Liquidity commonality under normal and a boom/bust conditions: Evidence from the Saudi stock exchange

Kais Tissaoui [1, *], Mondher Kouki [2, 3], Mounir Jouadi [4]

[1]Community College, University of Hail, Hail, Saudi Arabia
[2]The International Finance Group, Faculty of Management and Economic Sciences of Tunis, El Manar University, Tunis, Tunisia
[3]College of Humanities and Administrative Sciences, Al Jouf University, Sakakah, Saudi Arabia
[4]College of Business Administration, University of Hail, Hail, Saudi Arabia

ABSTRACT

This study explores the commonality in liquidity for Saudi equities by using data from 105 shares covering the period January 2008 to December 2014. Our market model regression results present evidence a strong commonality in liquidity on the Tadawul stock market. In addition, we show the existence of significant commonality in liquidity over time during normal conditions. Furthermore, this study documents also that the liquidity commonality in the Saudi stock market is stronger in boom/bust stock market conditions than in boom/bust oil market conditions. Then, our time series analysis finds that commonality in liquidity is important across all size-based quartiles. Under the boom/bust stock market condition, the first quartile for firms with a small market capitalization is the most susceptible to liquidity commonality, while the last quartile, regrouping the firms with a large market capitalization, is the least sensitive to commonality in liquidity. However, under boom/bust oil market conditions, the small market capitalization quartile is, in general, least susceptible to market-wide liquidity, while the second quartile is more sensitive to liquidity commonality.

1. Introduction

Market microstructure research has recently focused on the common determinants of liquidity, known as "commonality in liquidity," after previously concentrating on specific determinants of liquidity. Thus, understanding the stock liquidity–market liquidity relationship is important for liquidity risk pricing. After the Asian crisis in 1997–1998, the risk of liquidity evaporation in financial markets motivated financial researchers to explore systematic liquidity as a determinant of stock liquidity. Since this crisis, many researchers have revealed that commonality in liquidity is omnipresent in order-driven markets and quote-driven markets (Chordia et al., 2000; Brockman and Chung, 2002; Fabre and Frino 2004; Hasbrouck and Seppi, 2001; Huberman and Halka, 2001; Brockman et al., 2009; Karolyi et al. 2012; Bruno and Shin, 2013; Lee et al., 2014; Foran el al., 2015; Tissaoui et al., 2015).

Most studies agree about the fundamental sources that drive the commonality in liquidity, namely supply-side sources of commonality in liquidity related to the funding constraints of financial intermediaries, demand-side sources driven by correlated trading activity, the level of institutional ownership, investor sentiment, and public–private information flow in the financial market. Furthermore, the literature has remained largely silent, until very recently, on the effects of the oil market on the stock liquidity–market liquidity relationship, particularly given the special interdependence between the stock market and the oil market. Gatfaoui (2016) and Bouri (2015) confirmed that an energy market can reinforce the stock market or damage its stability and/or evolution. The existence of dangers such as oil volatility shocks and financial contagion can cause fear among economic agents about the negative effect of turbulence in energy markets on the stability of the financial market. In sharp contrast to the volume of work investigating the commonality in liquidity phenomena in developed and emerging markets, there is a lack of research on this topic in Arab countries. Our research contributes to this asset pricing literature by studying the Saudi stock market, which has recently attracted considerable

attention from both practitioners and academics. The Saudi Stock Exchange (Tadawul) is bigger than all the bourses in the six-nation Gulf Cooperation Council combined. At the end of 2015, the total market capitalization of Tadawul reached SAR1, 579.06 billion (USD421.10 billion). This position was reinforced by the existence of more than 180 listed firms and the opening of trade to foreign investors. Thus, the goal of the Capital Market Authority (CMA) is to ensure an important level of confidence and stability in the Saudi capital market, especially after the flight of capital abroad in 2006. Then, the outbreak of the financial crisis 2007 meant the Saudis were obliged to retrieve their capital. Since the crisis, theoretical and empirical research has shown that the greatest danger threatening the financial markets is the risk of evaporating liquidity. Hence, the major objective of Capital Market Authority is to maintain an acceptable level of liquidity in Tadawul, with Saudi Arabia being a predominantly oil-based economy (Instefjord, 1999). In this light, Arouri and Fouquau (2009) and Jaghoubi (2015) have affirmed that analyzing the interaction between oil prices and stock markets in GCC countries is interesting, for several reasons. First, GCC countries (including Saudi Arabia) are major suppliers of oil in world energy markets, which means their stock markets may be susceptible to changes in oil prices. Second, the GCC markets differ from those of developed and other emerging countries in that they are largely segmented from the international markets, and are overly sensitive to regional political events. Finally, GCC markets represent promising areas for regional and world portfolio diversification. Using data collected from Bloomberg (These data were collected from the Bloomberg Database), Table 2 shows that the correlation coefficient between the Tadawul All Shares Index (TASI) (Saudi stock market) and oil prices is 31%.This value is positive, but is considered below average. In other words, a change in one variable (TASI or oil price) does not necessarily lead to a move in the other variable. Studying the influence of oil price shocks on GCC stock market returns is important for investors to make necessary investment decisions and for policymakers to regulate stock markets effectively. This study investigates the nexus between stock liquidity and market liquidity, depending on boom/bust cycles in the Saudi stock market and the international oil market. We use the approach proposed by Chordia et al. (2000), based on a market model adapted to liquidity. The data set includes Tadawul-listed firms for the period January 1, 2008, to December 31, 2014.

Our main contributions are threefold. First, unlike prior studies that have investigated the effect of abnormal boom/bust cycles (crash periods and crisis periods) in the stock market on liquidity commonality, our study is the first to analyze the effects of normal boom/bust cycles on liquidity commonality. Second, this work is the first in microstructural literature to explore the impact of normal boom/bust cycles in the international oil market on the liquidity stock–market liquidity interaction. To the best of our knowledge, the dependency between the oil market and liquidity commonality has not been debated sufficiently in the literature. Third, our study examines the Saudi stock market, which has not been considered in prior research. The remainder of this paper is organized as follows. Section 2 provides a literature review on the commonality liquidity–stock liquidity nexus. Section 3 presents our data and methodology. Section 4 discusses the estimation results, and Section 5 concludes the paper, including identifying possible areas for future.

2. Literature review

One of the most significant trends in microstructural markets over the last 20 years has been the liquidity commonality phenomenon. The literature on the subject is quite rich in developed and emerging countries. The general consensus based on these studies is that liquidity commonality exists in order-driven markets and in specialist and dealer markets. Liquidity commonality has many important economic and financial implications. First, it has considerable implications for investors. Liquidity commonality constitutes a systematic risk factor and, hence, investors need compensation for a stock with liquidity that co-moves with market liquidity (Acharya and Pederson 2005; Lee, 2011). Understanding liquidity pricing in the financial market helps investors to enhance their trading strategies to manage liquidity risks. This leads to an optimal allocation of the investors' resources by increasing their confidence level (Chordia et al., 2003). Second, liquidity commonality appears to be important for central banks and regulators. Several studies have shown that the financial turmoil during the 1990s was started by a commonality in a liquidity shock. According to Fernando et al. (2008), commonalities in liquidity shocks affect investors' beliefs about market trends, and lead to a drop in the market. Coughenour and Saad (2004) affirmed that the existence of a liquidity commonality could help researchers to understand the dynamics of liquidity, while helping regulators and other participants to improve the market design.

