Measuring Liquidity in Emerging Markets

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Abstract: We propose a new low-frequency liquidity measure which can be interpreted as a no-trading-day adjusted Amihud measure. Based on the transaction-level data for 20 emerging markets from 1996 to 2007, we conduct a comparison study focusing on the performance of our new liquidity measure and the other existing liquidity proxies in relative to the two liquidity benchmarks: the effective bid-ask spread and the price impact of *Lambda*. We find that our new liquidity measure is the best liquidity proxy showing the highest cross-sectional correlations with the two liquidity benchmarks in all the markets and the highest time-series correlations in the majority of the markets. *ZeroVol*, which is the proportion of zero trading volume days within a month, and the Amihud measure are the second best liquidity proxies and their performance is related to the trading activeness of the market. Investigation of cross-country determinants of liquidity indicates that the effective bid-ask spread is smaller in markets with less country risk and more liberalization.

Keywords: Liquidity, Effective bid-ask spread, Price impact of *Lambda*, *Illiq_Zero*, Correlation

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1. Introduction

While there is an increasing interest in the role of liquidity in equity markets, the basic question of how to measure liquidity remains unsolved. By its very nature, liquidity has two dimensions depending on the market state. The first dimension relates to transaction cost such as commissions or bid-ask spreads. The second dimension refers to how easily investors can trade without impacting the stock price. To measure the transaction cost, studies usually use the bid-ask spread, which is the price investors have to pay for buying a stock and then immediately selling it. Depth is also considered one of basic liquidity measures in a sense that it indicates how many more shares the market is capable of accommodating under current circumstances. To measure the price impact, a regression approach is often used, where the return is regressed on trading volume, to examine the cost of demanding a certain amount of liquidity. All these liquidity measures require the use of high-frequency transactions and quotes data, which may not be available for some markets, especially for emerging markets.

To overcome this problem, a bunch of studies has proposed several low-frequency liquidity proxies, which can be grouped into two categories. The first category of liquidity proxies is more trading based. Roll (1984) develops an implicit measure of the effective bid-ask spread on the basis of the serial covariance of daily price changes. Hasbrouck (2004) uses a Bayesian estimation approach to estimate the Roll model and proposes a Gibbs measure of liquidity. The data used to develop this measure is also daily stock price. Lesmond, Ogden, and Trzcinka (1999) argue that stocks with lower liquidity and higher transaction costs are more likely to have either zero volume and zero return days or positive volume and zero return days, so they propose the use of the proportion of zero return days as a proxy for liquidity. Liu (2006) proposes a liquidity measure of *LMx*, which is a standardized turnover-adjusted number of zero daily trading volumes over the prior *x* months. The second group focuses on the price impact of trades. Amihud (2002) develops a price impact measure based on the daily price response associated with one dollar of trading volume. Pastor and Stambaugh (2003) focus on the temporary price change accompanying order flow and construct a Gamma measure of liquidity using a regression approach. The Amivest liquidity measure is the average ratio of volume to absolute returns.

Based on different liquidity measures, many studies have explored the effect of liquidity on asset pricing (Acharya and Pedersen (2005), Pastor and Stambaugh (2003), Sadka (2006), Watanabe and Watanabe (2008), Goyenko (2006), and Bekaert, Harvey, and Lundblad (2007), among others), market efficiency (Chordia, Goyal, Sadka, Sadka and Sivakumar (2008), and Tetlock (2008)), and corporate finance (Heflin and Shaw (2000), Lipson and Mortal (2009), Lerner and Schoar (2004), among others). These studies make great contributions to the development of financial economics. One basic assumption of these studies is that the employed liquidity proxies are capable of capturing the actual liquidity, which is, unfortunately, rarely examined. Actually, using different liquidity measures to address the same question could result in contradictory conclusions. For example, in the context of stock splits, O'Hara and Saar (2001) and Gray, Smith and Whaley (2003), among others, show that splits lower the stock price levels but stocks become less liquid following the splits using the bid-ask spread as a liquidity measure. However, Lin, Singh and Yu (2008) show that stock splits improve liquidity if Liu's *LM12*, the standardized turnover adjusted number of days with zero trading volume over the prior 12 months, is used to measure liquidity.

The hypothesis that various low-frequency liquidity proxies are able to capture the underlying liquidity is rarely tested until recently. Lesmond, Ogden, and Trzcinka (1999) compare their zero return measure to the sum of the proportional bid-ask spread and a representative commission (S+C). The time-series analysis shows that the zero return measure is significantly and positively correlated with the S+C measure for the time period of 1963 through 1990 for stocks listed on the NYSE/AMEX. Hasbrouck (2009) tests various measures of transaction costs estimated from both high-frequency and low-frequency data for the sample period of 1993 to 2003 for the US stock market. His results indicate that posted spreads and the effective spreads are highly correlated but price impact measures and other statistics from dynamic models are only moderately correlated with each other. The Gibbs measure, among the set of proxies constructed from daily data, performs best with a correlation of 0.944 with the corresponding TAQ estimate. Goyenko, Holden and Trzcinka (2009) propose several new liquidity measures at both low-frequency and high-frequency levels and do a comprehensive comparison analysis of various liquidity measures using the effective spread, the realized spread and the price impact based on both TAQ and Rule 605 data as liquidity benchmarks. The results show that, during the sample period of 1993 to 2005, there is a close relationship between many of the liquidity measures constructed from the low-frequency data and the liquidity benchmarks. Their results indicate that the assumption that liquidity proxies measure liquidity generally holds. However, these studies focus on the US market which is believed to be the most liquid market in the world.

With the enhanced globalization of stock markets, emerging markets grow rapidly. Investors in emerging markets are attracted by the high return potential but, at the same time, are scared by the liquidity risk in the market. Compared to the developed markets such as the US market, emerging markets are characterized by wider bid-ask spread, lower trading volume and higher liquidity risk (see, e.g., Bekaert, Harvey, and Lundblad (2007)). A 1992 survey by Chuhan shows that foreign investors consider illiquidity one of important factors in deciding whether or not to invest in the emerging markets. Thus, examining liquidity in emerging markets is particularly meaningful for both researchers and practitioners. Indeed, we have seen a growing literature with the focus on liquidity in emerging markets. However, different studies use different liquidity measures: trading volume in Bailey and Jagtiani (1994), the Amivest measure in Amihud, Mendelson and Lauterach (1997) and Berkman and Eleswarapu (1998), a variation of the Roll measure in Domowitz, Glen and Madhavan (1998), turnover in Rouwenhorst (1999) and Levine and Schmukler (2006), and the proportion of zero daily returns in Lee (2006) and Bekaert, Harvey, and Lundblad (2007). However, the lack of a consensus liquidity measure weakens the indications of the findings in these studies. Moreover, to the extent that different liquidity measures can capture different dimensions of the underlying liquidity, as more and more new liquidity measures are developed, researchers are often required to employ multiple liquidity measures to make their findings be more convincing. This process could be time-consuming for studies focusing on emerging markets which typically are composed of multiple markets.

