A Multi-Factor Measure for Cross-Market Liquidity Commonality

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Jian-Xin Wang is Senior Lecturer in the Australian School of Business, University of New South Wales. The author thanks Anthony Baluga and Pilipinas Quising for their research assistance. Comments and suggestions from Maria Socorro G. Bautista, Joseph Zveglich, and participants at the Seminar on Measuring Liquidity Commonality among Asian Stock Markets held 5 July 2010 at the ADB Headquarters, are greatly appreciated. The author accepts responsibility for any errors in the paper.
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Abstract

Liquidity commonality is defined as liquidity co-movements across assets or markets. In the current literature, it is measured relative to a single factor, i.e., the average liquidity across assets or markets. However, liquidity co-movements may not be fully captured by this single factor. Other factors, e.g., aggregate return and volatility, may also contribute to liquidity co-movements. Using Asian stock markets as an example, this paper shows that cross-market liquidity commonality is much higher when measured relative to a set of regional and global factors instead of the single factor. Over the sample period from January 2000 to April 2010, cross-market commonality explains around 9% of daily liquidity variations for Asian emerging markets, and around 14% of daily liquidity variations for Asian developed markets. When measured relative to the average regional liquidity, these estimates are less than 2%, similar to those in existing studies. The paper finds that regional factors affect liquidity commonality through shocks in liquidity and volatility, while global factors affect liquidity commonality through return and volatility. Cross-market liquidity commonality in Asia increased significantly during and after the recent global financial crisis.
I. Introduction

Liquidity is a key measure of market quality and a critical precondition for financial market growth and development. It is a major factor affecting asset pricing efficiency (Chordia, Roll, and Subrahmanyam 2008), and is directly linked to investors' required returns on investments (Amihud and Mendelson 1986), which in turn determine companies' costs of capital. Liquidity plays a central role in hedging and risk management (Das and Hanouna 2009, Acharya and Schaefer 2006), and in triggering and propagating financial crises (Borio 2004), particularly in the most recent episode (Brunnermeier 2009, Gorton 2009). While traditionally liquidity is measured and analyzed for individual assets, Chordia, Roll, and Subrahmanyam (2000); Hasbrouck and Seppi (2001); and Huberman and Halka (2001) are the first to show a common liquidity component among stocks in the United States. This finding has been confirmed in other markets, e.g., Hong Kong, China (Brockman and Chung 2002); Australia (Fabre and Frino 2004); and Thailand (Pukthuanthong-Le and Visaltanachoti 2009). Chordia, Roll, and Subrahmanyam (2000) call the common component “liquidity commonality.” Huberman and Halka (2001) call it “systematic liquidity.” Although the presence of marketwide liquidity has long been recognized by investors, the academic studies allow us to estimate its magnitude and variations over time. They also raise the issue whether shocks in liquidity constitute a nondiversifiable systematic risk, and therefore should be compensated by higher required returns. This has been confirmed by subsequent studies, e.g., Pastor and Stambaugh (2003), Acharya and Pedersen (2005), Sadka (2006), and Korajczyk and Sadka (2008).


In the current literature, liquidity commonality is measured relative to the weighted average liquidity across assets or markets. The daily variations of individual stock liquidity are regressed on variations of this market average liquidity, similar to the market model for stock returns. The liquidity commonality of a stock is measured by either the
beta coefficient of the market liquidity factor or the regression $R^2$. This is the approach proposed by Chordia, Roll, and Subrahmanyam (2000) and adopted by most subsequent studies. This paper asks whether the market average liquidity is the single most important factor in determining liquidity co-movements, and examines the liquidity impact of other common factors, e.g., aggregate return and volatility. As pointed out by Hasbrouck and Seppi (2001, page 405), “unlike returns in the CAPM [capital asset pricing model] … there is no theory motivating a capitalization-weighted liquidity factor.” In addition, the empirical asset pricing literature has shown that multi-factor models (Carhart 1997) provide much better explanations for the variations in returns than the single-factor CAPM. A natural extension would suggest that multi-factor models for liquidity are likely to provide better explanations for liquidity variations than the current single-factor model.

Unlike Brockman, Chung, and Pérignon (2009) and Zhang, Cai, and Cheung (2009) who examine cross-market liquidity commonality using individual stock data, liquidity is measured in this study at the market level, using broad market indices and trading volume. Such cross-sectional aggregation helps to reduce the effects of firm-specific liquidity factors. The liquidity measure used is a modified version of the Amihud (2002) measure, where the absolute return is replaced by daily volatility. As in the case of multi-factor models for returns, there is no theoretical guidance on the choice of common liquidity factors. The paper uses three sets of liquidity factors: one set based on markets in the United Kingdom (UK) and the United States (US) representing the global factors, one set based on Asian developed markets, and one set based on Asian emerging markets. The two sets of Asian regional factors are motivated by the diverse economic and financial development within the region. Factors from developed markets are expected to have greater regional impacts than factors from emerging markets. In addition to the cross-market average liquidity, each set of liquidity factors also includes cross-market average volatility and return. Hameed, Kang, and Viswanathan (2010) show a strong positive relation between stock liquidity and returns. High risk increases the cost of and the required return for supplying liquidity. Given the aim of modelling daily liquidity dynamics, other factors such as the total market capitalization (Brockman, Chung, and Pérignon 2009) remain relatively stable. The choice of liquidity factors is discussed in detail in Section IV.

Several empirical issues are addressed in detail in this study. First, most studies follow Chordia, Roll, and Subrahmanyam (2000) and use the first difference of their liquidity measures. This has been criticized by Hasbrouck and Seppi (2001) for overdifferencing that leads to autocorrelation in residuals. Chordia, Sarkar, and Subrahmanyam (2005) use liquidity level after removing time trend and seasonality. This paper uses a similar procedure for seasonality adjustments. The augmented Dickey–Fuller (ADF) test shows no unit root in the adjusted liquidity series. Second, using the modified R/S statistic of Lo (1991), the paper shows that the modified Amihud measure has long-run dependency, similar to volume and volatility (Bollerslev and Jubinski 1999) and the bid–ask spread (Plerou, Gopikrishnan, and Stanley 2005). This long-run dependency is captured by the
heterogeneous autoregressive (HAR) model of Corsi (2009). Third, the sample from early 2000 to early 2010 includes several major bull–bear market cycles. The paper uses several tests to identify structural breaks and report the weighted average parameters across subperiods.

The measure for cross-market liquidity commonality is the partial $R^2$ of the common liquidity factors, after controlling local market factors such as lagged liquidity, volatility, and returns. The main empirical findings are the following:

(i) Factors from Asian developed markets have greater liquidity impact on local markets than factors from Asian emerging markets. The global factors have the smallest impact.

(ii) The regional and global factors affect local market liquidity through different channels. The regional effects come from the (unexpected) liquidity and volatility. Regional returns have little impact on liquidity commonality. The effects of the global markets come mostly from lagged return and volatility.

(iii) Over the sample period from January 2000 to April 2010, liquidity commonality explains around 9% of daily liquidity variations for Asian emerging markets, and around 14% of daily liquidity variations for Asian developed markets. When measured relative to a single global average liquidity, as in previous studies, liquidity commonality explains only 1.5% of local market liquidity.

(iv) The time trend of liquidity commonality varies significantly across markets. Some had strong increases in recent years. Others peaked early in the sample period. On average, commonality of Asian emerging markets was relatively flat until 2008–2010, while commonality of Asian developed markets has increased steadily since 2002. The bull–bear market cycles do not appear to have a strong effect on liquidity commonality. Commonality increased in Asian emerging markets during the global financial crisis from late 2007 to early 2009, surging sharply in Asian developed markets. It continued to rise during the postcrisis market rebound in 2009 and early 2010.