The first interesting study on liquidity commonalities was that of Chordia et al. (2000). The authors exploited a simple market model, adapted to market liquidity, for a market portfolio composed of 1,169 shares listed on the New York Stock Exchange (NYSE) in 1992. They pointed out that firm liquidity, represented by the bid–ask spread and depth, is explained significantly by changes in market liquidity. The authors find evidence to support significant liquidity commonality, even after controlling for individual determinants of liquidity, including price, volume, and volatility. Huberman and Halka (2001) studied a sample of 240 NYSE shares in 1996, divided into four quartiles of 60 shares each. Their contribution lies in the use of both

dimensions derived from the bid–ask spread to measure liquidity: the absolute spread ratio and the spread/mid-quote ratio. In addition to these variables, they used two dimensions derived from the depth at best limit: depth in quantity and depth in dollars. They report the existence of a common liquidity shock. Hasbrouck and Seppi (2001) used the principal component analysis (PCA) approach on a cross-sectional sample of the 30 stocks with the highest liquidity level on the NYSE in 1994, showing that the phenomenon of commonality characterizes order flows and returns.

Unlike previous empirical and theoretical studies that focus on the dealer markets, Brockman and Chung (2002) examine common factors in the Hong Kong Stock Exchange. They report the existence of commonality liquidity in an order-driven market structure. Based on the Australian Stock Exchange, Fabre and Frino (2004) investigated liquidity commonality using a market model and a data set of 660 individual securities quoted in 2000.The authors find evidence to support the liquidity commonality, but it was lower than that detected on the NYSE market. Using data from the Thailand Stock Exchange for the period 1996–2003, Pukthuanthong-Le and Visaltanachoti (2009) showed strong evidence for market-wide commonality in liquidity. Industry-wide commonality was found to be stronger than market-wide commonality in liquidity. Recently, Karolyi et al. (2012) exploited daily data of 27,447 securities from 40 developed and emerging equity markets for the period January 1995 to December 2009. They reported that the liquidity commonality was higher during periods characterized by high market volatility. Wang (2013) proposes a multi-factor model for measuring liquidity commonality. For a sample period from January 2000 to April 2010, they find evidence that liquidity commonality determines around 9% of daily liquidity variations for Asian emerging markets, and around 14% of daily liquidity variations for Asian developed markets. Syamala et al. (2014) document the existence of a liquidity commonality for equity and options on emerging order-driven markets. They showed that the market-wide and industry-wide commonalities are important, even after controlling for specific variables related to securities. More recently, Lee et al. (2014) explored the commonality in liquidity for country exchange-traded funds (ETFs). Using data from 21 countries, their empirical findings document strong liquidity commonality among country ETFs. Tissaoui et al. (2015) applied the market model approach proposed by Chordia et al. (2000) to an intraday data set for the 38 stocks quoted continuously on the Tunisian Stock Exchange (TSE) for the period October 2008 to June 2009. They showed that the effect of market-wide common factors on stock liquidity is stronger than that of industry-wide commonality. Then, Bai and Qin (2015) document the existence of liquidity commonality in 18 emerging markets. They argue that liquidity commonality is higher in emerging markets than in developed markets. Applying the asymptotic PCA approach, Foran et al. (2015) investigated UK equities using a large sample of daily data, finding strong evidence of commonality in liquidity across stocks.

The above-mentioned studies have provided evidence of significant commonality in liquidity among stocks. Several empirical studies have proposed fundamental sources of liquidity commonalities. The first group of studies suggest supply-side sources, for example, the funding-liquidity mechanism (Coughenour and Saad 2004; Brunnermeier and Pedersen, 2008; Hameed et al., 2010; Rösch and Kaserer, 2014; Lee et al., 2014); co-variations in stock volatility and co-variations in inventory risk (Bai and Qin, 2015). The second group explore demand-side sources, for example, the liquidity demand of stocks' investors (Koch et al., 2016); the level of institutional ownership and individual investors (Kamara et al., 2008); institutional ownership and investor sentiment trading by investors (Karolyi et al., 2012; Lee et al., 2014); trading activity (Chordia et al., 2000; Hasbrouck and Seppi, 2001). The third group of studies document sources related to inventory position, information asymmetry, and public–private information flow (Chordia et al., 2001; Tissaoui et al., 2015).

3. Tadawul market structure, data, and liquidity measures

The Saudi Stock Exchange (Tadawul)[†] is a joint stock company and the sole entity authorized in the Kingdom to act as a Securities Exchange (the "Exchange"), carrying out listing and trading in securities. In 2015, Tadawul successfully deployed NASDAQ'S X-Stream INET trading system. The system is regarded as being among the top trading platforms globally. Securities listed on the Exchange are traded by way of order matching, according to price, and then time priority. Transactions are executed through brokers, on behalf of a client or for the broker. Cash availability is required to buy orders. The availability of securities is required for all sell orders. Trade finality and legal finality are simultaneously recorded on the trading and depository and settlement systems. The activities of Tadawul are subject to the control of the Capital Market Authority (CMA).

The CMA regulates and develops the Saudi capital market by issuing required rules and regulations for implementing the provisions of the Capital Market Law. The basic objectives of the CMA are to create an appropriate investment environment, boost confidence, and reinforce transparency and disclosure standards in all listed companies. Moreover, the CMA protects investors and dealers from illegal acts in the market, and ensures an effective and integrated system of corporate governance and issuer disclosure. There are many

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† www.tadawul.com.sa

traded instruments in the market, including equities, sukuk/bonds, right entitlements; ETFs; REITs, negotiated deals; over-the-counter transactions, and relevant regulations. The Saudi Stock Exchange is an order-driven market. Therefore, we document many types of orders, including limit orders, market orders, hidden orders, fill-and-kill orders, fill-or-kill orders, day orders, call-only orders, and good-till-date orders. Finally, the market is essentially accessible to several types of investors, including Saudi investors, resident foreign investors and GCC resident investors, GCC corporates, and non-resident foreign investors.

To explore whether there is liquidity commonality in the Saudi Stock market, we use a database of transaction closing prices and traded volume. First, the data set is obtained from the official site of the stock exchange of Saudi Arabia (Tadawul) over a seven-year period from January 2008 to December 2014. The choice of this period is justified for two reasons: (i) the availability of the database during this period; and (ii) the need to study the Saudi stock market after the return of capital after the financial crisis in 2007 and before the decision to move towards market liberalization by authorizing foreign direct investments in locally quoted shares from the first half of 2015. As in Chordia et al. (2000), Fabre and Frino (2004), and Pukthuanthong-Le and Visaltanachoti (2009), we apply the following stock selection criterion: the selected securities are stocks that are present in each year in the sample period. After applying this criterion, 105 stocks were selected from the 190 that were available. To examine commonality in liquidity, we use the Amihud illiquidity measure (Amihud, 2002). This is calculated by dividing the absolute

daily return by the trading volume, denoted in US dollars:

$$\text{Amihud ILLIQ}_t = \frac{|r_t|}{P_t * \text{Vol}_t} \qquad (1)$$

where r_t represents the daily holding period return, and Vol_t represents the daily trading volume. To calculate the stock return r_t, we apply the following formula:

$$r_t = [100 * (\ln(P_t) - \ln(P_{t-1}))] \qquad (2)$$

where P_t: is the closing transaction price on day t, and P_{t-1}: is the closing transaction price on day t – 1.Similarly to the return, the trading volume indicates the number of shares traded each day. We measure this using the following formula:

$$\text{Vol}_t = [(\ln(\text{NAE}_t)] \qquad (3)$$

where NAE_t represents is the number of stocks traded on day t. Table 1 reports the summary statistics of the liquidity measure Amihud ILLIQ_t. As anticipated, we observe that the liquidity variable fluctuates overtime.

The liquidity variable has a standard deviation of 0.00876. The coefficient of skewness (Sheskin, 2011) is greater than 0 (12.0676>0). This implies that there is a positively skewed distribution or that it is skewed to the right. The kurtosis coefficient (Westfall, 2014) is greater than 3(213.858>3), which means that the empirical distribution of market-wide liquidity is leptokurtic. Thus, it is essential to note that the liquidity distribution is a non-normal distribution.