Very little work is done on the comparison of liquidity measures in emerging markets.

Lesmond (2005) uses hand-collected quarterly bid-ask quotes data and compares the bid-ask spread to low-frequency liquidity proxies such as the Roll measure, the LOT measure, the Amihud measure, the Amivest measure and turnover during the period from 1987 to 2000 for 31 emerging markets. The within-country analysis shows that bid-ask spread is significantly correlated with all the low-frequency liquidity proxies except turnover while the cross-country correlation indicates that the LOT measure and the Roll measure are able to better represent the cross-country differences in liquidity than the Amihud measure and turnover. While this study expands our understanding of the performance of different liquidity proxies in emerging markets, the quarterly liquidity measures are not quite consistent with the majority of the literature in which liquidity proxies are employed on a monthly or even finer basis.

This study proposes a new liquidity proxy, *Illiq_Zero*, which can be interpreted as a no-trading-day adjusted Amihud measure. This measure captures at least two dimensions of liquidity: price impact and trading frequency. Armed with the new measure, we can differentiate two stocks with the same value of the Amihud measure but with different trading frequencies over certain period. Next, on obtaining transactions and quoted data in emerging markets, we run a horserace of our new liquidity measure and other liquidity proxies such as Roll, Gibbs, turnover, Zeros, Amihud, Amivest and Gamma constructed from the low-frequency data, using the effective bid-ask spread and the price impact of *Lambda* as the liquidity benchmarks. The reason for employing two liquidity benchmarks is that the effective bid-ask spread may not be able to capture the trading cost for larger trades. Using the correlation as the main performance metric, we find ample evidence that our new liquidity measure outperforms the other low-frequency liquidity proxies. It shows the highest correlations with the liquidity benchmarks in the cross-section in all the emerging markets and in the time-series in the majority of the markets.

Focusing on the low-frequency liquidity proxies other than our new liquidity measure, we show that *ZeroVol*, which is the proportion of zero trading volume days within a month, and the Amihud measure are relatively more able to capture liquidity. Furthermore, their performance depends on the trading activeness of the market: Amihud is better in markets with more trading activity while *ZeroVol* or Zeros is better in markets with more no-trading days. This finding makes sense from the perspective of the definitions of these two proxies. When the market is more developed and more active, like the case of China and Korea stock markets, the value of *ZeroVol* is likely to be zero but the value of Amihud is meaningful. On the other hand, in less developed or active markets with more zero-trading days, such as Mexico and Brazil, *ZeroVol* contains more information on liquidity than Amihud. This result also justifies our new liquidity measure, which essentially is a combination of them. The Gibbs measure seems to be more likely to capture the effective bid-ask spread in the time-series than in the cross-section. Liquidity proxies such as Gamma, Amivest or turnover are usually dominated by others in both the cross-sectional and the time-series analyses.

We also investigate the country variables which could have an impact on market liquidity and expect that these factors have similar effects on the liquidity benchmarks and on the low-frequency liquidity proxies. Our results suggest that the effective bid-ask spread is smaller in markets with less country risk and/or more liberalization. Among the liquidity proxies, it is our new liquidity measure that gets the most similar effects from these country variables, supporting its relatively better performance. On the other hand, the same country variable could have opposite effect on the spread and on the other liquidity proxy. For instance, the composite risk index is negatively related to market illiquidity measured by the effective bid-ask spread but is also negatively related to turnover. Our results for the control variables suggest that liquidity is higher in markets with larger market capitalization, lower volatility, higher trading volume and higher stock prices.

The main hypothesis in our study is that various liquidity proxies can capture the cross-sectional or time-series variation of the liquidity benchmarks. Our findings and indications contribute to the literature in the following ways. First, this paper, for the first time, examines the performance of various monthly liquidity measures constructed from low-frequency data in emerging markets, using the effective bid-ask spread and the price impact of *Lambda* constructed from the intraday data as liquidity benchmarks. The comparison analysis at the monthly frequency may have particularly important implications to the literature investigating the effects of liquidity on asset pricing and market efficiency. Second, we propose a new easily constructed liquidity measure, *Illiq_Zero*, and we show that this measure is the best liquidity proxy in capturing the cross-sectional and the time-series variations of the effective bid-ask spread and the price impact of *Lambda* in emerging markets. Our new measure facilitates the cross-country analysis focusing on the effects of liquidity in emerging markets, which needs a consistent liquidity proxy across countries. Third, determinants of market liquidity in emerging markets are investigated and the results are indicative to investors caring liquidity in emerging markets.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 presents our methodology and empirical design. Construction of liquidity measures is shown in Section 4. Section 5 presents our results on the cross-sectional and the time-series correlation analyses. Section 6 reports the results on determinants of market liquidity. Section 7 concludes the paper.

2. Data construction

Our sample spans from January 2nd, 1996 to December 31st, 2007. We retrieve the intraday data used to calculate the effective bid-ask spread and the price impact of *Lambda* from TAQTIC developed by SIRCA, which is a not-for-profit financial services research organization involving twenty-six collaborating universities across Australia and New Zealand. TAQTIC is similar to the New York Stock exchange Trades and Automated Quotations (TAQ) in that transactions and quotes data are provided according to their occurring time. But instead of focus exclusively on the US market, TAQTIC covers over 244 exchanges and OTC markets around the world. The daily data such as daily price and trading volume used to construct the low-frequency liquidity proxies are from the Thomson Datastream. We only include common stocks from major exchanges defined as having the majority of listed stocks in that country. In our sample, all markets have one major exchange expect China which has both Shenzhen and Shanghai stock exchanges. Based on data availability and the definitions of emerging markets in EMDB and MSCI, we include 20 markets as emerging markets in our sample.

We only include common stocks covered by both datasets. Due to the lack of a common identifier, we use different mechanisms to merge the two databases depending on the markets. For some markets such as China, we can directly link the two datasets.

For others, however, we have to merge them by hand using the company names as the main matching instrument. To improve the accuracy, we further require that at least 60% of the daily prices in each year from the two datasets be same. Otherwise, stocks are dropped over the year. By doing this, we are able to match around 70% of stocks from the Datastream.