Overall, cross-market liquidity commonality based on a multi-factor model is much higher than reported in Brockman, Chung, and Pérignon (2009) and Zhang, Cai, and Cheung (2009). It is also higher than the $R^2$s from the market model for stock liquidity in Chordia, Roll, and Subrahmanyam (2000) and Hameed, Kang, and Viswanathan (2010). While commonality is higher in developed markets, it is not always in line with economic or financial development: Malaysia and Thailand have higher commonality with external markets than the Republic of Korea and Taipei, China. Future research should explore the reasons behind the cross-sectional differences and time-series variations in commonality.
The next section explains the data, liquidity measure, and seasonality adjustments. The long memory in liquidity is tested in Section III, which also presents the HAR model of liquidity. Section IV discusses the liquidity factors, the extension to the HAR-Liq model, measures for liquidity commonality, and tests of parameter stability. The findings on liquidity factors and liquidity commonality for each market are discussed in Section V for the full sample and in subperiods. Section VI offers some concluding remarks.

II. Data and Preliminary Analysis

This section examines liquidity commonality across 12 stock markets in Asia, including eight emerging markets: the People’s Republic of China (PRC); India (IND); Indonesia (INO); the Republic of Korea (KOR); Malaysia (MAL); the Philippines (PHI); Taipei,China (TAP); and Thailand (THA). The four regional developed markets are Australia (AUS); Hong Kong, China (HKG); Japan (JPN); and Singapore (SIN). The global markets are represented by the United States (USA) and the United Kingdom (UKG). Table 1 lists the local indices representing these markets. The daily high, low, and closing prices are taken from Bloomberg. The sample period is from 1 January 2000 to 30 April 2010. The Asian financial crisis period in the late 1990s and its related issues are avoided.

Table 1: Markets and Indices

<table>
<thead>
<tr>
<th>Market</th>
<th>Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>China, People’s Rep. of</td>
<td>Shanghai Composite Index</td>
</tr>
<tr>
<td>India</td>
<td>SENSEX Index</td>
</tr>
<tr>
<td>Indonesia</td>
<td>Jakarta Composite Index</td>
</tr>
<tr>
<td>Korea, Rep. of</td>
<td>KOSPI Index</td>
</tr>
<tr>
<td>Malaysia</td>
<td>Kuala Lumpur Composite Index</td>
</tr>
<tr>
<td>Philippines</td>
<td>PSE Index</td>
</tr>
<tr>
<td>Taipei,China</td>
<td>[Taipei,China] Weighted Index</td>
</tr>
<tr>
<td>Thailand</td>
<td>SET Index</td>
</tr>
<tr>
<td>Australia</td>
<td>All Ordinaries Index</td>
</tr>
<tr>
<td>Hong Kong, China</td>
<td>Hang Seng Index</td>
</tr>
<tr>
<td>Japan</td>
<td>Nikkei 225 Index</td>
</tr>
<tr>
<td>Singapore</td>
<td>Straits Times Index</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>FTSE 100 Index</td>
</tr>
<tr>
<td>United States</td>
<td>S&amp;P 500 Index</td>
</tr>
</tbody>
</table>

Figure 1 shows that these markets went through similar cycles—the downtrend in 2000 to 2002; a strong bull run in 2003 to 2007; the global financial crisis from late 2007 to early 2009; and the recent rebound. Liquidity commonality will be estimated in the subperiods and in different market cycles.

1 The volume for the S&P 500 is taken from DataStream. The volume from Bloomberg is much lower than those of DataStream and Yahoo Finance.
Figure 1: Asian Stock Market Performance

Source: Author's estimates.
A. Liquidity Measure

Liquidity has many facets. According to Kyle (1985, page 1316), “[T]hese include ‘tightness’ (the cost of turning around a position over a short period of time), ‘depth’ (the size of an order flow innovation required to change prices a given amount), and ‘resiliency’ (the speed with which prices recover from a random, uninformative shock).” Not surprisingly there is a variety of liquidity measures in the literature. Korajczyk and Sadka (2008) examine the common component of eight liquidity measures. Goyenko, Holden, and Trzcinka (2009) run a horse race of 24 liquidity measures. This study examines the daily variation of the overall market liquidity, which rules out regression-based liquidity measures that are estimated over a longer period, e.g., Lesmond, Ogden, and Trzcinka (1999) and Pastor and Stambaugh (2003). Trading volume-based measures, e.g., volume and turnover ratio, have been criticized for not reflecting changes in trading costs during high volatility periods (see Lesmond 2005). Transaction cost-based measures, e.g., the quoted and effective bid–ask spreads, require intraday data that are not readily accessible for many markets in the sample.

A widely used liquidity measure is the ratio of absolute return to trading volume proposed by Amihud (2002). Let \( r \) be the daily return and \( v \) be the daily trading volume, the Amihud measure is \( |r|/v \). It is a price impact measure, as opposed to a trading cost measure such as the bid–ask spread. It measures illiquidity: for a given volume \( v \), price change \( |r| \) should be small in a deep and liquid market. Korajczyk and Sadka (2008, Table 10) find that the Amihud measure is one of the two liquidity measures (among eight) that are priced in the cross-section of stock returns. Hasbrouck (2009, Table 2) shows that it is highly correlated with two measures of liquidity based on microstructure data.\(^2\)

This paper uses a modified version of the Amihud measure: a market’s liquidity on a trading day is measured as \( L = \ln(1+v/\sigma) \), where \( \sigma \) is the daily volatility. The motivation is that daily volatility is better than the absolute daily return \( |r| \) in capturing the price variation during a trading day, especially when intraday prices are used to measure daily volatility. Volatility is measured as \( \ln(P^H/P^L) \) where \( P^H \) and \( P^L \) are the daily high and low prices. Studies have shown (Alizadeh, Brandt, and Diebold 2002) that the log price range is an efficient estimator of the daily volatility. The logarithmic transformation mitigates the effect of extremely low volatility. The measure is a monotonic transformation of the volume required to increase volatility by one unit. The higher the measure is, the deeper the market is in the sense of Kyle (1985), and the greater liquidity the market has.\(^3\)

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\(^2\) Recent studies using the Amihud measure as the main liquidity measure include Acharya and Pedersen (2005); Avramov, Chordia, and Goyal (2006); Watanabe and Watanabe (2008); Kamara, Lou, and Sadka (2008); Korajczyk and Sadka (2008); and Hasbrouck (2009), among others.

\(^3\) Karolyi, Lee, and van Dijk (2009) use a similar log transformation of the Amihud measure: \(-\ln[1+|r|/(p^v)]\) where \( p \) is the end-of-day price.
Table 2: Summary Statistics of Daily Variables

<table>
<thead>
<tr>
<th>Return (percent)</th>
<th>Mean</th>
<th>St Dev</th>
<th>Skew</th>
<th>Kurt</th>
<th>$\rho(1)$</th>
<th>Q5</th>
<th>ADF</th>
</tr>
</thead>
<tbody>
<tr>
<td>China, People's Rep. of</td>
<td>0.029</td>
<td>1.72</td>
<td>-0.08</td>
<td>6.92</td>
<td>0.011</td>
<td>10.3</td>
<td>-16.6</td>
</tr>
<tr>
<td>India</td>
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<td>-0.19</td>
<td>8.84</td>
<td>0.074</td>
<td>20.1</td>
<td>-16.2</td>
</tr>
<tr>
<td>Indonesia</td>
<td>0.058</td>
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<td>-0.67</td>
<td>8.69</td>
<td>0.133</td>
<td>45.8</td>
<td>-17.2</td>
</tr>
<tr>
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<td>7.57</td>
<td>0.023</td>
<td>8.67</td>
<td>-17.4</td>
</tr>
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<td>0.96</td>
<td>-0.85</td>
<td>11.8</td>
<td>0.168</td>
<td>75.0</td>
<td>-15.8</td>
</tr>
<tr>
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<td>0.017</td>
<td>1.45</td>
<td>0.52</td>
<td>18.7</td>
<td>0.123</td>
<td>46.1</td>
<td>-16.8</td>
</tr>
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<td>1.61</td>
<td>-0.14</td>
<td>4.85</td>
<td>0.057</td>
<td>18.4</td>
<td>-17.5</td>
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<td>20.0</td>
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<td><strong>0.077</strong></td>
<td><strong>30.5</strong></td>
<td><strong>-16.7</strong></td>
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<tr>
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<td><strong>9.96</strong></td>
<td><strong>-0.076</strong></td>
<td><strong>57.8</strong></td>
<td><strong>-17.4</strong></td>
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<table>
<thead>
<tr>
<th>Volume (billion)</th>
<th>Mean</th>
<th>St Dev</th>
<th>Skew</th>
<th>Kurt</th>
<th>$\rho(1)$</th>
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<th>ADF</th>
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<td><strong>5.2</strong></td>
<td><strong>0.82</strong></td>
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continued.
Table 2: continued.