Table 1: Cross-sectional statistics for time series means

	Number of stocks	Mean	Median	Std. Dev	MIN	MAX	Skewness	Kurtosis
Amihud ILLIQ_t	105	0.006009	0.00398	0.00876	0.000017	0.195982	12.0676	213.858

Table 2: The annual change in the TASI index (Tadawul) and in oil prices and the correlation coefficient between them

Year	TASI value	Change %	OIL PRICE($/Barril)	Change %
2008	4803		44.5	
2009	6122	27.5%	79.4	78.4%
2010	6621	8.2%	91.4	15.1%
2011	6418	-3.1%	98.8	8.1%
2012	6801	6.0%	91.8	-7.1%
2013	8536	25.5%	98.4	7.2%
2014	8333	-2.4%	53.3	-45.8%
	The correlation coefficient			31%

4. Evidence of liquidity commonality

The simple first step in our empirical research commences with section 4.1, which reports the empirical interaction between individual stock liquidity and market-wide liquidity. In section 4.2, we focus on the effect of boom/bust cycles related to the stock market on the market liquidity–stock liquidity relationship. In the last section, we introduce boom/bust cycles related to the oil market and their effect on the market liquidity–stock liquidity nexus.

4.1. Basic empirical evidence: Original market model

We estimate the commonality in liquidity following the approach of Chordia et al. (2000). We estimate a simple market model using time series regressions. The model is as follows:

$$L_{j,t} = \alpha_j + \beta_1 L_{M,t} + \beta_2 L_{M,t+1} + \beta_3 L_{M,t-1} + \delta_1 R_{M,t} + \delta_2 R_{M,t+1} + \delta_3 R_{M,t-1} + \delta_4 R^2_{j,t} + \varepsilon_{j,t} \qquad (4)$$

where $L_{j,t}$ is the individual liquidity of stock j at the day on t. To represent this liquidity, we use the

Amihud illiquidity measure. Here, $L_{M,t}$ is the weighted cross-sectional average of the market-wide liquidity variable, and $L_{M,t+1}$ and $L_{M,t-1}$ are the one-period lead and lag of the average market liquidity variable, respectively. We integrate these variables as control variables in order to allow for non-contemporaneous adjustments in liquidity produced by thin transactions. All market average liquidity variables are calculated using all firms in the market, except firm j. Here, $R_{M,t}$, $R_{M,t+1}$, and $R_{M,t-1}$ represent the concurrent, lead, and lag of the equally weighted market returns, respectively. The role of these variables is to remove any spurious dependence in the relationship between returns and liquidity measures. Then, $R^2_{j,t}$ is the return volatility for firm j on day t, measured as the average squared return. The return volatility is used because changes in firm-specific volatility could influence the liquidity variables. However, we can deduce from the extant empirical literature that all explanatory variables integrated in the market model represent the control variables, except the variable of contemporaneous market liquidity. Table 3 regroups the mean of the concurrent coefficient β_1;, the mean of the lead coefficient β_2; the mean of the lag coefficient β_3, the number (percentage) of firms with positive coefficients, the number (percentage) of firms with positive and statistically significant coefficients, the number (percentage) of firms with positive and statistically insignificant coefficients, the number (percentage) of firms with negative coefficients, the number (percentage) of firms with negative and statistically insignificant coefficients, and the number (percentage) of firms with negative and statistically significant coefficients. Then, SUM is defined as the sum of the concurrent, lag, and lead coefficients of the market liquidity variables (i.e., $\beta_1 + \beta_2 + \beta_3$), and the p-value is taken from the sign test for the null hypothesis of H0: SUM=0. Table 3 provides strong evidence of liquidity commonality in the Saudi stock market. The mean coefficient on the concurrent market liquidity variable, under normal market conditions, is 0.215, with an associated t-statistic of 6.944. Approximately 84% of these individual β_1 are positive, while 88.57% are positive and significant. This empirical finding shows the existence of liquidity commonality in an order-driven market structure.

Comparing our results with those of other studies, our market liquidity coefficient is lower than that reported by Chordia et al. (2000), Brockman and Chung (2002), Pukthuanthong-Le and Visaltanachoti (2009), and Foran et al. (2015). In addition to the SUM value, the liquidity of Tadawul stocks appears to respond significantly to market-wide liquidity over time. The empirical evidence in Table 3 shows that the sums of the concurrent, lead, and lag coefficients are highly significant. We turn now to explore the link between the size of firms and the liquidity. Following recent research, such as Chordia et al. (2000), Fabre and Frino (2004), Pukthuanthong-Le and Visaltanachoti (2009), and

Tissaoui et al. (2015), we divide our sample into four quartiles based on the market capitalization at the end 2014, and calculate an equal weighted average of the liquidity measure for each quartile. Table 4 explicitly reveals the size effect on the coefficient of the market-wide average liquidity variable. All four quartiles of the Amihud illiquidity measure exhibit significant liquidity commonality in both concurrent and aggregated times. However, the first quartile, relating to firms with lower market capitalizations, is the most susceptible to liquidity commonality. Empirically, the results in Table 4 show that small firms have a relatively large market-wide coefficient (β_1: 0.349 (t-stud: 8.023)). The last quartile, relating to firms with higher market capitalizations, is the least sensitive to liquidity commonality. Table 4 indicates that big firms have a relatively small market-wide coefficient (β_1: 0.153 (t-stud: 6.629)). Our findings are in line with those of Chordia et al. (2000) and Pukthuanthong-Le and Visaltanachoti (2009). However, they also differ considerably to those of Brockman and Chung (2002) and Tissaoui et al. (2015). Then, our results show that the aggregated concurrent, lag, and lead times (i.e., β1 +β2 +β3) are significant for all quartiles. As in the above results, the small-firm quartile is the most sensitive to changes in the SUM market-wide liquidity, with a mean of 0.568 (t-stud: 9.147). Nevertheless, the large-firm quartile is the least sensitive to changes in the SUM market-wide liquidity, with a mean of 0.205 (t-stud: 9.020).

4.2. Evidence on liquidity commonality in boom/bust cycles in the stock market

In this section, we report a test that considers whether the boom/bust cycles related to the stock market have a significant effect on the liquidity commonality. Our methodology estimates the commonality in liquidity using a simple market model of time series regressions, as in Chordia et al. (2000). Then, we examine the incremental effect of the boom/bust cycles related to the stock market on commonality using the following regression models:

Bust case

$$L_{j,t} = \alpha_j + \beta_1 L_{M,t} + \beta_2 L_{M,t+1} + \beta_3 L_{M,t-1} + \beta_4(L_{M,t} * Bust.Stock\ market_t) + \beta_5(L_{M,t+1} * Bust.Stock\ market_t) + \beta_6(L_{M,t-1} * Bust.Stock\ market_t) + \delta_1 R_{M,t} + \delta_2 R_{M,t+1} + \delta_3 R_{M,t-1} + \delta_4 R^2_{j,t} + \varepsilon_{j,t} \qquad (5)$$

Boom case

$$L_{j,t} = \alpha_j + \beta_1 L_{M,t} + \beta_2 L_{M,t+1} + \beta_3 L_{M,t-1} + \beta_4(L_{M,t} * Boom.Stock\ market_t) + \beta_5(L_{M,t+1} * Boom.Stock\ market_t) + \beta_6(L_{M,t-1} * Boom.Stock\ market_t) + \delta_1 R_{M,t} + \delta_2 R_{M,t+1} + \delta_3 R_{M,t-1} + \delta_4 R^2_{j,t} + \varepsilon_{j,t} \qquad (6)$$

The above models (Eq. 5 and Eq. 6) differ to Eq. 4 because we have added dummy variables with coefficients β_4, β_5, and β_6. The goal of this process is to measure the marginal effect of a bust-period of a stock return and a boom-period of a stock return on

an individual firm's commonality. First, we define the dummy variable $Bust.Stockmarket_t$ in model 5, taking the value one if the stock return on any given day is negative, and zero otherwise. Second, we define the dummy variable $Boom.Stockmarket_t$ in model 6, taking the value one if the stock return on any given day is positive, and zero otherwise.