To make the data clean, we exclude a trade or quote if (1) the trading volume and/or quoted depth below zero or above the 99.5th percentile of the quoted depth of all the stocks over each year; (2) it has negative bid-ask spreads; and (3) its effective bid-ask spread exceeding 0.3. We further require stocks to have trades on at least 5 days within one month. We also follow Ince and Porter (2006) to set daily stock returns to be missing if

$$\begin{aligned} & R_{i,t} \geq 100\% \text{ or } R_{i,t-1} \geq 100\% \\ \text{but} \quad & (1+R_{i,t})(1+R_{i,t-1})-1 \leq 0.50 \end{aligned} \tag{1}$$

where $R_{i,t}$ and $R_{i,t-1}$ are the stock returns of firm *i* on day *t* and *t-1*, respectively. In addition, we require each market to have at least 10 stocks in a month and have at least 20 months over time. Finally, we only include stocks traded in local currency.

3. Empirical design

In this paper, we run a horserace among the low-frequency liquidity proxies using the effective bid-ask spread and the price impact of *Lambda* as the liquidity benchmarks. The current literature in comparing different liquidity measures mainly employs a method of correlation analysis (see Hasbrouck (2009), and Goyenko, Holden and Trzcinka (2009)). Specifically, liquidity measures such as the bid-ask spread are assumed to more accurately capture the underlying liquidity. Then the correlation between various liquidity proxies constructed from low-frequency data and the bid-ask spread is examined, with the higher correlation a sign of better performance of the liquidity proxy. Consistent with the literature, we also rely on the correlations as the main method in comparing the performance of liquidity proxies. Specifically, we employ three performance metrics. The first one is the average cross-sectional correlations between the high-frequency liquidity benchmark and the low-frequency liquidity proxy. The correlation is calculated on individual stock basis. To test the difference in two correlations, we follow Goyenko, Holden and Trzcinka (2009) by running a *t*-test in a way similar to Fama-MacBeth. To be specific, in each month and for each liquidity proxy, we calculate its cross-sectional correlation with the liquidity benchmark. To compare the performance of liquidity proxy *A* and *B*, we get the difference in their cross-sectional correlations with the liquidity benchmark in each month and obtain the time series of the difference in correlations. We further assume that the time series of the differences is i.i.d over time and test whether their average is different from zero. To adjust the possible autocorrelation, we correct the standard error by the Newey-West method using four lags for the monthly data. The liquidity proxy with consistently higher correlations with the liquidity benchmark in all the markets is considered a better liquidity measure.

Asset pricing studies might be more interested in the time-series performance of liquidity proxies because most of these studies examine the co-movement over time. So our second performance metric is the time-series correlation between the high-frequency liquidity benchmark and the low-frequency liquidity proxy. In contrast to the stock level analysis when examining the cross-sectional correlations, we are going to investigate the time-series correlations at the market portfolio level since the asset pricing research usually involves forming portfolios. Specifically, we form an equally-weighted market portfolio across all the stocks within one market in each month. The liquidity of the portfolio is the average of the liquidity across all the stocks in that month. We then calculate the time-series correlations between the liquidity benchmarks and each liquidity proxy. To test the pair-wise difference in correlations, we follow Cohen and Cohen (1983) by doing a *t*-test of the significance of the difference between dependent correlations. Specifically, suppose *X*, *Y* and *V* are three variables from the same sample and the corresponding correlations between them are r_{XY} , r_{VY} and r_{XV} . Now we can test the difference between r_{XY} and r_{VY} using the following *t*-statistic with *n-3* degrees of freedom:

$$t = \frac{(r_{XY} - r_{VY})\sqrt{(n-1)(1+r_{XV})}}{\sqrt{2\left(\frac{n-1}{n-3}\right)|R| + \bar{r}^2(1-r_{XV})^3}} \qquad (2)$$

where

$$\bar{r}^2 = \frac{r_{XY} + r_{VY}}{2}$$

and $$|R| = 1 - r_{XY}^2 - r_{VY}^2 - r_{XV}^2 + 2r_{XY}r_{VY}r_{XV}$$

Since all the liquidity proxies other than turnover, Amivest and Gamma are actually illiquidity measures, we multiply these three measures by -1 when the correlations involve them.

Investors may be keen to know what factors affect the market liquidity in emerging markets. So our third performance metric is related to the effects of the country-level variables on various liquidity measures. We first show the effects of these factors on the liquidity benchmarks and then on the liquidity proxies. If a liquidity proxy is a good measure of liquidity, we expect that the same set of factors would have similar effects on the liquidity benchmark as on the liquidity proxy of interest.

4. Liquidity measures

In this section, we first introduce our new liquidity measure. Next the method to construct other liquidity measures including the two liquidity benchmarks, namely, the effective bid-ask spread and the price impact of *Lambda*, and the liquidity proxies constructed from low-frequency data is summarized.

4.1. A new liquidity measure

We construct our new liquidity measure, $Illiq\_Zero$, based on the Amihud measure and define it as

$$Illiq\_Zero = [\ln(Amihud)] \times (1 + NT\%) \qquad (3)$$

where $Amihud$ is developed by Amihud (2002) and is the average ratio of daily absolute return to the dollar trading volume on that day, and $NT\%$ is the percentage of no-trading days within a month. We measure the trading volume in the Amihud measure in billions of US dollars so that $\ln(Amihud)$ is positive. This is because $Illiq\_Zero$ is essentially an illiquidity measure and larger values imply low liquidity. Suppose two stocks have the same value of the Amihud measure in one month, the one has larger value of *NT%*, that is, more no-trading days, is less liquid. However, if the value of $\ln(Amihud)$ is negative, the stock with larger value of $NT\%$ turns out to have smaller value of $Illiq\_Zero$ and thus more liquid. [1] In addition, we take the natural logarithm of the Amihud measure to account for its large extreme values.

Our new liquidity measure can be interpreted as a no-trading-day adjusted Amihud measure. When $NT\%$ takes a value of 0, meaning that there are trades on each trading day, $Illiq\_Zero$ essentially becomes the Amihud measure. Due to the fact that intraday data used to construct classic liquidity measures such as bid-ask spread are not available in most of the emerging markets, the current literature examining the role of liquidity uses liquidity proxies estimated from daily data and most of the proxies are proposed to capture only one dimension of liquidity. The Amihud measure proposed by Amihud (2002) is meant to capture the price impact of trades and is one of the most commonly used liquidity proxies. But in emerging markets characterized by thin tradings, the Amihud measure may not work well for firms or countries with many zero trading days within certain period. Consider two stocks with the same value of the Amihud measure. Then the stock with more zero volume days or traded less frequently is less liquid. Note that $NT\%$ is highly correlated with the Zeros measure proposed by Lesmond et al. (1999), which is another quite commonly used liquidity proxy (Bekaert, Harvey, and Lundblad (2007), Lee (2006), and Goyenko and Sarkissian (2008), among others) and is designed to capture the trading cost. However, it is very possible that the Zeros measure become zero for stocks with high turnover and thus can not capture liquidity. Our new measure of liquidity, $Illiq\_Zero$, can deal with these issues by (1) adding a dimension of trading frequency to the Amihud measure; and (2) adding a dimension of price impact to the Zeros measure. Therefore, we expect our new liquidity proxy to work well on both low-turnover markets where the Amihud measure may not well capture liquidity and high-turnover markets where the Zeros measure may not function well.