<table>
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<tr>
<th>Volatility (percent)</th>
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<th>St Dev</th>
<th>Skew</th>
<th>Kurt</th>
<th>p(1)</th>
<th>Q5</th>
<th>ADF</th>
</tr>
</thead>
<tbody>
<tr>
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<th>St Dev</th>
<th>Skew</th>
<th>Kurt</th>
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<th>Q5</th>
<th>ADF</th>
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<td><strong>0.71</strong></td>
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</table>

ADF = augmented Dickey–Fuller test.
Note: p(1) is the first-order autocorrelation. Q5 is the Ljung–Box Q statistic for five lags.
Source: Author’s estimates.
A word of caution is required when comparing the liquidity measure across different markets. Because of the substantial differences in share prices and exchange rates, it may take US$1 million to buy 100,000 shares in market A but only US$10,000 to buy the same number of shares in market B. Therefore market A appears to be more active than B, while B may actually have greater trading value. Ideally one would like to measure price impact (therefore liquidity) based on the dollar value traded. However trading value is not available for most markets in the sample. Fortunately the focus is on how liquidity changes over time, not liquidity differences across markets. When liquidity is measured consistently over time, the cross-market price level effect should not significantly affect liquidity dynamics.

B. Summary Statistics

Table 2 presents the summary statistics of daily return, volatility, and liquidity. Daily returns are calculated as $100 \times \ln(P_t/P_{t-1})$, where $P_t$ is the closing index value on day $t$. Over the sample period, returns in emerging markets are much higher than returns in developed markets and in the UK and the US; are more volatile; and are more negatively skewed. These statistics are consistent with the stylized contrast between emerging and developed markets. Emerging markets all show return persistence, with the first-order autocorrelation $\rho(1) > 0$. Such persistence is particularly strong for Indonesia, Malaysia, and the Philippines. While most developed markets show return reversal, i.e., $\rho(1) < 0$, the UK and the US have stronger return reversals than Asian developed markets. With a critical value of 11.07, the Ljung–Box Q statistic for five lags shows significant serial correlation for most emerging markets, the UK, and the US. While the stationarity of some liquidity measures has been questioned in some studies (Chordia, Roll, and Subrahmanyam 2000), it is clearly not an issue for daily returns. The ADF test strongly rejects the presence of unit roots.4

Trading volume is extremely high in the People's Republic of China (PRC) and Taipei, China, where the average daily volumes for the represented indices are 4.3 and 3.2 billion shares, respectively. On the other hand, the average daily volume for the SENSEX Index in India is only 40 million shares. On average, trading volumes in Asian emerging markets are much higher than volumes in Asian developed markets. Singapore’s average volume is particularly low at 190 million shares per day. Volumes in Asian developed markets have higher skewness and kurtosis, indicating more frequent volume spikes. Volumes in Asian emerging markets tend to be more persistent than volumes in developed markets. The ADF test rejects unit roots in volume series.

4 The augmented Dickey–Fuller test is run with a constant and both with and without time trend. Both tests reach the same conclusion. The test statistic with time trend is reported. The critical value at 5% significance is $-3.66$. 
The daily volatility measure, calculated as $100 \times \ln(P_H/P_L)$, is on average slightly higher than the volatility estimates from the end-of-day price in the return panel. High-volume markets do not always have high volatility: India and the Republic of Korea have low volume but high volatility. Asian emerging markets have the highest volatility on average but the lowest volatility persistence, measured by the first-order autocorrelation and the Ljung–Box Q statistic for five lags. Asian developed markets have higher volatility skewness and kurtosis, indicating more frequent surges in daily volatility. The UK and the US have the highest volatility persistence. There is no unit root in volatility.

The liquidity measure shows a wide disparity of liquidity among emerging markets in Asia. Liquidity in the PRC; Indonesia; Taipei, China; and Thailand is higher than in most developed markets. However, liquidity in India, the Republic of Korea, Malaysia, and the Philippines is much lower. Asian emerging markets have the highest liquidity skewness and kurtosis, indicating more frequent liquidity spikes. On the other hand, Singapore as a developed market has very low liquidity due to its low trading volume. The UK and the US have higher average liquidity and lower liquidity skewness and kurtosis than Asian developed and emerging markets. As mentioned before, cross-market liquidity ranking can be very different if trading value were used to measure liquidity. Liquidity persistence is similar across the three groups.

A key issue in measuring liquidity commonality is whether liquidity is stationary and whether the level of liquidity or its first difference should be used. Chordia, Roll, and Subrahmanyam (2000, 10) point to the potential problem of nonstationarity in the time series of liquidity levels and opt to use the first difference of their liquidity measures. Hasbrouck and Sappi (2001, 405) suggest that the bid–ask spread and other liquidity measures generally do not have unit roots and argue against overdifferencing as it induces autocorrelation in computed residuals. In later studies, many have used the first difference, (Zhang, Cai, and Cheung 2009; Brockman, Chung, and Pérignon 2009). Some have used liquidity levels adjusted for seasonality (Chordia, Sarkar, and Subrahmanyam 2005); while some have used both (Hameed, Kang, and Viswanathan 2010). Most studies do not provide a formal test on the stationarity of their liquidity measures. This paper addresses this issue using the ADF test for unit roots. As mentioned, the test is run with and without a time trend. In both cases, it safely rejects the presence of unit roots in the modified Amihud measure for all markets.

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5 Zhang, Cai, and Cheung (2009) report that Singapore has the second lowest number of trades per stock and the third highest bid–ask spread among six Asian developed markets.

6 In comparison to $\ln(1+v/o)$, $\ln(1+v/|r|)$, which is a monotonic transformation of the Amihud (2002) measure, has much higher skewness and kurtosis and much lower persistence.
C. Seasonality Adjustments

Chordia, Sarkar, and Subrahmanyam (2005) demonstrate the presence of strong seasonality in their measures of stock and bond liquidity. For example, liquidity is much higher on Monday and Tuesday and during the summer months of July to September, and much lower surrounding holidays and during crisis periods. After removing the seasonality, they report that the ADF and the Phillips–Perron tests both reject unit roots in their adjusted liquidity measures. Since this paper does not seek to explain liquidity variations associated with these seasonalties, a similar procedure as Hameed, Kang, and Viswananathan (2010) is followed to remove them. Therefore, let \( L_{i,t} = \ln(1 + v_{i,t} / \sigma_{i,t}) \) be the liquidity in market \( i \) on day \( t \). Regress \( L_{i,t} \) on a set of seasonality variables:

\[
L_{i,t} = \beta_0 + \beta_1 t + \beta_2 t^2 + \sum_{d=1}^{4} \beta_{3,d} \text{DAY}_{t,d} + \sum_{m=1}^{11} \beta_{4,m} \text{MONTH}_{t,m} + \beta_5 \text{HOLIDAY}_t + u_{i,t}
\]

where \( t \) and \( t^2 \) are time trend and its square; \( \text{DAY}_{t,d}, d = 1,\ldots,4 \), are dummies for Monday to Thursday; \( \text{MONTH}_{t,m}, m = 1,\ldots,11 \), are dummies for January to November; and \( \text{HOLIDAY}_t \) is the dummy for the day before and the day after a holiday. The residual \( u_{i,t} \) is used to construct the following variance equation:

\[
\log(u_{i,t}^2) = x_{i,t}' \gamma + \nu_{i,t}
\]

where \( x_{i,t} \) is the same set of variables as in equation (1). The standardized residual is then given by \( \hat{e}_{i,t} = \hat{u}_{i,t} / \exp(x_{i,t}' \hat{\gamma} / 2) \). Let \( a_i \) be the mean of \( L_{i,t} \) and \( b_i \) be set to \( [\text{var}(L_{i,t}) / \text{var}(\hat{e}_{i,t})]^{1/2} \). The adjusted liquidity, calculated as \( L_{i,t}^{\text{adj}} = a_i + b_i \hat{e}_{i,t} \), has the same mean and variance as the original series \( L_{i,t} \). In all subsequent analyses, \( L_{i,t} \) denotes the adjusted liquidity to simplify notation. Figure 2 shows a comparison between the original and the adjusted liquidity series for Australia. It seems that the detrending worked better in the early sample period. There was a surge in liquidity associated with the market rebound after the recent global financial crisis (see Figure 1). Table 3 reports the summary statistics of the adjusted daily liquidity. The mean and standard deviation are the same as the original liquidity series by design. The kurtosis is slightly higher. The first-order autocorrelation and the Ljung–Box Q5 statistic show much lower persistence over time. The ADF statistic shows stronger rejection of null of unit roots.
Figure 2: Original and Adjusted Daily Liquidity

Original Daily Liquidity of Australia

Source: Author’s estimates.
Table 3: Summary Statistics for the Adjusted Daily Liquidity

<table>
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<tr>
<th>Country</th>
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<th>St Dev</th>
<th>Skew</th>
<th>Kurt</th>
<th>ρ(1)</th>
<th>Q5</th>
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ADF = augmented Dickey–Fuller test, MRS = modified R/S test.
Note: ρ(1) is the first-order autocorrelation. Q5 is the Ljung–Box Q statistic for five lags.
Source: Author’s estimates.

In addition to daily liquidity, other variables in Table 1 are also filtered through the above procedure to remove any seasonality. While the original volume and volatility are used to construct the daily liquidity measure, they are taken logarithms and then filtered through the above procedure for subsequent analysis. The logarithmic transformation is often used in volatility modelling. Andersen, Bollerslev, and Diebold (2007) show that the log volatility has much lower skewness and kurtosis than volatility itself. Plerou, Gopikrishnan, and Stanley (2005) show that liquidity measures such as the bid–ask spread is a logarithmic function of the number of transactions and the trading volume.

D. Sample Construction

To measure liquidity commonality, the daily liquidity measures need to be matched across markets. Many markets do not have the same trading days. If only the common trading days across 12 markets were used, the sample size would be reduced to 1,740 days from over 2,500 days for individual markets. In addition to a substantial reduction in sample size, the missing days are also likely to distort the daily liquidity dynamics.
To overcome this problem, a trading day is removed only if more than half of the markets are not open. For example, if the PRC is trading on a given day, calculate the average liquidity of emerging markets (without the PRC), the average liquidity of Asian developed markets, and the average liquidity of the UK and the US. These averages are calculated when more than half of the markets in the group are trading on the day. This process preserves most trading days even if one or two markets are not trading. The final sample size ranges from a low of 2,442 for the PRC to a high of 2,540 for Australia.

III. Long Memory in Liquidity

Studies, e.g. Bollerslev and Jubinski (1999), have shown that both volume and volatility have long-run dependence, often termed as long memory. The liquidity measure is based on volume and volatility, therefore may also have long memory. If present, long memory should be accounted for when modelling liquidity dynamics. Otherwise the standard “omitted variable bias” applies when the “omitted” long memory is correlated with any of the explanatory variables (Greene 2008, 133).

A. Testing for Long Memory

The modified R/S (MRS) statistic of Lo (1991) is used to test the presence of long memory in the daily liquidity series. It is a modification of the classical R/S test of Mandelbrot (1972), which often fails to reject long memory when there is none. Consider a time series $X_1, X_2, \ldots, X_T$. The sample mean, variance, and autocovariance of $j$th order are given by $\bar{X}$, $\sigma^2_0$, and $\hat{\gamma}_j$ respectively. The modified sample variance, after taking into account of autocovariance, is given by $\hat{\sigma}^2(q) = \sigma^2_0 + \sum_{j=1}^{q} \left(1 - \frac{1}{q+1}\right) \hat{\gamma}_j$ where $q$ is the number of lags with $0 < q < T$. The modified R/S statistic is defined as

$$Q_T(q) \equiv \frac{1}{\hat{\sigma}(q)} \left[ \max_{1 \leq k \leq T} \sum_{j=1}^{k} (X_j - \bar{X}) - \min_{1 \leq k \leq T} \sum_{j=1}^{k} (X_j - \bar{X}) \right]$$

(3)

The numerator is the range of the running sums of deviations from the sample mean, while the denominator is the modified standard deviation (hence the name R/S test). Instead of $\hat{\sigma}(q)$, the classical R/S statistic uses the sample standard deviation $\sigma_0$ in the denominator. Lo (1991) suggests to choose the lag value $q$ as the integer part of

$$\left(\frac{T}{2}\right)^{1/3} \left(\frac{\sigma}{1 - \rho^2}\right)^{2/3}$$

with $\rho$ being the first-order autocorrelation coefficient of $X$. Lo (1991) derives the asymptotic distribution of $\text{MRS}(q) = Q_T(q) / \sqrt{T}$. For a one-sided test of the null hypothesis of no long memory, the null is rejected when $\text{MRS}(q) > 1.862$.

The last column of Table 2 reports the estimated MRS for the liquidity series. The number of lags $q$ is selected base on Lo’s suggestion. For all markets, the null hypothesis of no long memory in liquidity is strongly rejected. In fact, the MRSs of liquidity are much higher than those of volatility (not reported here). India has an exceptionally high MRS,
which leads to a high average value for Asian emerging markets. The median MRS of Asian emerging markets is very similar to that of Asian developed markets. The UK and the US have the lowest MRS. The results of the modified R/S test are consistent with the autocorrelation functions depicted in Panels A and B of Figure 3. For both emerging markets (Panel A) and developed markets (Panel B), the decay in autocorrelation is very slow. The correlations between today’s liquidity and that of 100 days ago are statistically significant and above 0.1 for nine of the 12 markets. India has a correlation of 0.34 and Japan and the UK have a correlation of 0.22 after 100 days.

**B. Modelling Long Memory**

Given the strong evidence of long memory, a model is required to capture its effect on daily liquidity variations. In the volatility literature, long memory is traditionally captured by fractionally integrated models, e.g., Andersen, Bollerslev, Diebold and Labys (2003). Corsi (2009)\(^7\) proposes a heterogeneous autoregressive model for realized volatility (HAR-RV) based on the “heterogeneous market hypothesis” of Müller et al. (1993 and 1997). The HAR-RV model provides a simple way to capture volatility long memory and has been widely adopted in recent studies.\(^8\) In this paper, the heterogeneous autoregressive model is adopted to capture long memory in liquidity and is labelled as the HAR-Liq model.