Table 3: Individual liquidity and Market-wide liquidity, for 105 stocks, January 2008-December 2014

	Concurrent		Lead		Lag		Sum	
	β1	t_stud	β2	t_stud	β3	t_stud	β1+β2+β3	t_stud
Mean of estimated Coefficient	0.2145	6.944*	0.018	1.439	0.085	1.628	0.317	8.627*
Number of firms with a positive coefficient (%)	103(98.09%)		82(78.09%)		80(76.19%)		103(98.09%)	
Number of firms with a positive coefficient and insignificant t-statistic (%)	10(9.52%)		39(37.14%)		45(42.86%)		3(2.86%)	
Number of firms with a positive coefficient and significant t-statistic (%)	93(88.57%)		43(40.95%)		35(33.33%)		100(95.24%)	
Number of firms with a negative coefficient (%)	2(1.90%)		23(21.9%)		25(23.81)		2(1.9%)	
Number of firms with a negative coefficient and insignificant t-statistic (%)	0(0.00%)		21(20.00%)		20(19.05%)		1(0.95%)	
Number of firms with a negative coefficient and significant t-statistic (%)	2(1.90%)		2(1.90%)		5(4.76%)		1(0.95%)	
Adj-R2 (%)				61,2				
LLH				5664.474				

Notes: the t_stud: is the student statistic. The significance of the coefficients is determined as follows: if t_stud > 2.5759, the coefficient is significant at 1%*; if 1.96 < t_stud < 2.5759, the coefficient is significant at 5%**; if 1.6449 < t_stud < 1.96, the coefficient is significant at 10%***. This note is valuable for all flowing tables. This table shows regression results on the estimated commonality coefficients of only the market liquidity variables; estimated coefficients of the additional regressors (i.e., the stock return and return volatility variables) are not reported.

Table 4: Liquidity commonality by size quartile, for 105 stocks, January 2008-December 2014

Size of quartile	No. of firms	Mean Coefficient β_1 of market liquidity (t-stud)	No. of firms (percent) with a positive coefficient (β_1) and significant t-statistic	No. of firms (percent) with a positive coefficient (β_1) and insignificant t-statistic	No. of firms (percent) with a negative coefficient (β_1) and significant t-statistic	No. of firms (percent) with a negative coefficient (β_1) and insignificant t-statistic	SUM: $\beta_1 + \beta_2 + \beta_3$ (t-stud)
Quartile 1	27	0.349 (8.023)	22 (81.48%)	5 (18.52%)	0 (0.0%)	0 (0.0%)	0.568 (9.147)
Quartile 2	26	0.177 (5.989)	22 (84.62%)	2 (7.69%)	2 (7.69%)	0 (0.0%)	0.273 (7.678)
Quartile 3	26	0.173 (7.092)	24 (92.31%)	2 (7.69%)	0 (0.0%)	0 (0.0%)	0.211 (8.641)
Quartile 4	26	0.153 (6.629)	25 (96.15%)	1 (3.85%)	0 (0.0%)	0 (0.0%)	0.205 (9.020)

Notes: the t_stud: is the student statistic. The significance of the coefficients is determined as follows: if t_stud > 2.5759, the coefficient is significant at 1%*; if 1.96 < t_stud < 2.5759, the coefficient is significant at 5%**; if 1.6449 < t_stud < 1.96, the coefficient is significant at 10%***. This note is valuable for all flowing tables

As in Brockman and Chung (2008), we use $\beta_4, \beta_5,$ and β_6 as control variables to account for any problems related to non-synchronous trading. Therefore, we define SUM as the sum of the concurrent, lead, and lag coefficients of the market liquidity and the boom/bust dummy variables. The p-value refers to a sign test for the null hypothesis of H0: SUM=0.

Table 5 presents the findings of the commonality in liquidity taking into account the effect of bust-cycles in the stock market (Model 5). The mean coefficient on the concurrent market liquidity variable, under normal conditions, is positive and not statistically significant. It has a value of 0.0539, with an associated t-statistic of 1.569. This coefficient is positive and significant for 52.38% of the regressions, positive and non-significant for 23.81%, negative and non-significant for 12.38%, and negative and significant for only 11.43%. Moreover, the mean of the sum of the coefficients of market liquidity ($\beta_1 + \beta_2 + \beta_3$) remains positive and significant (0.177), with an associated t-statistic of 3.061, despite showing an important decrease from the original specification. This empirical finding implies that the stock liquidity is influenced by market liquidity over time, under normal conditions. In addition, the empirical estimation shows that the mean coefficient of the bust-stock market variableβ_4 is 0.722, with an associated t-statistic of 17.245. This

coefficient is positive and significant for 91.43% of the regressions, positive and non-significant for 4.76%, negative and non-significant for 0.95%, and negative and significant for 2.86%. The sum of all bust-stock return coefficients (i.e., $\beta_4 + \beta_5 + \beta_6$) is positive and highly significant (0.788), with an associated t-statistic of 14.435. Therefore, the effect of liquidity commonality persists overtime under bust-stock conditions. Overall, the Amihud illiquidity test clearly reveals an increase in liquidity commonality under bust-periods compared to under normal conditions ($\beta_4 = 0.722 > \beta_1 = 0.0539$). It is clear that taking into account the bust-cycle effect in the market model (Eq. 5) decreases the mean coefficient β_1 compared to the case of the market model (Eq. 4), without the bust-cycle effect.

Next, we analyze the nexus between the size of firms and the commonality during bust periods. The results are reported in Table 6. The empirical findings are very similar to those shown above. More specifically, the first quartile, regrouping firms with lower market capitalizations, is more sensitive to liquidity commonality, with a significant mean coefficient β_4(0.973 (t − stud = 18.580)). However, the last quartile, regrouping firms with higher market capitalizations, is the least susceptible to liquidity commonality. It has a positive and significant mean coefficient β_4 with a value of 0.518 (t-stud=14.847). Hence, the effect of liquidity

commonality on individual stock liquidity remains positive and significant for the smallest quartile, but becomes weaker for the largest quartile. Furthermore, the results of the estimation of augmented bust-cycle specifications, reported in Table 5, show an improvement in the incremental explanatory power of changes in the maximum likelihood values. There is an increase in the log-likelihood value (LLV) (5845.560) after the introduction of incremental variables in the original specifications compared with the log-likelihood value (5664.474) presented in Table 2.

We extend our investigation by studying the effect of boom-cycles on the liquidity commonality. Table 7 shows evidence of commonality in liquidity after considering the effect of boom-cycles (Eq. 5). The mean coefficient on the concurrent market liquidity variable β_1, under normal stock conditions, is positive and significant. It has a value of 0.149, with an associated t-statistic of 5.288. This coefficient is positive and significant for 87.62% of the regressions, positive and non-significant for 10.48%, negative and non-significant for 0%, and negative and significant for only 1.9%.