4.2 Liquidity benchmarks constructed from high-frequency data[2]

4.2.1 Trade-based liquidity benchmark

[1] By deflating the trading volume by 1 billion U.S dollars, we lose 14 observations, accounting for less than 0.01% of the sample size.

[2] We do not use depth as the liquidity measure because many of its values are missing in TAQTIC. Also, as Kang and Yeo (2007) suggest, depth is not a very good measure in capturing liquidity.

In this study, two high-frequency liquidity benchmarks are employed. The first one is the effective bid-ask spread (*PESPR*)[3], to capture the transaction cost. For a particular stock on the k^{th} trade, *PESPR* is defined as:

$$2 \times \left| \mathrm{P_k} - M_k \right| / M_k \tag{4}$$

where P_k is the trading price of a particular stock on the k^{th} trade, and M_k is the prevailing mid-quote when the k^{th} trade occurs. We use trade volume measured in number of shares as the weight to get the daily *PESPR* and then average it over the month.

4.2.2 Price impact benchmark

Bid-ask spread may be more appropriate for small or medium trades. For large trades, however, the price impact measure might be able to measure liquidity in a better way. We follow Hasbrouck (2009) by constructing our second high-frequency liquidity benchmark, which is the price impact measure of *Lambda*. To be specific, using data from every 30-minute period *n* in time interval *i*, *Lambda* is defined as the slope coefficient of the regression

$$r_n = \lambda_i \times S_n + u_n \tag{5}$$

where r_n is the stock return over the n^{th} 30-minute period, S_n is the signed square-root dollar volume over the n^{th} 30-minute period, that is, $S_n = \sum_k Sign(v_{k,n})\sqrt{|v_{k,n}|}$, where $v_{k,n}$ is the signed dollar volume of the k^{th} trade in the n^{th} 30-minute period, and u_n is the error term for the n^{th} 30-minute period. The sign of trading volume is defined based on Lee and Ready algorithm. We run regression (5) over a month for each stock to get a monthly price impact measure of *Lambda*.

The time-series variation of the two liquidity benchmarks averaged across all the emerging markets is shown in Figure 1. They show similar patterns over time. In down market such as the second half of 1997, we see a large increase in the effective bid-ask spread and the price impact measure of *Lambda*. After 1999, the two liquidity

[3] As a robust check, we also use the quoted bid-ask spread, defined as the absolute value of the difference between the best ask price and the best bid price divided by the corresponding mid-quote, as the liquidity benchmark. The correlation between the effective bid-ask spread and the quoted bid-ask spread is around 0.90 and using the quoted bid-ask spread as the benchmark produces qualitatively similar results to those using the effective bid-ask spread as the benchmark.

benchmarks gradually decreases, indicating an improvement in liquidity over time in emerging markets.

[Insert Figure 1 here]

4.3 Liquidity proxies constructed from low-frequency data

4.3.1 Trade-based liquidity proxies

4.3.1.1 Roll

Roll (1984) develops an implicit measure of the effective bid-ask spread based on the serial covariance of the changes in stock price. Two key assumptions are that market is informationally efficient and the probability distribution of observed price changes is stationary. Let P_t be the last observed trade price on day *t* and assume that it evolves as

$$P_t = V_t + \frac{1}{2} S Q_t \tag{6}$$

where V_t is the unobserved fundamental value of the stock on day *t* and it fluctuates randomly, *S* is the effective spread to be estimated and Q_t is a buy or sell indicator for the last trade on day *t* that equals 1 for a buy and -1 for a sell. Assuming that Q_t is equally likely to be 1 or -1, is serially uncorrelated and is independent of the public information shocks on day *t*, Roll shows that we can estimate the effective spread as

$$S = 2 \times \sqrt{-Cov(\Delta P_t, \Delta P_{t-1})}_t \tag{7}$$

where Δ is the change operator. The beauty of this Roll measure is that it is quite simple to estimate since the only data requirement is daily price. However, this measure is not meaningful when the sample serial covariance is positive, which is more likely to happen in emerging markets with low market efficiency. Therefore, as in Goyenko, Holden and Trzcinka (2009), we modify the Roll measure as follows:

$$Roll = \begin{cases} 2 \times \sqrt{-Cov(\Delta P_t, \Delta P_{t-1})} & \text{when } Cov(\Delta P_t, \Delta P_{t-1}) < 0 \\ 0 & \text{when } Cov(\Delta P_t, \Delta P_{t-1}) \geq 0 \end{cases} \tag{8}$$

4.3.1.2 Gibbs

Hasbrouck (2004) advocates a Bayesian estimation of the Roll model. In this approach, posterior density of parameters in the Roll model is obtained by random draws based on their prior distribution and the random draws are generated using a Gibbs sampler. To be specific, Hasbrouck restates the Roll model as

$$\begin{aligned} v_k &= v_{k-1} + u_k \\ p_k &= v_k + c \times q_k \end{aligned} \qquad (9)$$

where v_k is the efficient price, defined as the log mid-quote prevailing prior to the k^{th} trade, u_k is the public information shock and is assumed to be normally distributed with mean of zero and variance of σ_u^2 and be independent of q_k, p_k is the log trade price, c is the effective cost to be estimated, and q_k is the direction indicator, which equals 1 for a buy and -1 for a sell. The data sample is $p \equiv \{p_1, p_2, \ldots\ldots, p_T\}$, where T is the number of days in the time period, and the model parameters $\{c, \sigma_u^2\}$, the latent buy/sell indicators $q \equiv \{q_1, q_2, \ldots\ldots, q_T\}$, and the latent efficient prices $v \equiv \{v_1, v_2, \ldots\ldots, v_T\}$ are to be numerically estimated. The approach of the Gibbs sampler is an iterative process in which one sweep consists of three steps. First, use a Bayesian regression to estimate the effective cost, c, based on the sample of prices, starting values of q, and priors for $\{c, \sigma_u^2\}$. Second, make a new draw of σ_u^2 from an inverted gamma distribution based on p, q, the prior for σ_u^2, and the updated estimate of c. Last, make new draws of q and v based on the updated estimate of c and the new draw of σ_u^2. Each sampler is run for 1,000 sweeps for which the first 200 are discarded to remove the effect of starting values and the mean value of c in the remaining 800 sweeps serves as the point estimate of the effective cost. Thanks to Hasbrouck that he provides the MATLAB codes to compute the Gibbs measure on his website. We use these codes directly without changing their main routines.