As in the basic HAR-RV model, the HAR-Liq model includes past liquidity aggregated over different time horizons as explanatory variables. The average liquidity in the past \(h\) days is \(L_{i,t-1}^k = \frac{1}{h} \sum_{s=t-h}^{t-1} L_{i,s}\), with \(k = D\) (day), \(W\) (week), \(M\) (month), and \(Q\) (quarter) for \(h = 1, 5, 22,\) and 66 respectively. The HAR-Liq model is given by

\[
L_{i,t} = \beta_0 + \sum_{k=D}^{Q} \beta_k L_{i,t-1}^k + \epsilon_{i,t}
\]

Table 4 reports the estimation of equation (4) for individual markets. Bold numbers are statistically significant at the 5% level. Most of the lagged daily, weekly, and monthly liquidity are highly significant. For unknown reasons, the lagged weekly liquidity has the strongest impact on today’s liquidity. This has been found in volatility studies of equities and bonds (Andersen, Bollerslev, and Diebold 2007) and exchange rates (Wang and Yau 2000). Since the lagged quarterly liquidity is significant only for three of the 12 markets, it is not included in the subsequent analysis. With lagged daily, weekly, and monthly liquidity, most of the long-run dependency is removed. Panel C of Figure 3 presents the autocorrelation function of the HAR-Liq residuals. The residual autocorrelations are very close to zero for the PRC, India, and Japan. The same holds true for all the other markets. By mixing of a small number of lagged liquidity with different aggregation frequencies, the HAR-Liq model produces a good approximation to long-run dependencies in liquidity.

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\(^7\) The working paper was circulated in 2003.

\(^8\) Recent studies using the HAR-RV model includes Andersen, Bollerslev, and Diebold (2007); Andersen, Bollerslev, and Huang (2010); Bollerslev, Kretschmer, Pigorsch, and Tauchen (2009); Corsi, Kretschmer, Mittnik, and Pigorsch (2005); Forsberg and Ghysels (2007); and Maheu and McCurdy (2010).
Figure 3: Liquidity Autocorrelation

Panel A: Emerging Markets

Panel B: Advanced Markets

Panel C: Autocorrelation of HAR(3) Residuals

Source: Author’s estimates.
### IV. Model Specification

This section extends the baseline HAR-Liq model to include additional local, regional, and global factors. The aim is to estimate the percentage variation of the individual market liquidity explained by a common set of regional and global factors, i.e., to measure cross-market liquidity commonality. A proper measure can only be achieved when the impact of local liquidity factors are included.
A. Liquidity Factors

There are several well-known liquidity determinants in the literature, especially for equities. These include stock return and volatility, firm size and index inclusion, insider holdings and ownership concentration, market sentiment and noise trading, information risk such as the probability of informed trading and order imbalance, etc. This study focuses on the overall market liquidity and its daily variations, which limits the choice of liquidity factors. Market size and ownership structure are relatively stable on a day-to-day basis. Information risk measures are individual stock-based and require intraday data, which are not available for many markets. Market sentiment and noise trading are not directly observable and often approximated by other market variables.

This leaves the market return and volatility as the key liquidity determinants. Market return has a direct impact on investor confidence and sentiment, and on investors’ ability to obtain funding to supply liquidity, e.g., Brunnermeier and Pedersen (2009). Hameed, Kang, and Viswanathan (2010) present strong evidence of a causal effect from stock return to liquidity. Volatility reflects risks from various sources, e.g., asset fundamentals, information precision, noise trading, etc. High risks increase the cost of and the required return for supplying liquidity. It is well documented that higher volatility leads to higher bid–ask spread and lower liquidity (see Wang 1999, Wang and Yau 2000).

Several studies have documented liquidity commonality as a determinant of individual asset liquidity. Chordia, Roll, and Subrahmanyam (2000) were the first to show a significant contemporaneous co-movement between the market average liquidity and individual stock liquidity in the US. The relationship is similar to the CAPM model for stock returns and the co-movement is termed “liquidity commonality.” Recently Brockman, Chung, and Pérignon (2009); Karolyi, Lee, and van Dijk (2009); and Zhang, Cai, and Cheung (2009) all provide evidence of liquidity commonality in international settings. Motivated by these findings, the average regional or global liquidity measures are included as co-determinant factors for individual market liquidity.

B. Extensions to the HAR-Liq Model

Given the liquidity factors identified above, the empirical model used to measure liquidity commonality can now be specified. The starting point is the baseline HAR-Liq model in equation (4). In addition to lagged local liquidities, local return and volatility are important factors as discussed above. The regional and global factors include return, volatility, and liquidity. The global factors are calculated as the average values of the UK and the US. The regional factors are calculated as the average values across Asian markets, excluding the market being analyzed.

Since markets in London and New York open after most Asian markets are closed, there is little contemporaneous effect from these markets to Asia. Therefore only lagged global

9 There is a one-and-half hour overlapping trading period between New Delhi and London. Other Asian markets do not have overlapping trading hours with London and New York.
factors are added to the HAR-Liq model. The lagged values for global liquidity, volatility, and return are calculated in the same way as the lagged liquidity in equation (4). Only lagged daily and weekly liquidity ($L_{g,t-1}^D$ and $L_{g,t-1}^W$), volatility ($\sigma_{g,t-1}^D$ and $\sigma_{g,t-1}^W$), and return ($r_{g,t-1}^D$ and $r_{g,t-1}^W$) are included.

Given the diversity in economic and financial market development within the region, Asian markets are split into Asian emerging markets and Asian developed markets. Therefore there are two sets of regional factors: one from Asian developed markets and another from Asian emerging markets. Each set includes the average liquidity, volatility, and return, excluding the market being analyzed. The challenge is to find a parsimonious way to examine contemporaneous and lagged effects of local, subregional, and global factors.

For liquidity and volatility, the contemporaneous and lagged values are decomposed into the expected and unexpected components using the structure of the heterogeneous autoregressive model in equation (4). Let $X_{j,t-1} = \{r_{j,t-1}, L_{j,t-1}^D, L_{j,t-1}^W, L_{j,t-1}^M, V_{j,t-1}^D, V_{j,t-1}^W, V_{j,t-1}^M, r_{j,t-1}^D, r_{j,t-1}^W, r_{j,t-1}^M\}$, where $j = "AD"$ for Asian developed markets and "AE" for Asian emerging markets. The following regression is estimated via ordinary least squares: $Y_{j,t} = \beta_0 + \beta_1 X_{j,t-1} + \eta_{j,t}$, with $Y_{j,t}$ being either $L_{j,t}$ or $V_{j,t}$. The expected component is $Y_{j,t}^{EP} = \beta_0 + \beta_1 X_{j,t-1}$ and the unexpected component is $Y_{j,t}^{U} = \eta_{j,t}$. The decomposition is motivated by the market efficiency argument that it is the unexpected component that carries new information on the economic and market conditions. The expected component captures the long-run, low-frequency variations in liquidity and volatility. The effects from the lagged variables of different time aggregations are reflected in the expected component, resulting in a more parsimonious model. Returns are generally regarded as unpredictable. The contemporaneous and lagged daily returns, $r_{j,t}$ and $r_{j,t-1}^D$, are included as explanatory variables for individual market liquidity.

The baseline HAR-Liq model in equation (4) includes the lagged local market liquidities as explanatory variables. The contemporaneous volatility of market $i$ is decomposed into its expected and unexpected components using the same procedure outlined above, with the subscript $j$ replaced by the market indicator $i$. The contemporaneous and lagged daily market returns are also included. The final model, incorporating local, regional, and global liquidity factors, is given by

$$L_{i,t} = \beta_0 + \beta_1 L_{i,t-1}^D + \beta_2 L_{i,t-1}^W + \beta_3 L_{i,t-1}^M + \beta_4 \sigma_{i,t}^E + \beta_5 \sigma_{i,t}^U + \beta_6 r_{i,t} + \beta_7 r_{i,t}^D + \beta_8 r_{i,t}^W + \beta_9 r_{i,t}^M + \beta_{10} \sigma_{i,t}^D + \beta_{11} \sigma_{i,t}^W + \beta_{12} r_{i,t}^D + \beta_{13} r_{i,t}^W + \beta_{14} L_{AD,t}^E + \beta_{15} L_{AD,t}^U + \beta_{16} \sigma_{AD,t}^E + \beta_{17} \sigma_{AD,t}^U + \beta_{18} r_{AD,t} + \beta_{19} r_{AD,t}^D + \beta_{20} r_{AD,t}^W + \beta_{21} r_{AE,t} + \beta_{22} \sigma_{AE,t}^E + \beta_{23} \sigma_{AE,t}^U + \beta_{24} r_{AE,t} + \beta_{25} r_{AE,t}^D + \epsilon_{i,t}$$

Pástor and Stambaugh (2003), Acharya and Pedersen (2005), and Korajczyk and Sadka (2008) use some versions of the autoregressive process to estimate the unexpected component of their liquidity measures.
C. Measures for Liquidity Commonality

Most studies of liquidity commonality across individual stocks use the “market model” of Chordia, Roll, and Subrahmanyam (2000) to measure liquidity commonality: the first difference of a stock’s liquidity measure, i.e., the average bid–ask spread, is regressed against a market liquidity factor calculated as the first difference of the average liquidity across all remaining stocks. Commonality is measured either as the coefficient of the market liquidity factor or the $R^2$ of the regression. Zhang, Cai, and Cheung (2009) explain the size of the estimated coefficient in terms of stock characteristics such as size, international cross-listing, etc. Koch, Ruenzi, and Starks (2009) show that stocks with high mutual fund ownership have greater liquidity co-movement with each other. Hameed, Kang, and Viswanathan (2010) show that the monthly estimated $R^2$ is higher when stock market declines.