Table 5: Individual liquidity and Market-wide liquidity in Bust cycles on stock market, for 105 stocks, January 2008-December 2014

	Market								Boom Cycle							
	Concurrent		Lead		Lag		Sum		Concurrent		Lead		Lag		Sum	
	β_1	t_stud	β_2	t_stud	β_3	t_stud	$\beta_1+\beta_2+\beta_3$	t_stud	B_4	t_stud	B_5	t_stud	B_6	t_stud	$B_4+\beta_5+\beta_6$	t_stud
Mean of estimated coefficient	0.0539	1.569	0.049	1.404	0.074	0.655	0.177	3.061	0.722	17.245	0.048	2.673	0.018	0.729	0.788	14.435
Number of firms with a positive coefficient (%)	80 (76.19%)		92 (87.62%)		53 (50.48%)		95 (90.48%)		101 (96.19%)		89 (84.76%)		69 (65.71%)		100 (95.24%)	
Number of firms with a positive coefficient and insignificant t-statistic (%)	25 (23.81%)		42 (40.00%)		32 (30.48%)		18 (17.14%)		5 (4.76%)		23 (21.90%)		40 (38.10%)		98 (93.33%)	
Number of firms with a positive coefficient and significant t-statistic (%)	55 (52.38%)		50 (47.62%)		21 (20.00%)		77 (73.33%)		96 (91.43%)		66 (62.86%)		29 (27.62%)		2 (1.90%)	
Number of firms with a negative coefficient (%)	25 (23.81%)		13 (12.38%)		52 (49.52%)		10 (9.52%)		4 (3.81%)		16 (15.24%)		36 (34.29%)		5 (4.76%)	
Number of firms with a negative coefficient and insignificant t-statistic (%)	13 (12.38%)		8 (7.62%)		37 (35.24%)		7 (6.67%)		1 (0.95%)		10 (9.52%)		23 (21.90%)		2 (1.90%)	
Number of firms with a negative coefficient and significant t-statistic (%)	12 (11.43%)		5 (4.76%)		15 (14.29%)		3 (2.86%)		3 (2.86%)		6 (5.71%)		13 (12.38%)		3 (2.86%)	
Adj-R² (%)							0.693									
LLH							5845.560									

Notes: the t_stud: is the student statistic. The significance of the coefficients is determined as follows: if t_stud > 2.5759, the coefficient is significant at 1%*; if 1.96 < t_stud < 2.5759, the coefficient is significant at 5%**; if 1.6449 < t_stud < 1.96, the coefficient is significant at 10%***. This note is valuable for all flowing tables. This table shows regression results on the estimated commonality coefficients of only the market liquidity variables; estimated coefficients of the additional regressors (i.e., the stock return and return volatility variables) are not reported.

Table 6: Liquidity commonality by size quartile and Bust cycles on stock market, for 105 stocks, January 2008-December 2014

Size of quartile	Number of firms	Mean Coefficient β_4 of market liquidity (t-stud)	Number of firms (percent) with a positive coefficient (β_4) and significant t-statistic	Number of firms (percent) with a positive coefficient (β_4) and insignificant t-statistic	Number of firms (percent) with a negative coefficient (β_4) and significant t-statistic	Number of firms (percent) with a negative coefficient (β_4) and insignificant t-statistic	SUM: $\beta_4+\beta_5+\beta_6$ (t-stud)
Quartile 1	27	0.973(18.580)	23(85.19%)	4(14.81%)	0(0.00%)	0(0.00%)	0.888(16.486)
Quartile 2	26	0.731(17.149)	25(96.15%)	0(0.00%)	1(3.85%)	0(0.00%)	0.841(14.078)
Quartile 3	26	0.657(18.351)	25(96.15%)	0(0.00%)	0(0.00%)	1(3.85%)	0.741(14.985)
Quartile 4	26	0.518(14.847)	24(92.31%)	0(0.00%)	2(7.69%)	0(0.00%)	0.667(12.110)

Notes: the t_stud: is the student statistic. The significance of the coefficients is determined as follows: if t_stud > 2.5759, the coefficient is significant at 1%*; if 1.96 < t_stud < 2.5759, the coefficient is significant at 5%**; if 1.6449 < t_stud < 1.96, the coefficient is significant at 10%***. This note is valuable for all flowing tables.

Table 7 shows the mean of the sum of the coefficients of market liquidity ($\beta_1+\beta_2+\beta_3$). The value is positive and significant (0.147), with an associated t-statistic of 4.351. This finding shows that the effect of liquidity commonality persists over time during normal conditions. However, this effect is least important in comparison with those obtained for the standard specification and augmented bust-cycle specifications. Consistent with the bust-cycle context, the results reveal that the mean coefficient of the boom-stock market variable β_4 is 0.872, with an associated t-statistic of 11.317. This coefficient is positive and significant for 80.00% of the regressions, positive and non-significant for 16.19%, negative and non-significant for 3.81%, and negative and significant for 0%. The sum of all boom-stock

return coefficients (i.e., $\beta_4+\beta_5+\beta_6$) is positive and highly significant (1.171), with an associated t-statistic of 9.747. Indeed, this finding implies that the effect of liquidity commonality on the stock liquidity persists over time under boom-stock conditions. Overall, the Amihud illiquidity test clearly reveals a strong liquidity commonality in boom-periods compared to the case under normal conditions ($\beta_4 = 0.872 > \beta_1 = 0.147$). Considering that the boom-cycle effect in the market model (Eq. 6) decreases the mean coefficient β_1 compared to that revealed in the market model (Eq. 4) without the boom-cycle effect. We now identify which firms are most susceptible to increasing liquidity commonality during boom-periods in the stock market. The empirical evidence provided in Table 8 suggests that

the first quartile, regrouping the firms with lower market capitalizations, is the most susceptible to liquidity commonality. The mean coefficient β_4 has a positive and significant value 1.483 (t-stud=6.638).

Table 7: Individual liquidity and Market-wide liquidity in Boom cycles on stock market, for 105 stocks, January 2008-December 2014

	Market								Bust Cycle							
	Concurrent		Lead		Lag		SUM		Concurrent		Lead		Lag		SUM	
	β_1	t_stud	β_2	t_stud	β_3	t_stud	$\beta_1+\beta_2+\beta_3$	t_stud	B_4	t_stud	B_5	t_stud	B_6	t_stud	$B_4+\beta_5+\beta_6$	t_stud
Mean of estimated coefficient	0.149	5.288	-0.006	-0.731	0.062	0.597	0.147	4.351	0.872	11.317	0.150	1.030	0.148	2.253	1.171	9.747
Number of firms with a positive coefficient (%)	103 (98.10%)		82 (78.10%)		78 (74.29%)		104 (99.05%)		101 (96.19%)		85 (80.95%)		84 (80%)		99 (94.29%)	
Number of firms with a positive coefficient and insignificant *t*-statistic (%)	11 10.48%		42 40.00%		43 40.95%		4 3.81%		17 16.19%		50 47.62%		38 36.19%		8 7.62%	
Number of firms with a positive coefficient and significant *t*-statistic (%)	92 87.62%		40 38.10%		35 33.33%		100 95.24%		84 80.00%		35 33.33%		46 43.81%		91 86.67%	
Number of firms with a negative coefficient (%)	2 (%)		23 (21.9%)		2 (25.71%)		1 (0.95%)		4 (3.81%)		20 (19.05%)		21 (20%)		6 (5.71%)	
Number of firms with a negative coefficient and insignificant *t*-statistic (%)	0 0.00%		21 20.00%		21 20.00%		0 0.00%		4 3.81%		19 18.10%		12 11.43%		5 4.76%	
Number of firms with a negative coefficient and significant t-statistic (%)	2 1.90%		2 1.90%		6 5.71%		1 0.95%		0 0.00%		1 0.95%		9 8.57%		1 0.95%	
Adj-R² (%)							0.662									
LLH							5781.888									

Notes: the t_stud: is the student statistic. The significance of the coefficients is determined as follows: if t_stud > 2.5759, the coefficient is significant at 1%*; if 1.96 < t_stud < 2.5759, the coefficient is significant at 5%**; if 1.6449 < t_stud < 1.96, the coefficient is significant at 10%***. This note is valuable for all flowing tables. This table shows regression results on the estimated commonality coefficients of only the market liquidity variables; estimated coefficients of the additional regressors (i.e., the stock return and return volatility variables) are not reported.

