is alleviated due to its information sharing character. Therefore, an individual firm's liquidity on electronic trading shows a response to the concurrent industry's movements. Another possible explanation is that the use of different sample periods as commonality might be time varying. Our evidence on the existence of industry-wide commonality is consistent with that reported by Chordia et al. (2000), Brockman and Chung (2002) and Pukthuanthong-Le and Visaltanachoti (2009), but inconsistent with that reported by Fabre and Frino (2004), Galariotis and Giouvris (2007) and Tayeh et al. (2015).

Finally, after the inclusion of industry-wide commonality the coefficients of concurrent market-wide liquidity decrease compared with those reported in Table 3, except for modified

effective spread regression on both trading systems. Our results also mostly show that the industry-wide component has smaller coefficients than their market component counterpart, which means that commonality in the same market is stronger than the commonality in the same industry. This is inconsistent with Chordia et al. (2000) and Pukthuanthong-Le and Visaltanachoti (2009) but consistent with Brockman and Chung (2002).

4.4. A Specification Check
In previous sections, we examined the existence of commonality by testing the significance of the average coefficients of concurrent market-wide and concurrent industry-wide liquidity using t-tests. The reliability of t-tests' results reported above depends on the assumption that residuals are independent across estimated regression. To check for residuals' independence, we apply the method used by Chordia et al. (2000). First, the residuals are obtained from the joint estimation of commonality (i.e., market and industry regression Equation 6). The residuals are then arranged alphabetically to estimate the following time-series regressions between adjacent residuals:

$$\varepsilon_{i+1,t} = \gamma_{i,0} + \gamma_{i,1}\,\varepsilon_{i,t} + \xi_{i,t} \tag{7}$$

Where, $\gamma_{i,0}$ and $\gamma_{i,1}$ are the estimated coefficients and $\xi_{i,t}$ is an estimated disturbance. The t-statistics of the estimated coefficient

Table 5: Check for cross-section dependence in estimation error

Liquidity Regression	Average correlation	Mean t	Median t	|t|>1.645 (%)	|t|>1.96 (%)
DILLIQ					
Floor	0.052	−0.047	−0.149	15.31	7.14
Electronic	−0.033	0.085	−0.108	10.17	8.47
DTOV					
Floor	0.206	0.276	−0.160	12.93	10.34
Electronic	−0.014	0.084	−0.160	12.10	8.06
DES					
Floor	0.153	0.215	0.054	16.50	8.74
Electronic	0.017	0.154	0.115	9.84	8.20
DMES					
Floor	0.129	0.193	0.270	14.81	7.41
Electronic	−0.040	0.159	0.071	10.48	6.45

This table presents the results of pair-wise regression equation (Equation 7) during the two sub-sample periods; the floor trading period (Floor) and the electronic trading period (Electronic), where the residuals for stock i+1, that are obtained from the time-series regression equation (Equation 6), are regressed on stock's i residuals. the results reported here include the mean correlation coefficient, the mean and median t-statistic of the slope coefficient $\gamma_{i,1}$, and the frequency of the absolute value of t-statistic for the slope, which is beyond typical critical levels 10% and 5% using two-tails test. Liquidity measures *ILLIQ, TOV, ES,* and *MES* are as defined in Table 1. "D" preceding the acronyms of liquidity variable e.g., *DILLIQ*, denotes the proportional change in the variables; for example, the liquidity measure Li, $DLi_t=(Li/Li_{t-1})-1$

of stock's i residuals, $\gamma_{i,1}$, provide evidence about the cross equation dependence. Table 5 reports the results of this specification test, which show that there is no cross equation dependence. The mean t-statistics is insignificant and range between −0.047 and 0.276 on floor trading systems and between 0.084 and 0.159 on electronic trading systems. This implies that any adjustment for cross-equation dependence would yield insignificant changes in the results.

5. CONCLUSION

The issue of commonality in liquidity has been explored in previous literature, where one setting of the trading environment is considered in the analysis. However, the empirical work of Chordia et al. (2000) suggests that asymmetric information could be a plausible reason for the co-variation in individual stock liquidity. Consequently, it is expected that different trading systems, floor/electronic, may lead to different degrees of pervasiveness in commonality due to the varying level of information asymmetry across the trading systems. This study, therefore, examined whether the move from traditional floor trading systems to electronic trading systems affects commonality in liquidity in an emerging market i.e., the ASE.

Our empirical findings confirm the presence of commonality on both floor and electronic trading systems, which are consistent with the findings of previous studies. However, a particularly interesting result is the difference in individual stock responsiveness to the changes in market-wide liquidity between floor and electronic trading systems; commonality is more pervasive on an electronic trading system. The results, for example, show that the mean coefficient of concurrent market-wide liquidity in turnover ratio and modified effective spread regressions in an electronic trading system is larger than that in a floor trading system. Also, the average market-wide coefficients in effective spread regression are only statistically significant on an electronic trading system. This implies that the level of information asymmetry is different across trading systems.

We find that commonality in turnover ratio and spreads is important across nearly all size groups, especially after the automation of a trading system. Except for the effective spread, where commonality increases monotonically, the commonality in turnover ratio and modified effective spread shows, respectively, an inverted U-shape and a U-shape pattern. Commonality in the majority of size groups is stronger on an electronic trading system than on a floor trading system. Finally, the results provide evidence on the presence of commonality within the same industry, after controlling for market-wide liquidity, which is also more pervasive on an electronic trading system. The mean coefficient of concurrent industry-wide liquidity is statistically significant only during the automated period.

In sum, the results have identified a variation in systematic liquidity (i.e., commonality in liquidity) across trading systems, which is perhaps due to their different characteristics. This may suggest that the floor trading system has more ability to alleviate asymmetric information problems compared to its counterpart (i.e., the electronic trading system). Therefore, more policy implications are required to improve and increase the information flow in electronic trading systems.

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