In this study, commonality is defined as liquidity variations associated with a set of common factors, and is measured by the partial $R^2$ of the common factors. In addition to the marketwide average liquidity, a stock’s liquidity may covary with other common factors such as marketwide return and volatility. There is no theoretical reason for the market average liquidity to be the only—or even the main—common factor affecting individual stock liquidity. As shown by Koch, Ruenzi, and Starks (2009), adding additional common factors, e.g., a portfolio of stocks with high mutual fund ownership, increases the estimated liquidity co-movements. The same logic applies to estimating cross-market liquidity commonality. In this case, the common factors come from regional market averages and the global markets represented by the UK and the US. As mentioned before, if relevant factors/variables are “omitted”, the estimated coefficient of the included factor may be biased, and cross-market liquidity co-movements may be underestimated.

Statistically the regression coefficients and the regression $R^2$ capture different aspect of the explanatory variables. The coefficients are scaled covariances between the dependent variable and the explanatory variables, and are evaluated using an arbitrary statistical significance level. By definition, the $R^2$ measures the proportion of the variation in the dependent variable explained by the explanatory variables. Although they are positively correlated, a high $R^2$ does not necessarily imply a large and significant coefficient, and vice versa. In this study, commonality is measured by the partial $R^2$ of the common factors. It is important to control the impact of the local factors. Given the strong correlations between the local and common factors, the $R^2$ of the common factors tend to be inflated when the local factors are excluded.

D. Testing for Parameter Stability

While our sample sizes are over 2,400—large enough for a model with 25 explanatory variables—the issue of parameter stability becomes more acute as the number of parameters increases. As shown by Figure 1, the sample period covers several large
market cycles, which suggests a high likelihood of parameter changes over the sample period. Ignoring the structural changes in a model leads to biased estimates of the true parameters.

The parameter stability of (5) is examined using structural break tests discussed by Hansen (1997). These include the Quandt or supF test and the expF and aveF tests proposed by Andrews and Ploberger (1994). I here give a brief discussion of the supF test. Details of the expF and aveF tests can be found in Andrews and Ploberger (1994) and Hansen (1997). Let \( \hat{t} \) be a potential structural break date, from which onward the parameters in model (5) may change. The parameters of the unrestricted model in the subsample \([1, \hat{t} - 1]\) are allowed to be different from those in the subsample \([\hat{t}, T]\), where \( T \) is the full sample size. On the other hand, the parameters of the restricted model are kept the same in the two subsamples. The F statistic is calculated as \( F(\hat{t}) = \frac{T(SSR_R - SSR_U)}{SSR_U} \), where \( SSR_R \) and \( SSR_U \) are the sums of squared residuals for the restricted model and the unrestricted model respectively. It is calculated for every date between \( \pi_0 T \) and \( (1 - \pi_0) T \). The trim parameter \( \pi_0 \in (0, 1) \) is the fraction of sample trimmed at each end of the sample. It is often set to 15%, which is used here. The first \( \pi_0 T \) sample points are used to estimate the initial parameters. The supF statistic is given by \( supF = \max\{F(\hat{t})\} \) for \( \pi_0 T < \hat{t} < (1 - \pi_0) T \). The null of no change is rejected if supF is too large, in which case the \( \hat{t} \) that maximizes \( F(\hat{t}) \) is the estimated date of a structural break. A break date is selected if two of the three p-values are smaller than 5%. After a structural break is found, the procedure is repeated for the subperiods. It is stopped when either the length of the subperiod is shorter than \( \pi_0 T \) or no new break is found.

Table 5 reports the structural break dates for the 12 markets. Structural breaks are more often in emerging markets than they are in developed markets. The PRC has the most frequent breaks at seven, while Singapore has only one break. Not surprisingly the global financial crisis in 2008–2009 is associated with frequent structural breaks. Emerging markets also had frequent breaks in 2001. The distribution of structural breaks over time is roughly consistent with major market cycles depicted in Figure 1. I do not explore the events that led to the structural breaks in each market. The aim of the structural break analysis is to ensure the statistical integrity of the parameters estimated, which is critical in assessing the ability of the liquidity factors in explaining local liquidity variations.

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11 For the PRC, the first break point is found at the first date after 0.15T. When \( n_0 \) is set to 0.1, the first break moves to a date before 0.15T. So \( n_0 \) is set to 0.1 for the PRC only for identifying the first break point.

12 The tests are carried out using the Gauss program provided by Hansen, which is gratefully acknowledged.
Table 5: Structural Break Dates

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Note: This table reports structural breaks in equation (5) estimated over the sample period January 2000 to April 2010. The break dates are reported as month/day in a given year.
Source: Author’s estimates.

V. Empirical Findings

Based on the structural break dates in Table 5, the coefficients of equation (5) are estimated for each market and each subperiod. The weighted average coefficients and t-statistics are then calculated, where the weight is the length of the subperiod relative to the full sample size. In this section, the findings on liquidity factors and liquidity commonality are presented and discussed.

A. Significance of Local and Common Liquidity Factors

Table 6 reports the weighted average coefficients and t-statistics for local and global factors. Again bold numbers are statistically significant at 5% level. The coefficients of the lagged local liquidities are slightly small than those in Table 3 but remain highly significant. Again the lagged weekly liquidity has the biggest impact on today’s liquidity. The unexpected local volatility has a strong negative impact on liquidity in all markets. Although trading volume generally rises with volatility, Table 5 shows that their ratio v/σ declines as the unexpected volatility rises. This is consistent with Levy, Schmukler, and Horen (2008) who find the Amihud measure |r|/v rises during volatile markets. The impact of the expected volatility is mixed; positive in emerging markets (Indonesia; the
Philippines; and Taipei, China); and negative in developed markets (Australia and Japan). Both the contemporaneous and the lagged returns have significant positive effects on liquidity, with the lagged returns having greater impact in most markets. Hameed, Kang, and Viswanathan (2010) focus on the impact of the lagged return and find the same effect.

The weighted average coefficients of the lagged global factors, represented by the UK and the US, are not significant for most Asian emerging markets except Taipei, China. Among Asian developed markets, the lagged global factors are statistically significant for Hong Kong, China. The one-day lagged global volatility is significant for four markets, but the sign of the coefficients is opposite to that of the unexpected local volatility. After controlling the unexpected local volatility, the one-day lagged global volatility increases local market liquidity in Hong Kong, China; Japan; Singapore; and Taipei, China. As discussed below in Table 6, the same positive liquidity impact holds for other external volatilities, e.g., the unexpected volatility in Asian developed and Asian emerging markets. This pattern appears to be puzzling at the first look. However, given the liquidity measure

\[
L_{i,t} = \ln(1 + \frac{v_{i,t}}{\sigma_{i,t}})
\]

the positive effect is not surprising. Cross-market volatility spill-over is well documented, e.g., Hamao, Masulis, and Ng (1990) and Ng (2000). There is a strong positive contemporaneous correlation between volume and volatility, e.g., Jones, Kaul, Lipson (1994) and Andersen (1996). Therefore external volatility increases local volatility and trading volume. Once the negative effect of local volatility is accounted for, external volatility increases local liquidity by increasing trading volume.