Table 8: Liquidity commonality by size quartile and Boom cycles on stock market, for 105 stocks, January 2008-December 2014

Size of quartile	No. of firms	Mean Coefficient β_4 of market liquidity (t-stud)	No. of firms (percent) with a positive coefficient (β_4) and significant t-statistic	No. of firms (percent) with a positive coefficient (β_4) and insignificant t-statistic	No. of firms (percent) with a negative coefficient (β_4) and significant t-statistic	No. of firms (percent) with a negative coefficient (β_4) and insignificant t-statistic	SUM: $\beta_4+\beta_5+\beta_6$ (t-stud)
Quartile 1	27	1.483(6.638)	20(74.07%)	0	5(18.52%)	2(7.41%)	2.012(5.802)
Quartile 2	26	0.696(11.656)	22(84.62%)	1(3.85%)	1(3.85%)	2(7.69%)	0.923(10.189)
Quartile 3	26	0.691(13.624)	23(88.46%)	0	1(3.85%)	2(7.69%)	0.884(11.840)
Quartile 4	26	0.596(13.533)	21(80.77%)	3(11.54%)	2(7.69%)	0	0.833(11.309)

Notes: the t_stud: is the student statistic. The significance of the coefficients is determined as follows: if t_stud > 2.5759, the coefficient is significant at 1%*; if 1.96 < t_stud < 2.5759, the coefficient is significant at 5%**; if 1.6449 < t_stud < 1.96, the coefficient is significant at 10%***. This note is valuable for all flowing tables.

However, the last quartile, regrouping firms with higher market capitalizations, is the least susceptible to liquidity commonality, with a significant and positive mean coefficient β_4 with a value of 0.596(t-stud=13.533). Comparing our findings, the boom-cycle results are approximately similar to the standard specification results and the bust-cycle results. In addition, the effect of liquidity commonality on individual stock liquidity remains positive and significant for the smallest quartile and the last quartile. Indeed, the existence of periods with positive stock returns affects all quartiles positively, and particularly the quartile regrouping the smallest firms. Moreover, the estimates of the augmented boom-cycle models show the improvement of the exploratory power manifested in the increase of log-likelihood values from 5664.474 in the original market model to 5781.888 in the augmented boom-cycle models.

4.3. Evidence of liquidity commonality with boom/bust cycles in the oil market

We present a test examining whether the boom/bust cycles related to the oil market have a significant effect on the liquidity commonality. Our methodology uses the market model approach employed in the above section to estimate the liquidity commonality using a simple market model with time series regressions, as in Chordia et al. (2000). Then, we examine the incremental effect of the boom/bust cycles related to the oil market on commonality using the following regression models:

Bust case:
$$L_{j,t} = \alpha_j + \beta_1 L_{M,t} + \beta_2 L_{M,t+1} + \beta_3 L_{M,t-1} + \beta_4 (L_{M,t} * Bust.Oil\,market_t) + \beta_5 (L_{M,t+1} * Bust.Oil\,market_t) + \beta_6 (L_{M,t-1} * Bust.Oil\,market_t) + \delta_1 R_{M,t} + \delta_2 R_{M,t+1} + \delta_3 R_{M,t-1} + \delta_4 R^2_{j,t} + \varepsilon_{j,t} \qquad (7)$$

Boom case:
$$L_{j,t} = \alpha_j + \beta_1 L_{M,t} + \beta_2 L_{M,t+1} + \beta_3 L_{M,t-1} + \beta_4 (L_{M,t} * Boom.Oil\,market_t) + \beta_5 (L_{M,t+1} * Boom.Oil\,market_t) + \beta_6 (L_{M,t-1} * Boom.Oil\,market_t) + \delta_1 R_{M,t} + \delta_2 R_{M,t+1} + \delta_3 R_{M,t-1} + \delta_4 R^2_{j,t} + \varepsilon_{j,t} \qquad (8)$$

The above models (Eq. 7 and Eq. 8) differ to Eq. 4 because we add dummy variables with coefficients $\beta_4, \beta_5,$ and β_6. The main objective of this process is to measure the marginal effect of a bust-period of the oil return and a boom-period of the oil return on an individual firm's commonality. First, we define the dummy variable $Bust.Oil market_t$ in model 7, taking the value one if the oil return on any given day is negative, and zero otherwise. Second, we define the dummy variable $Boom.oil market_t$ in model 8, taking the value one if the stock return on any given day is positive, and zero otherwise. We employ $\beta_4, \beta_5,$ and β_6 as control variables to account for any problems related to non-synchronous trading. Therefore, we define SUM as the sum of the concurrent, lead, and lag coefficients of the market liquidity and the boom/bust dummy variables. The p-value refers to a sign test for the null hypothesis of H0: SUM=0. Referring to Table 9, we confirm the existence of liquidity commonality when we consider the effect of bust-cycles related to the oil

market (Eq. 7). The mean coefficient on the concurrent market liquidity variable β_1, under normal conditions, is positive and significant. It has a value 0.213, with an associated t-statistic of 6.686. This coefficient is positive and significant for 87.62% of the regressions, positive and non-significant for 10.48%, negative and non-significant for 0.00%, and negative and significant for only 1.90%. Similarly, the mean of the sum of the coefficients of market liquidity ($\beta_1 + \beta_2 + \beta_3$) is positive and significant (0.314), with an associated t-statistic of 8.199. The sum coefficient is slightly lower than that in the original specification (0.317), and significantly lower than the augmented boom/bust stock market specifications (0.788 and 1.171). This empirical evidence shows that the stock liquidity is explained by market liquidity over time, during normal conditions, as in the above cases. Indeed, the impact of liquidity commonality is strong and persists over time during normal conditions. In addition, we find again that the mean coefficient of the bust-oil market variable β_4 is 0.184, with an associated t-statistic of 3.614. This coefficient is positive and significant for 80.00% of the regressions, positive and non-significant for 16.19%, negative and non-significant for 3.81%, and negative and significant for 3.81%. The sum of all bust-oil market coefficients (i.e., $\beta_4 + \beta_5 + \beta_6$) is positive and highly significant (0.297), with an associated t-statistic of 3.545. Consequently, this finding implies that the effect of liquidity commonality on stock liquidity persists over time under bust-stock conditions. Overall, the Amihud illiquidity measure clearly shows a strong liquidity commonality under normal conditions, as compared to the commonality in liquidity under bust-oil conditions ($\beta_4 = 0.184 < \beta_1 = 0.213$), and we can compare these empirical findings with the output from the original specification. We conclude that the effect of market liquidity on stock liquidity remains significant and positive during bust-oil periods, but is slightly lower than that in the original model market ($\beta_1 = 0.214$) (Eq.4).Furthermore, the liquidity commonality becomes least important in the bust-oil cycles ($\beta_4 = 0.184$) compared with those in the bust-stock market ($\beta_4 = 0.722$) and boom-stock market ($\beta_4 = 0.872$) cycles related to the stock market. Next, we investigate the interaction between the size of firms and the commonality. Table 10 clearly shows the size effect on the coefficient of the market-wide average liquidity variable. All four size quartiles of the Amihud illiquidity measure show strong commonality in liquidity for both concurrent and aggregated times. In contrast to the boom/bust stock market case, the first quartile, regrouping the firms with lower market capitalizations, is the least susceptible to liquidity commonality. Empirically, the findings note that small firms have a low market-wide coefficient (β_4: 0.094 (t-stud: 3.307)). The second quartile, relating to firms with medium market capitalizations, is the most sensitive to liquidity commonality. Table 10 indicates that medium-sized firms have a relatively large market-wide coefficient (β_4: 0.248(t-stud: 3.680)). Next, our