The algorithm of constructing the Gibbs measure assumes that successive daily stock prices are independent and expects the bid-ask bounce. In contrast to stock price data from CRSP in the US market, Datastream does not report negative daily price if there is no trades on that day. Furthermore, we observe many days with zero trading volume in emerging markets. To overcome the dependency problem, we follow Hasbrouck's suggestion by throwing out the days with zero trading volume in estimating the monthly Gibbs measure in emerging markets. The daily price is converted to US dollar using the exchange rate at the end of previous month. We first use the raw daily price as the input and get the Gibbs measured in US cents. Then we divide it by the monthly average of daily price to obtain the Gibbs measured in percentage.

4.3.1.3 Zeros

Lesmond, Ogden, and Trzcinka (1999) develop a model to estimate transaction costs in which the only data requirement is the time series of daily stock returns. The basic assumption is that, on average, a zero return is observed if expected return does not exceed the transaction cost threshold. Therefore, high transactions costs result in zero-return days. In addition, investors have relatively low incentive to obtain private information for stocks with high transaction costs and, as a results, most trades are noise trades which more likely lead to zero-return, and possibly positive volume, days. Bekaert, Harvey, and Lundblad (2007) use the Zeros measure as one of liquidity measures in examining liquidity and expected return in emerging markets and find that this measure is able to significantly predict future returns.

Specifically, the Zeros measure is defined as

$$Zeros = \frac{Number\ of\ days\ with\ zero\ returns}{T} \tag{10}$$

where T is the number of trading days in a month. The Zeros measure essentially has two components. The first one is to capture the noise trading. Goyenko, Holden and Trzcinka (2009) propose an alternative version of Zeros, Zeros2, which is the proportion of trading days with zero return but positive trading volume within one month. The argument is that stocks with higher transaction costs tend to have less private information acquisition so these stocks are more likely to have no-information-revelation zero returns even on positive volume days. The second component is about trading frequency. Since illiquid stocks are traded less frequently and, therefore, are more likely to have zero trading volume days, we propose another version of Zeros, *ZeroVol*[4], which is defined as

$$ZerosVol = \frac{Number\ of\ days\ with\ zero\ volume}{T} \tag{11}$$

4.3.1.4 Liu's *LMx* measure

[4] Note that the value of *ZeroVol* is same to the value of *NT%* in our new liquidity measure.

Liu (2006) proposes a standardized turnover-adjusted number of zero daily trading volumes over the prior x months:

$$LMx = \left[Number\ of\ zero\ daily\ volumes\ \ in\ prior\ x\ months + \frac{1/(x - month\ \ turnover)}{Deflator} \right]$$
$$\times \frac{21x}{NoTD} \tag{12}$$

where $x - month\ \ turnover$ is the turnover over the prior x months, $NoTD$ is the total number of trading days in the market over the prior x months and $Deflator$ is chosen such that

$$0 < \frac{1/(x - month\ \ turnover)}{Deflator} < 1 \tag{13}$$

for all sample stocks. We calculate *LM1*, *LM6* and *LM12* but only report the results for *LM1*. The deflator is same for all the emerging markets such that (13) holds cross markets.

4.3.2 Price impact proxies

4.3.2.1 Amihud

Amihud (2002) develops a measure of illiquidity which can be interpreted as the daily stock price impact of a dollar of trading volume. This measure defines stock illiquidity as the average ratio of daily absolute return to the dollar trading volume on that day:

$$Amihud = \frac{1}{N_{i,m}} \sum_{t=1}^{N_{i,m}} \frac{|R_{i,t}|}{VOL_{i,t}} \tag{14}$$

where $N_{i,m}$ is the number of non-zero trading volume days of stock i in month m, $|R_{i,t}|$ is the absolute value of return on stock i on day t, and $VOL_{i,t}$ is the trading volume in US dollar of stock i on day t.

4.3.2.2 Amivest

As used by Cooper, Groth, and Avera (1985), Khan and Baker (1993), Amihud, Mendelson, and Lauterback (1997), among others, the Amivest measure of liquidity is defined as

$$Amivest = \frac{1}{N_{i,m}} \sum_{t=1}^{N_{i,m}} \frac{VOL_{i,t}}{|R_{i,t}|} \tag{15}$$

where $N_{i,m}$ is the number of non-zero return days of stock *i* in month *m*, $\left|R_{i,t}\right|$ and $VOL_{i,t}$ are same as defined for the Amihud measure. The Amivest measure is related to the Amihud measure but their information content is different. When the Amihud measure is calculated, we delete days with zero volume; but when the Amivest measure is constructed, we exclude days with zero returns. Therefore, the Amihud measure does not contain information on non-trading but does on noise trading. However, the Amivest measure captures neither of them.

4.3.2.3 Gamma

Pastor and Stambaugh (2003) propose a measure of price impact of Gamma which captures the reverse of the previous day's order flow shock. Specifically, they construct this measure by running the regression

$$r_{t+1}^{e} = \theta + \phi \times r_t + \gamma \times sign(r_t^{e}) \times Vol_t + \varepsilon_n \tag{16}$$

where r_t^e is the stock's excess return above the value-weighted market return on day *t*, and Vol_t is the trading volume in US dollars on day *t*. Gamma should have a negative sign and larger absolute values indicate larger price impact and lower liquidity.

The summary statistics of various liquidity measures are shown in Table 1. A few notable patterns are observed. First, liquidity measures exhibit large cross-market dispersion. For example, the effective bid-ask spread is 0.314% in China but is 6.174% in Indonesia. Second, compared to the developed markets such as US, emerging markets are characterized by relatively low liquidity. Goyenko, Holden and Trzcinka (2009) show that on average 14.3% of days within a month have zero returns in the US market from 1993 to 2005. We find that in emerging markets, the zero-return days on average account for 20.118% of all trading days in a month, and 44.16% (8.884/20.118) of these zero-return days do not have trades. In addition, Hasbrouck (2009) find that the mean of the annual Gibbs liquidity measure (expressed in log) is 0.0112, corresponding to the effective cost of about 1.126%, using data from 1993 to 2005 for the US market. The mean of the monthly Gibbs measure in our sample is 1.739%, indicating the larger transaction costs in emerging markets. A similar pattern is observed for the Roll's measure.