Table 7 presents the weighted coefficients and t-statistics for factors from Asian developed markets and Asian emerging markets. There are four features in this table. First, the expected regional liquidities have little effect on individual market liquidity and none for the expected regional volatilities. Second, regional returns have little contemporaneous or lagged effects on individual market liquidity. Third, the link between these regional markets and individual market liquidity mostly comes from the unexpected liquidity and volatility. There is strong positive spillover from the unexpected regional liquidity. Holding local volatility constant, the unexpected regional volatility enhances local market liquidity. The mechanism is the same as the positive impact from the lagged global volatility discussed above. Fourth, in almost all cases, factors from Asian developed markets have stronger links with individual market liquidity than factors from Asian emerging markets. The finding suggests that using combined regional factors may underestimate their liquidity impact.
### Table 6: Weighted Average Parameter Estimates: Local and Global Factors

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<td>$M_{i,t}^N$</td>
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<td>-0.42</td>
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</table>

**Note:** This table reports the weighted average parameters across structural break subperiods. The t-statistics under the estimated coefficients are based on the Newey–West robust covariance with automatic lag selection using Bartlett kernel. Bold numbers are statistically significant at the 5% level.

**Source:** Author’s estimates.
Table 7: Weighted Average Parameter Estimates: Advanced and Emerging Markets

<table>
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<th>Developed Markets</th>
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</table>

Note: This table reports the weighted average parameters across structural break subperiods. The t-statistics under the estimated coefficients are based on the Newey-West robust covariance with automatic lag selection using Bartlett kernel. Bold numbers are statistically significant at the 5% level.

Source: Author’s estimates.
B. Common Liquidity Factors and Cross-Market Liquidity Commonality

The overall contributions of common liquidity factors and the cross-market liquidity commonality are reported in Table 8. $P_{G}$, $P_{AD}$, and $P_{AE}$ are the weighted average partial $R^2$s of factors representing the global markets, Asian developed markets, and Asian emerging markets respectively. As discussed before, these partial $R^2$s do not directly reflect the statistical significance of the corresponding factors reported in Tables 6 and 7. For example, the global factors are not statistically significant at 5% level for liquidities in the PRC and the Republic of Korea, while four of the six factors are significant for Taipei, China. However, the global factors collectively explain a greater portion of liquidity variations in the PRC and the Republic of Korea than they do for Taipei, China. Table 8 shows that on average, $P_{AD} > P_{AE} > P_{G}$. Factors from Asian developed markets have greater liquidity impact on local markets than factors from Asian emerging markets. The global factors have the smallest liquidity impact on local markets. The average values of $P_{G}$, $P_{AD}$, and $P_{AE}$ are greater for Asian developed markets than they are for Asian emerging markets, indicating Asian developed markets are more vulnerable to external liquidity factors than Asian emerging markets.

The column labelled $P_{CA}$ in Table 8 reports the partial $R^2$ for contemporaneous factors from Asian markets, including $L_{AD,t}$, $\sigma_{AD,t}$, $r_{AD,t}$, $L_{AE,t}$, $\sigma_{AE,t}$, and $r_{AE,t}$. Recall from Section IV(B) that the expected values of the external factors on day $t$ are determined by lagged factors. The unexpected components and the contemporaneous return carry new information on market and economic conditions. Here $P_{CA}$ is used to gauge whether liquidity commonality reflects a common reaction to new information, or whether it is driven by lagged information and momentum. New information plays an important role in liquidity commonality for Malaysia and Indonesia. On the other hand, liquidity commonality in the PRC, the Philippines, and Thailand is mainly driven by lagged factors. Among Asian developed markets, Singapore and Hong Kong, China have a much higher information component than Australia and Japan.

The cross-market liquidity commonality is measured by the partial $R^2$ of all common factors, $P_{CF}$. Philippine has the lowest liquidity commonality with external markets. It is somewhat surprising that the Republic of Korea and Taipei, China, the relatively more advanced markets in the group, have below-average liquidity commonality. Taipei, China has low exposure to the global factors while the Republic of Korea has low exposure to the regional factors. Malaysia and Thailand have the highest liquidity commonality in the group. While one can speculate the reasons behind the relative rankings, more systematic analyses should be undertaken in future research to explain the cross-market variations. The level of liquidity commonality is more homogeneous among Asian developed markets. Singapore has a low exposure to the global factors and the highest exposure to factors from other Asian developed markets. On average, liquidity commonality accounts for 9.4% of liquidity variations in Asian emerging markets and
13.7% in Asian developed markets. The regression $R^2$ shows that equation (5) captures most of the daily variations in individual market liquidity, with $R^2$ ranging from a low of 61% for the Philippines to a high of 85% for the PRC and Thailand. The model works equally well for both developed and emerging markets, with an average $R^2$ of 75%.

Liquidity commonality accounts for a significant portion of the explained liquidity variations in each market. The ratio $P/R^2$ varies from 10% for the Republic of Korea and the Philippines; to 21% for Singapore; and 22.6% for Hong Kong, China.

Table 8: Common Liquidity Factors and Cross-Market Liquidity Commonality (percent)

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<tr>
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<th>$PR^2_G$</th>
<th>$PR^2_AD$</th>
<th>$PR^2_AE$</th>
<th>$PR^2_CA$</th>
<th>$PR^2_CF$</th>
<th>$R^2$</th>
<th>$PR^2_CF$</th>
<th>$PR^2_SF$</th>
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<td>0.76</td>
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<td>2.6</td>
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<td>8.2</td>
<td>73</td>
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<td><strong>75</strong></td>
<td><strong>11.1</strong></td>
<td><strong>1.35</strong></td>
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Note: This table reports the weighted average partial $R^2$ of different factors in explaining the daily variations in local market liquidity. $PR^2_G$, $PR^2_AD$, and $PR^2_AE$ are the partial $R^2$s of the global factors, factors from Asian developed markets, and factors from Asian emerging markets respectively, in equation (5). $PR^2_CA$ is the partial $R^2$ of the Asian contemporaneous variables. $PR^2_CF$ is the partial $R^2$ of all common factors. $R^2$ is the coefficient of determination of equation (5). $PR^2_CF$ is the adjusted partial $R^2$ of the common factors. $PR^2_SF$ is the adjusted partial $R^2$ of the single factor in equation (6).

Source: Author’s estimates.

To facilitate comparisons with Brockman, Chung, and Pérignon (2009) and Zhang, Cai, and Cheung (2009), Table 8 also reports the weighted average adjusted partial $R^2$ for the common factors ($PR^2_{CF}$). In their equation (3), Brockman, Chung, and Pérignon (2009) examine the impact of the global average liquidity and average return on the average local market liquidity. They report an average adjusted $R^2$ between 3.8% and 5.6%, slightly lower than the average $PR^2_{CF}$ in Table 8. However, the contemporaneous local market volatility is also included in their equation (3) hence the calculation of the adjusted $R^2$. Given the strong impact from the contemporaneous local market volatility as reported in Table 6, their adjusted $R^2$s are likely to be dominated by this variable and overstate the true explanatory power of global average liquidity and return. In Zhang, Cai, and Cheung (2009), cross-border liquidity commonality is measured relative to a selected
neighboring market. For example, Japan is used as the neighboring market for Australia and the Republic of Korea; Singapore is used as the neighboring market for Hong Kong, China, etc. They regress the change in firm liquidity on the changes in the average local liquidity and the average neighboring liquidity. They find that for the six Asian markets in their sample, the adjusted $R^2$ ranges from 0.2% for Singapore and 0.8% for Australia, to 16.3% for the Republic of Korea, and 17.6% for Japan. Singapore has the only significant liquidity beta for the neighboring market, but the beta is negative. Clearly the explanatory power for Japan and the Republic of Korea mainly comes from the average local liquidity. Compared to these studies, the global and regional factors used in this study provide greater explanatory power as measured by $\bar{R}^2_{CF}$.