evidence shows also that the aggregated time of the concurrent, lag, and lead times (i.e., $\beta_4 + \beta_5 + \beta_6$) is significant for all quartiles. Unlike the original and augmented boom/bust stock market specifications, the small size quartile is the least sensitive to changes in the SUM market-wide liquidity, with a mean of 0.164 (t-stud: 3.797). Then, the third size quartile is the most susceptible to changes in the SUM market-wide liquidity, with a mean of 0.400(t-stud: 3.588). Overall, periods with negative oil returns affect all quartiles positively and, particularly, the third quartile, regrouping those firms with important capitalizations. Moreover, the estimates of the augmented boom-cycles models show the improvement of the exploratory power, shown in the increased log-likelihood values, from 5664.474 in the original market model to 5704.388 in augmented bust-oil market model. Our analysis suggests that it is worthwhile extending our investigation to study the effect of boom-cycles in the oil market on the liquidity commonality. Table 11 shows the results obtained from the estimation of augmented market model with the boom-oil market variable (Eq. 8). The mean coefficient on the concurrent market liquidity variable β_1, under normal conditions, is positive and significant. It has a value of 0.213, with an associated t-statistic of 6.782. This coefficient is positive and significant for 88.57% of the regressions, positive and non-significant for 8.57%, negative and non-significant for 0.95%, and negative and significant for only 1.90%. The sum of all market liquidity coefficients ($\beta_1 + \beta_2 + \beta_3$) is positive and significant (0.315), with an associated t-statistic of 8.403. This evidence implies that the effect of liquidity commonality is strong and persists over time during normal conditions. Consistent with the boom/bust stock market cycles and the bust-oil market cycle, the research's results show that the mean coefficient of the boom-stock market variable β_4 is positive and significant, with a value of 0.150 and an associated t-statistic of 2.613. This coefficient is positive and significant for 67.62% of the regressions, positive and non significant for 27.62%, negative and non significant for 3.81%, and negative and significant for 0.95%. The sum of all boom-oil return coefficients (i.e., $\beta_4 + \beta_5 + \beta_6$) is positive and highly significant (0.251) with an associated t-statistic of 2.727. Indeed, this finding implies that the effect of boom-oil market cycles on liquidity commonality persists over time under boom-oil conditions. In general, the Amihud illiquidity measure clearly reveals a strong liquidity commonality under normal conditions, compared with the commonality in liquidity under boom-oil conditions ($\beta_4 = 0.150 < \beta_1 = 0.213$). Nevertheless, the effect of market liquidity on the stock liquidity remain significant and positive during boom-oil periods, but it is slightly lower than that in the original market model ($\beta_1 = 0.214$) (Eq. 4). However, the liquidity commonality becomes least important in the boom-oil cycles ($\beta_4 = 0.150$) compared with those in the bust-oil market ($\beta_4 = 0.184$), bust-stock market ($\beta_4 = 0.722$)), and boom-

stock market ($\beta_4 = 0.872$) cycles related to the stock market.

Next, we identify which firms are most susceptible to increasing liquidity commonality during boom-periods in the oil market. Table 12 suggests that the first quartile, regrouping the firms with lower market capitalizations, is the least susceptible to liquidity commonality.

The mean coefficient β_4 has a value positive and is significant 0.056 ($t-stud = 2.628$). However, the second quartile, regrouping firms with medium market capitalizations, is the most susceptible to liquidity commonality. It has a significant and positive mean coefficient β_4, with a value of 0.232 ($t-stud = 2.813$). In addition; the boom-oil market results are similar to those of the bust-oil market. Furthermore,

we prove that the aggregated concurrent, lag, and lead times (i.e., $\beta_4 + \beta_5 + \beta_6$) is significant for all quartiles. Quite surprisingly, the sum of all boom-coefficients related to the small-size quartile is the least sensitive. It is significant and negative, with a value of -0.048 (t-stud: 2.880). This negativity is due to the large negative values of β_5 and β_6. This empirical finding implies that the commonality affects the liquidity of securities composing the first quartile negatively over time, However, the second-size quartile is the most susceptible to changes in the SUM market-wide liquidity, with a mean of 0.479(t-stud: 3.265). Furthermore, the exploratory power shown in the log-likelihood values is almost equal between the original market model (5664.474) and the augmented boom-oil market model (5629.021).

Table 9: Individual liquidity and Market-wide liquidity in Bust cycles on oil market, for 105 stocks, January 2008-December 2014

	Market								boom Cycle							
	Concurrent		Lead		Lag		Sum		Concurrent		Lead		Lag		Sum	
	β_1	t_stud	β_2	t_stud	β_3	t_stud	$\beta_1+\beta_2+\beta_3$	t_stud	B_4	t_stud	B_5	t_stud	B_6	t_stud	$B_4+\beta_5+\beta_6$	t_stud
Mean of estimated coefficient	0.213	6.686	0.017	1.286	0.084	1.560	0.314	8.199	0.184	3.614	0.045	1.055	0.069	1.526	0.297	3.545
Number of firms with a positive coefficient (%)	103 (98.1%)		82 (78.10%)		78 (74.29%)		104 (99.05%)		101 (96.19%)		85 (80.95)		84 (80%)		99 (94.29%)	
Number of firms with a positive coefficient and insignificant *t*-statistic (%)	11 10.48%		42 40.00%		43 40.95%		4 3.81%		17 16.19%		50 47.62%		38 36.19%		8 7.62%	
Number of firms with a positive coefficient and significant *t*-statistic (%)	92 87.62%		40 38.10%		35 33.33%		100 95.24%		84 80.00%		35 33.33%		46 43.81%		91 86.67%	
Number of firms with a negative coefficient (%)	2 (1.9%)		23 (21.9%)		27 (25.71%)		1 (0.95%)		4 (3.81%)		20 (19.05%)		21 (20%)		6 (5.71%)	
Number of firms with a negative coefficient and insignificant *t*-statistic (%)	0 0.00%		21 20.00%		21 20.00%		0 0.00%		4 3.81%		19 18.10%		12 11.43%		5 4.76%	
Number of firms with a negative coefficient and significant t-statistic (%)	2 1.90%		2 1.90%		6 5.71%		1 0.95%		0 0.00%		1 0.95%		9 8.57%		1 0.95%	
Adj-R² (%)							0.618									
LLH							5704.388									

Notes: the t_stud: is the student statistic. The significance of the coefficients is determined as follows: if t_stud > 2.5759, the coefficient is significant at 1%*; if 1.96 < t_stud < 2.5759, the coefficient is significant at 5%**; if 1.6449 < t_stud < 1.96, the coefficient is significant at 10%***. This note is valuable for all flowing tables. This table shows regression results on the estimated commonality coefficients of only the market liquidity variables; estimated coefficients of the additional regressors (i.e., the stock return and return volatility variables) are not reported.

Table 10: Liquidity commonality by size quartile and Bust cycles on stock market, for 105 stocks, January 2008-December 2014

Size of quartile	No. of firms	Mean Coefficient β_4 of market liquidity (t-stud)	No. of firms (percent) with a positive coefficient (β_4) and significant t-statistic	No. of firms (percent) with a positive coefficient (β_4) and insignificant t-statistic	No. of firms (percent) with a negative coefficient (β_4) and significant t-statistic	No. of firms (percent) with a negative coefficient (β_4) and insignificant t-statistic	SUM: $\beta_4+\beta_5+\beta_6$ (t-stud)
Quartile 1	27	0.094(3.307)	23(85.19%)	3(11.11%)	0(0.0%)	1(3.70%)	0.164(3.797)
Quartile 2	26	0.248(3.680)	21(80.77%)	3(11.54%)	0(0.0%)	2(7.69)	0.373(3.382)
Quartile 3	26	0.233(3.861)	19(73.08%)	7(26.92%)	0(0.0%)	0(0.0%)	0.400(3.588)
Quartile 4	26	0.163(3.618)	21(80.77%)	4(15.38%)	0(0.0%)	1(3.85%)	0.255(3.402)

Notes: the t_stud: is the student statistic. The significance of the coefficients is determined as follows: if t_stud > 2.5759, the coefficient is significant at 1%*; if 1.96 < t_stud < 2.5759, the coefficient is significant at 5%**; if 1.6449 < t_stud < 1.96, the coefficient is significant at 10%***. This note is valuable for all flowing tables.