[Insert Table 1 here]

Focusing on the spread measures, we find that in most markets the Roll measure and the Gibbs measure are smaller than the effective bid-ask spread. However, in relative more active markets such as China, Korea and Taiwan, they are close to, or even larger than the spread benchmark. This is primarily because of the non-trading issue. When trading is less active, daily stock prices are more likely to be positively correlated, resulting more zeros in estimating the Roll's measure. Meanwhile, deleting the no-trading days in estimating the Gibbs measure also results in the underestimation of the spread. In addition, the Gibbs measure is closer to the effective bid-ask spread in magnitude than the Roll measure. The mean and median value of the price impact benchmark is 0.006 and 0.001, respectively. At its mean value, the price impact of *Lambda* implies that a buy order of US$10,000 would move the stock price by 0.6%. The mean and median values of the three price impact proxies and our new liquidity measure seem to be as expected. However, we can not directly compare them to the benchmark due to the different order of magnitude.

5. Results on correlations

5.1 Cross-sectional correlations with the effective bid-ask spread

[Insert Table 2 here]

Using the effective bid-ask spread as the liquidity benchmark, we report the time-series averages of the cross-sectional correlations in Table 2. In each market, the highest correlations with the effective bid-ask spread are indicated in bold. We sort all the emerging markets into three groups based on *%NT*, which is the percentage of no-trading days in the market to facilitate the analysis, as we expect that the performance of the Amihud measure and the Zeros measure in capturing the underlying liquidity depends on the market characteristics, especially trading activeness. Not surprisingly, the correlation between the various liquidity proxies and the effective bid-ask spread varies across markets. For instance, Amihud has a correlation of 0.816 with spread in Portugal but only 0.330 in Brazil. The correlation coefficient between Zeros and the effective bid-ask spread is 0.652 in Brazil but only 0.250 in Korea. Nevertheless, our first important finding is that there is a complementarity between the Amihud measure and the Zeros measure: the Amihud measure is more correlated with the effective bid-ask spread in markets with low *NT%* while the Zeros measure is more correlated with the spread in market with high *NT%*, which is consistent with our expectation[5]. In the last column, we show the difference in their correlations with the spread. In markets with low value of *NT%*, the correlation between Amihud and the bid-ask spread is all statistically higher than the correlation between Zeros and the spread. But in markets with high value of *NT%*, Zeros shows higher correlation with the bid-ask spread than Amihud in 5 out of 7 markets. For markets with medium value of *NT%*, we find mixed evidence of their performance. This finding justifies our new liquidity measure, which is a combination of the Amihud measure and *NT%*, which is highly correlated with the Zeros measure, and is able to capture two dimensions of liquidity.

Most importantly, we find that our new liquidity measure, *Illiq_Zero*, is highly correlated with the effective bid-ask spread in all the merging markets. The correlation coefficients range from 0.448 in Taiwan to 0.819 in Portugal and 90% of the correlations are larger than 0.55, equivalent to a R-square of 0.3 when the bid-ask spread is regressed on *Illiq_Zero*. This finding confirms the ability of *Illiq_Zero* in capturing multi-dimension of the liquidity. Furthermore, *Illiq_Zero* can greatly improve the performance of the Amihud measure or the Zeros measure when they are less correlated with the spread. Take Brazil as an example. The cross-sectional correlation between Amihud and the effective bid-ask spread is only 0.330 but *Illiq_zero* improves it to 0.660. On the other hand, Zeros shows a correlation of 0.369 with the spread in China but the correlation for *Illiq_Zero* is 0.682. These results indicate the better performance of our new liquidity measure in measuring bid-ask spread in the cross-section.

We also test the difference in correlations for other low-frequency liquidity measures. They are not indicated in Table 2 but are summarized as follows. First, among the low-frequency liquidity measures other than *Illiq_Zero*, the best two measures are *ZeroVol* and the Amihud measure and both of them show the highest correlation with the effective bid-ask spread in half of the emerging markets. This result suggests that *ZeroVol* (or Zeros) and Amihud are better liquidity proxies not only in the US market as shown by

[5] We also test the difference in correlations for the Amihud measure and *Zerovol* and find similar pattern of complementarity between them.

Goyenko, Holden and Trzcinka (2009), but also in markets with relatively thin tradings. Second, focusing on the three Zeros measures, we find that Zeros2 consistently has lower correlation with the effective bid-ask spread. *ZeroVol* outperforms Zeros in the sense that the correlation between *ZeroVol* and the spread is statistically higher than the correlation between Zeros and the spread in 5 of 20 markets but the latter is statistically higher than the former in only 1 market, indicating that the proportion of no trading days within one month is more capable of measuring liquidity than the proportion of zero-return days in emerging markets. Third, focusing on the Roll measure and the Gibbs measure, we find that the correlation between Gibbs and the effective bid-ask spread is statistically higher than that between Roll and the spread in 18 out of 20 markets while Roll does not outperform Gibbs in any market. Therefore, the ability of Gibbs in measuring the effective bid-ask spread is stronger than that of Roll not only in the US market as shown by Hasbrouck (2009), but also in emerging markets. One possible explanation might be that daily stock prices are more positively correlated in time series in emerging markets, resulting in more zero values of Roll. Fourth, *LM1* and *ZeroVol* show similar correlations with the effective bid-ask spread, suggesting that turnover is not a good liquidity measure[6]. Finally, turnover, Amivest and Gamma seem to be consistently dominated by other liquidity proxies.

[Insert Table 3 here]

It is possible that our findings on the cross-sectional correlations are driven by our sample period. We next break our sample into two equal time periods with each of them covering 6 years. We repeat our analysis and the results are reported in Table 3. Panel A shows the cross-sectional correlations for the sample period from 1996 to 2001 while Panel B presents the correlations for the period from 2002 to 2007. We have 17 markets in first time period because our data for Chile is available since 2002 and Portugal and Poland have less than 20 months during this sample period. We can see that the main results in Table 2 remain unchanged. Among the low-frequency liquidity proxies, our new measure of *Illiq_Zero* shows the highest cross-sectional correlation with the effective bid-ask spread in 15 out of 17 markets in Panel A and in all markets in Panel B.

[6] We also calculate *LM*6 and *LM1*2 and find similar results.

The next best two liquidity proxies are *ZeroVol* and Amihud and, similar to the results in Table 2, Amihud and Zeros are complementary to each other. The correlation between *LM1* and the spread and the correlation between *ZeroVol* and the spread are almost same. Actually, we find that the correlation between *LM1* and *ZeroVol* is as high as 0.99, both in the cross-section and in the time-series. So for the analysis hereafter, we will not report the results for *LM1*.