There are many potential reasons for the difference in the adjusted $R^2$. Brockman, Chung, and Pérignon (2009) use the firm-level bid–ask spread and depth. Zhang, Cai, and Cheung (2009) use the firm-level bid–ask spread. Both take the first difference of their daily liquidity measures and estimate the “market model” for liquidity as proposed by Chordia, Roll, and Subrahmanyam (2000). A key contribution of this study is to use other common factors, in addition to the market average liquidity, to measure liquidity commonality. To contrast the popular single factor model with equation (5) while isolating the effect from other model choices, here liquidity commonality is measured using a single factor, which is the global and regional average liquidity:

$$L_{i,t} = \beta_0 + \beta_1 L_{i,t-1}^D + \beta_2 L_{i,t-1}^W + \beta_3 L_{i,t-1}^M + \beta_4 \sigma_{i,t}^E + \beta_5 \sigma_{i,t}^U + \beta_6 \sigma_{i,t}^F + \beta_7 \tau_{i,t-1}^D + \beta_8 L_{SF,t} + \epsilon_{i,t} \quad (6)$$

The first seven explanatory variables are the same local factors as in equation (5). The last variable is the single factor calculated as the average liquidity across all other markets, including the UK and the US on day $t$. Equation (6) is tested for structural breaks and is estimated for each subperiod as before. The weighted averages of the adjusted partial $R^2$, $\bar{R}^2_{SF}$, are reported in the last column of Table 8. The values of $\bar{R}^2_{SF}$ are much smaller than the values of $\bar{R}^2_{CF}$. The ratio, $\bar{R}^2_{SF}/\bar{R}^2_{CF}$, ranges from 5% for the Philippines, to 32% for the Republic of Korea, with an average of 17%. The average unadjusted partial $R^2$ for $L_{SF,t}$ is 1.48% for emerging markets and 1.53% for developed markets. One can think of several explanations for the large differences. First, as shown in Tables 6 and 7, unexpected regional volatility is a significant liquidity factor for most markets. The lagged global return is significant for some markets. Second, cross-market liquidity commonality is likely to be driven by several subregional factors, each having different levels of impact. Using a single global aggregation reduces its explanatory power for local market liquidity. Third, Table 7 shows that the expected and unexpected components of liquidity factors clearly have different liquidity impact. The decomposition can better capture the co-movements between the local market liquidity and the common liquidity factors, thus increasing the partial $R^2$s. While not reported here, the coefficients of $L_{SF,t}$ are all positive. They are significant at 5% for seven of the 12 markets, i.e., 58%.
C. Cross-Market Liquidity Commonality in Subperiods

Table 5 shows that most markets experienced multiple structural breaks over the sample period. Therefore liquidity commonality in each market may vary significantly over time. Table 9 reports the time trend in liquidity commonality, measured as the weighted averages of the partial R$^2$s of the common factors in 2-year subperiods in the sample. The time trend varies significantly across markets. Several markets had strong surges in recent years, e.g., Hong Kong, China; Indonesia; Japan; and Malaysia. The Republic of Korea and Taipei, China peaked early. Singapore remained relatively flat over the sample period. Australia, India, and the Philippines have a U-shaped pattern. On average, liquidity commonality of Asian emerging markets was relatively flat until 2008–2010. Liquidity commonality of Asian developed markets has risen steadily since 2002 and a big surge in the last subperiod.

Table 9: Liquidity Commonality in 2-Year Subperiods

<table>
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<tr>
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</tbody>
</table>

Note: This table reports the liquidity commonality, measured as the partial R$^2$s of the common factors (PR$^2$$_{EP}$) in equation (5), over 2-year subperiods.
Source: Author’s estimates.

While the 2008–2009 period had the most structural breaks in Table 5, breaks do not always correspond to major market cycles, e.g., the global financial crisis. For investors and policy makers, it is of interest to know how liquidity commonality varies over broad market cycles. Table 10 divides the sample period into four market cycles based on Figure 1: a bear market from the start of the sample to the end of January 2003, a prolonged bull run from February 2003 to the end of September 2007, the global financial crisis from October 2007 to January 2009, and the market rebound in the remaining...
sample period. On average, there is no significant difference in liquidity commonality in the first bull–bear cycles. During the global financial crisis, many markets experienced sharp rises in liquidity commonality. On average, Australia; Hong Kong, China; India; Indonesia; Japan; and Malaysia doubled their liquidity commonality with the rest of the world. On the other hand, liquidity commonality in the Republic of Korea; Philippines; Singapore; and Taipei, China either remained unchanged or declined. Asian developed markets are more affected by the crisis than Asian emerging markets. After the crisis, commonality remained the same or declined for six of the 12 markets. It began to rise in the Republic of Korea and the Philippines, and continued to increase in Australia, Japan, Malaysia, and Thailand.

Table 10: Liquidity Commonality in Bull and Bear Markets

<table>
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<td><strong>8.0</strong></td>
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<td>14.5</td>
<td>8.6</td>
<td>17.5</td>
<td>26.3</td>
</tr>
<tr>
<td>Hong Kong, China</td>
<td>9.8</td>
<td>12.3</td>
<td>22.2</td>
<td>28.1</td>
</tr>
<tr>
<td>Japan</td>
<td>4.9</td>
<td>11.3</td>
<td>27.6</td>
<td>20.1</td>
</tr>
<tr>
<td>Singapore</td>
<td>13.9</td>
<td>14.4</td>
<td>14.5</td>
<td>14.5</td>
</tr>
<tr>
<td><strong>Mean</strong></td>
<td><strong>10.8</strong></td>
<td><strong>11.6</strong></td>
<td><strong>20.5</strong></td>
<td><strong>22.3</strong></td>
</tr>
</tbody>
</table>

Note: This table reports the liquidity commonality, measured as the partial R² of the common factors (PR²) in equation (5), over bull–bear market cycles.

Source: Author’s estimates.

VI. Conclusion

Using a multi-factor model, this paper estimates cross-market liquidity commonality among Asian stock markets. Over the sample period January 2000 to April 2010, common liquidity factors account for 9.4% of daily liquidity variations in Asian emerging markets and 13.7% in Asian developed markets. These percentages rise to 14% and 21%, respectively, in the last 2 years of the sample period and are considerably larger than previously documented for cross-asset liquidity commonality. The study also shows that regional factors affect liquidity commonality through shocks in liquidity and volatility,
while global factors affect liquidity commonality through volatility and return. Cross-market liquidity commonality in Asia increased significantly during and after the recent global financial crisis.

The large and rising liquidity commonality across regional markets has potential implications for international investors, economic policy makers, and market regulators. Liquidity cycles in different markets are likely to be more synchronized than expected, simultaneously affecting asset prices and portfolio investments in these markets. Liquidity commonality may play a role in the vanishing liquidity during market distress, which in turn may affect real economic activities. Future research should examine the reasons behind the cross-sectional differences and time-series variations in liquidity commonality, and explore the potential need and mechanism for regional regulatory coordination in managing liquidity risk.

References


About the Paper
Jian-Xin Wang shows that commonality factors explain around 9%–14% of the daily variations in liquidity in Asian equity markets. Global and regional factors affect liquidity through different channels. Cross-market co-movements in liquidity have increased significantly after the financial crisis in 2008.

About the Asian Development Bank
ADB’s vision is an Asia and Pacific region free of poverty. Its mission is to help its developing member countries substantially reduce poverty and improve the quality of life of their people. Despite the region’s many successes, it remains home to two-thirds of the world’s poor: 1.8 billion people who live on less than $2 a day, with 903 million struggling on less than $1.25 a day. ADB is committed to reducing poverty through inclusive economic growth, environmentally sustainable growth, and regional integration.

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