Table 11: Individual liquidity and Market-wide liquidity in Boom cycles on oil market, for 105 stocks, January 2008-December 2014

	Market								boom Cycle							
	Concurrent		Lead		Lag		Sum		Concurrent		Lead		Lag		Sum	
	β_1	t_stud	β_2	t_stud	β_3	t_stud	$\beta_1+\beta_2+\beta_3$	t_stud	B_4	t_stud	B_5	t_stud	B_6	t_stud	$B_4+\beta_5+\beta_6$	t_stud
Mean of estimated coefficient	0.213	6.782	0.017	1.394	0.085	1.540	0.315	8.403	0.150	2.613	0.020	0.868	0.081	1.703	0.251	2.727
Number of firms with a positive coefficient (%)	102(97.14%)		83(79.05%)		77(73.33%)		103(98.1)		100(95.24%)		77(73.33%)		100(95.24%)		100(95.24%)	
Number of firms with a positive coefficient and insignificant *t*-statistic (%)	9 8.57%		40 38.10%		41 39.05%		3 2.86%		29 27.62%		43 40.95%		46 43.81%		25 23.81%	
Number of firms with a positive coefficient and significant *t*-statistic (%)	93 88.57%		43 40.95%		36 34.29%		100 95.24%		71 67.62%		34 32.38%		54 51.43%		75 71.43%	
Number of firms with a negative coefficient (%)	3(2.86%)		22(20.95)		28(26.67%)		2(1.90)		5(4.76%)		28(26.67%)		5(4.76%)		5(4.76%)	
Number of firms with a negative coefficient and insignificant *t*-statistic (%)	1 0.95%		19 18.10%		21 20.00%		1 0.95%		4 3.81%		23 21.90%		4 3.81%		4 3.81%	
Number of firms with a negative coefficient and significant t-statistic (%)	2 1.90%		3 2.86%		7 6.67%		1 0.95%		1 0.95%		5 4.76%		1 0.95%		1 0.95%	
Adj-R² (%)							0.615									
LLH							5629.021									

Notes: the t_stud: is the student statistic. The significance of the coefficients is determined as follows: if t_stud > 2.5759, the coefficient is significant at 1%*; if 1.96 < t_stud < 2.5759, the coefficient is significant at 5%**; if 1.6449 < t_stud < 1.96, the coefficient is significant at 10%***. This note is valuable for all flowing tables. This table shows regression results on the estimated commonality coefficients of only the market liquidity variables; estimated coefficients of the additional regressors (i.e., the stock return and return volatility variables) are not reported.

Table 12: Liquidity commonality by size quartile and Boom cycles on stock market, for 105 stocks, January 2008-December 2014.

Size of quartile	No. of firms	Mean Coefficient β_4 of market liquidity (t-stud)	No. of firms (percent) with a positive coefficient (β_4) and significant t-statistic	No. of firms (percent) with a positive coefficient (β_4) and insignificant t-statistic	No. of firms (percent) with a negative coefficient (β_4) and significant t-statistic	No. of firms (percent) with a negative coefficient (β_4) and insignificant t-statistic	SUM: $\beta_4 + \beta_5 + \beta_6$ (t-stud)
Quartile 1	27	0.056(2.628)	18(66.67%)	7(25.93%)	0(0.0%)	2(7.41)	-0.048(2.880)
Quartile 2	26	0.232(2.813)	19(73.08%)	5(19.23%)	1(3.85%)	1(3.85%)	0.479(3.265)
Quartile 3	26	0.200(2.882)	19(73.08%)	7(26.92%)	0(0.0%)	0(0.0%)	0.333(2.458)
Quartile 4	26	0.116(2.128)	15(57.69%)	10(38.46%)	0(0.0%)	1(3.85%)	0.250(2.298)

Notes: the t_stud: is the student statistic. The significance of the coefficients is determined as follows: if t_stud > 2.5759, the coefficient is significant at 1%*; if 1.96 < t_stud < 2.5759, the coefficient is significant at 5%**; if 1.6449 < t_stud < 1.96, the coefficient is significant at 10%***. This note is valuable for all flowing tables.

5. Conclusion and implications

We analyze how the boom/bust cycles related to the stock market and oil market affect the nexus between commonality in liquidity and stock liquidity. We used the model market approach, adapted to liquidity, developed by Chordia et al. (2000), and employed a database downloaded from the Tadawul official website. Our study generates several interesting findings. First, our overall conclusion is that the Saudi stock market is an order-driven structure characterized by strong evidence of liquidity commonality under normal conditions. Second, unlike Wang (2013), we show that the boom/bust stock market cycles appear to have a strong effect on liquidity commonality. The original specification is augmented with relevant and exogenous variables representing the boom/bust market cycles relating to stock market. The estimates of these augmented models show that there is a strong increase in the effect of the liquidity market on the stock liquidity under boom/bust conditions. For the bust-stock market case, the existence of periods with negative stock return has a significant and positive effect on the stock liquidity. Therefore, the liquidity market improves significantly with the individual stock liquidity. Similarly, in the boom stock market case, taking into account the periods with positive stock returns contributes to a significant and positive effect of the liquidity market on the security liquidity. Hence, the liquidity market enhances the individual stock liquidity significantly. This impact is more pronounced in the boom conditions than it is in bust conditions. Third, the estimates of the augmented boom/bust oil market models reveal that there is a decrease in the effect of liquidity commonality on individual stock liquidity in boom/bust oil market conditions as compared to their effect in normal conditions. In the bust-oil market case, the existence of periods with negative oil returns contributes to a significant and positive effect of the liquidity market on the stock liquidity. However, this impact is less important than the effect in the bust stock market case. Similarly, in the boom-oil market case, our findings show that taking into consideration periods with positive oil returns has a significant effect on liquidity commonality. Nevertheless, this commonality in liquidity is weaker than it is in the boom-stock market case. Fourth, our paper sheds light on the interaction between the size of firms and the commonality. We found that commonality in liquidity is important across all size-based quartiles. The time-series analysis shows that the first quartile, showing firms with small market capitalizations, is the most susceptible to liquidity commonality, while the last quartile, with firms with large market capitalizations, is the least sensitive to commonality in liquidity. This empirical evidence is more pronounced in the original specification and boom/bust stock market specifications. However, the Amihud illiquidity measure related to individual liquidity is, in general, least susceptible to market-wide liquidity for firms in the small size quartile, but it is more sensitive to market-wide liquidity for firms in the large size quartile. This last result is more evident in the boom/bust oil market specification. In addition to detecting the existence of liquidity commonality phenomena, our research provides evidence about the determinants of commonality. It proposes that commonality in liquidity is explained by others factors, such as the boom/bust stock market cycles and the boom/bust oil stock cycles. Our study contributes in several important ways to the growing literature on commonality in liquidity, and has implications for market regulations and policy. First, the detection of a dependency relationship between liquidity and market-wide liquidity indicates that the Saudi stock market may be the subject of systematic liquidity risk (commonality in liquidity). Second, our results can be used by investors to mitigate the risk of evaporating liquidity in times of boom/bust stock markets and boom/bust oil markets by good timing for speculative and preventive operations. In addition, this latter finding can be employed by policymakers to improve investors' property rights and enhancing transparency in order to avoid sudden liquidity evaporation and the adverse selection problem related to insider trading. Third, understanding the dynamics of liquidity in the Saudi financial market can help investors to improve their trading strategies. On the behavioral side, the detection of factors affecting liquidity increases the level of confidence among investors, enabling them to make optimal allocations of their resources.

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