5.2 Cross-sectional correlations with the price impact of *Lambda*

We report the cross-sectional correlations between the liquidity proxies and the price impact of *Lambda* in Table 4. Here we do not examine Roll and Gibbs as they are designed to estimate the effective bid-ask spread. The difference in the cross-sectional correlations is tested in a same way as in Table 2.

[Insert Table 4 here]

In contrast to the cross-sectional correlations using the effective bid-ask spread as the liquidity benchmark, the cross-sectional correlations between the price impact proxies and the *Lambda* are usually smaller in magnitude, even though proxies such as Amihud, Amivest and Gamma are designed to be a price impact proxy. There is strong evidence that our new liquidity measure, *Illiq_Zero*, is the best price impact measure: it shows the highest correlations with the price impact of *Lambda* in all the markets. The second best price impact measure is the Amihud measure. If we assume *Illiq_Zero* does not exist, Amihud shows the highest correlations with *Lambda* in 90% of the markets, as shown in the last row. The better performance of the Amihud measure in capturing the price impact supports the convention that Amihud is a better price impact proxy. Amihud performs well in markets with low *NT%*, a similar finding as in Table 2, but we do not find that *ZeroVol* or the Zeros measure has high correlations with *Lambda* even in markets with high *NT%*, suggesting that the Zeros measure is more of a bid-ask spread proxy. Among the three zero measures, Zeros2 is dominated by either Zeros or *ZeroVol*. Turnover, Amivest and Gamma seem to have lower correlations with *Lambda* than other price impact proxies.

In summary, our cross-sectional analyses in comparing the liquidity proxies in emerging markets suggest that: (1) Our new liquidity measure, *Illiq_Zero*, is the best low-frequency liquidity measure using both the effective bid-ask spread and the price impact of *Lambda* as the liquidity benchmarks; (2) In addition to *Illiq_Zero*, *ZeroVol* (or Zeros) and Amihud show higher correlations with the effective bid-ask spread than other liquidity measures, and their performance depends on the trading activeness of individual market; (3) In addition to *Illiq_Zero*, the Amihud measure is most correlated with the price impact of *Lambda* but its correlation with the *Lambda* is usually smaller in magnitude than with the effective bid-ask spread.

5.3 Time-series correlations with the effective bid-ask spread

[Insert Table 5 here.]

The time-series correlations between the effective bid-ask spread and the low-frequency liquidity proxies are presented in Table 5. First, we notice that the time-series correlations are larger than the corresponding cross-sectional correlations. Some of the correlation coefficients are even larger than 0.9. There are two possible reasons for this result. One is that we calculate the time-series correlation at the market portfolio level and therefore, some measurement error affecting individual stocks might be diversified away. The other reason might be that the time-series correlations are themselves larger than the cross-sectional correlations. However, we also calculate the time-series correlations at the individual stock level and they turn out to be smaller than the corresponding cross-sectional correlations at the portfolio level. Therefore, the higher time-series correlations are a result of diversification effect.

Illiq_Zero seems to be not as strongly correlated with the effective bid-ask spread in time-series as in the cross-section. However, it remains the best low-frequency spread proxy since it shows the highest correlations in 11 out of 20 markets. The next best three spread proxies in are *ZeroVol*, the Gibbs measure and the Amihud measure. The high correlation of Gibbs with the spread is worth noting. On average, it shows a correlation of 0.603 with the effective bid-ask spread and half of them are larger than 0.55. Furthermore, The Gibbs measure is most correlated with the spread in time-series in 8 markets. This finding suggests that the Gibbs measure is more capable of capturing the effective bid-ask spread in the time-series than in the cross-section. *ZeroVol* and the Amihud measure have an average correlation of 0.583 and 0.597 with the spread and they have the highest correlations in 7 and 6 markets, respectively. We also find some evidence that, in time-series, Amihud is more correlated with the effective spread in markets with more tradings while *ZeroVol* or Zeros in markets with less tradings, as indicated in the last column. Turnover, Amivest and Gamma show relatively low time-series correlations with the bid-ask spread.

5.4 Time-series correlations with the price impact of *Lambda*

We report the time-series correlations between the price impact of *Lambda* and various price impact proxies in Table 6. The way to calculate the time-series correlations and test their difference is same as in Table 5.

[Insert Table 6 here.]

Although the time-series correlations between the *Lambda* and the price impact proxies are larger than the cross-sectional correlations due to the diversification effect, they are still smaller than the time-series correlations between the spread and the trade-based liquidity proxies. We find ample evidence that *Illiq_Zero* is the best price impact proxy in time-series. On average, it has a correlation of 0.485 with *Lambda* and half of them are larger than 0.55. *Illiq_Zero* is most correlated with the price impact of *Lambda* in 16 markets. The second best price impact proxy is Amihud and it is most correlated with *Lambda* in 14 markets, assuming our new liquidity measure does not exist. Compared to Zeros, the Amihud measure is more correlated with *Lambda* in markets with fewer no-trading days. Surprisingly, we find that the Amivest measure is also highly correlated with *Lambda* in time-series, with the highest correlations in 6 markets. Turnover, Gamma and Zeros2 are still the liquidity proxies dominated by others.

To summarize, our time-series analyses show the following. First, the time-series correlations between the liquidity benchmarks and the proxies are larger than the cross-sectional correlations due to the diversification effect. Second, our new liquidity measure, *Illiq_Zero*, is the best spread proxy and price impact proxy in the time-series. Third, Gibbs and Amivest are a better spread proxy and a better price impact proxy, respectively, in the time-series than in the cross-section. Last, Amihud is more correlated with the bid-ask spread and the price impact of *Lambda* in time-series in more active markets.

6. Determinants of liquidity

We have seen from Table 1 that liquidity varies from market to market. So we want to investigate whether country-level variables affect market liquidity and whether they have similar effects on all the liquidity measures. As one of important stock attributes, liquidity is related to information environment, development of the financial markets as well as other country-level institutions. La Porta et al. (1998) divide countries into two groups based on their legal origin and show that investor protection is different in countries with different legal origins. Common/code law countries tend to have stronger investor protection than civil law countries. Strong investor rights can protect investors from being expropriated by the managers and enable them to get paid on their investments. Low investor protection can result in thin trading in the financial market because (1) investors anticipate the expropriation of the managers and (2) firms might find it difficult to get external finance by going public. Using American depositor receipt (ADR) data on various countries, Chung (2006) shows that firm liquidity in countries with weaker investor protection is lower since weak investor protection leads to greater expropriation by managers and therefore greater asymmetric information costs. In this study, we expect that, when investors are more protected by laws, they are more likely to trade and the stock market becomes more liquid because they anticipate the lower level of expropriation from managers and less information asymmetry. We use the measure of shareholders rights index from La Porta et al (1998), which is the sum of the dummies identifying one-share/one-vote, proxy by mail, unblocked shares, cumulative vote/proportional representation, preemptive rights, oppressed minority, and percentage of shares needed to call a shareholders meeting.

Apart from the legal origin of law, the quality of law enforcement has large effects on the size and development of capital market (La Porta et al, 1997, 1998, 2000). Good quality of law enforcement provides strong investor protection against expropriation by insiders. La Porta et al (2000) indicate the role of the quality of law enforcement when they wrote:

> These laws and the quality of their enforcement by the regulators and courts are essential elements of corporate governance and finance (La Porta et al., 1997, 1998). When investors rights such as the voting rights of the shareholders and the reorganization and the liquidation rights of the creditors are extensive and

well enforced by regulators or courts, investors are willing to finance firms. In contrast, when the legal system does not protect outside investors, corporate governance and external finance do not work well.

We would expect higher level of liquidity in markets with higher quality of law enforcement. To measure the quality of law enforcement, we use five variables from La Porta et al (1998): efficiency of the judicial system, rule of law, corruption, risk of expropriation, and likelihood of contract repudiation by the government.

Other institutional variables at the country level also could affect the investors' participation in stock market and therefore the level of market liquidity. As suggested by Lesmond (2005), political risk could reduce the capital available to the market and leads to lower stock market liquidity if the government does not control corruption or does not provide protection for investors against the expropriation. The risks of the financial market and the whole economy might also play a role in determining the activeness of the stock market. We obtain the data on a composite risk index from the International Country Risk Guide (ICRG), with high values indicating less risk, and expect that liquidity is higher in markets with lower level of country risk. Opening domestic market to foreign investors could also encourages more investors to trade as Bae, Bailey and Mao (2006a) suggest that increased openness is associated with better information environment evidenced by the increase in firm-specific information and analyst coverage and the decrease in earnings management. We obtain market liberalization information from EMDB and follow Bekaert, Harvey and Landblad (2007) to measure market liberalization by the ratio of the market capitalization of the constituent firms comprising the S&P-IFC Investable Index to that of firms comprising the S&P-IFC Global Index for each country. In addition, market liquidity may also be related to the country's disclosure policy. High disclosure requirements, strong auditing and financial reporting standards increase investor's confidence on the disclosed information and mitigate the adverse selection problem, which motivates investors to trade in the financial markets. La Porta et al (2006) show that disclosure requirements are associated with larger and more developed stock markets. So we hypothesize that trading is more active, and therefore liquidity is higher in markets with higher level of disclosure requirements. La Porta et al (2006) construct a disclosure index covering delivering, insiders' compensation, ownership structure by large shareholders, insider ownership, contracts outside the normal course of business and transactions with related parties, for 49 countries in the world. We directly use this index in our analysis.

In addition, the stock market is greatly influenced by the state of the country's economy in the sense that it mirrors the economic growth if the country's economy is doing well. As a key indicator of the economy, GDP conveys information on the stock market. On the one hand, investors expect the high profitability of firms if GDP is high. On the other hand, high GDP means investors might have more money to invest on stocks. Therefore, we conjecture that the investors are more willing to trade in stock market in countries with higher GDP. The information on GDP per capita is retrieved from the Economist Intelligence Unit (EIU).

[Insert Table 7 here.]

The descriptive statistics for the country-level variables as well as for the control variables including market capitalization, trading volume, market volatility and price are shown in Table 7. We can see from Panel A that even in the merging markets, there is a reasonable variation in the country risk level. Market liberalization also varies from country to country: China is relatively less liberalized with an index of 0.38 but countries such as Greece, Israel and South Africa are more open with an index of almost 1. However, countries in emerging markets usually have low shareholders protection, as none of them has a shareholder rights index higher than 6. The Pearson correlations in Panel B indicate that countries with less risk are usually larger markets with stronger shareholder protection, higher quality of law enforcement, more disclosure requirements but lower level of market liberalization. Surprisingly, we find that more opened markets are associated with less disclosure. One possible explanation is that opening domestic market to foreign investors result in more firm specific information which is provided by financial intermediaries such as analysts but not by the policy on disclosure requirement.

To investigate the effects of the country-level variables on liquidity, we use a random effect model approach and use the monthly market liquidity, which is an equally-weighted average of liquidity across stocks in each market, as the dependent variable. The explanatory variables which include all the country-level factors mentioned above and the control variables are same for these regressions. We employ a random effect model since the dependent variable is by country-month while some of the independent variables such as the shareholders rights, law enforcement, disclosure and GDP per capita are at country level or by country-year.

[Insert Table 8 here]

The regression results are reported in Table 8. Focusing on the effective bid-ask spread, we find that it is smaller in markets with less composite risk, higher level of liberalization, larger market capitalization, lower volatility, more trading volume and higher price, which is consistent with our expectation. However, country-variables such as shareholder protection, law enforcement, disclosure and GDP per capita do not have significant effects on the effective bid-ask spread. On the other hand, large trades have smaller price impact measured by *Lambda* in markets which are more liberalized or have more shareholder rights and/or higher GDP. The result that shareholder protection has an effect on the price impact of *Lambda* but not on the effective bid-ask spread may reflect that they are capturing different dimensions of liquidity. Surprisingly, we also find that the price impact of *Lambda* is smaller in markets with lower quality of law enforcement.

Among the liquidity measures constructed from the low-frequency data, we find that country variables have the same effects on *Illiq_Zero* as on the effective bid-ask spread, confirming the better performance of our new liquidity measure. The country variables could have effects on other liquidity proxies which are opposite to our expectation. For instance, we find the Zeros measure has a smaller value in markets with low shareholders rights, lower GDP per capita and higher volatility. Another example is turnover. We expect that turnover to be higher in markets with higher composite risk index but it turns out they are negatively related. In general, the results for the control variables suggest that liquidity is high in markets with large market capitalization, low volatility, high trading volume and high price level.

7. Conclusions

With the importance of liquidity on asset pricing, corporate finance and market efficiency in emerging markets, which liquidity proxy could capture the underlying liquidity at the monthly frequency remains an open issue. In this study, on obtaining the transactions and quotes data in emerging markets from the TAQTIC, we examine the various existing liquidity proxies plus our new measure, *Illiq_Zero*, which can be interpreted as a no-trading-day adjusted Amihud measure. This measure is motivated by our hypothesis that the performance of the Amihud measure depends on the trading activeness of the market. By adjusting the Amihud measure by the proportion of no-trading days in a month, *Illiq_Zero* has an advantage of capturing both the price impact and the trading frequency dimensions of liquidity. Our main mechanism to compare the performance of liquidity proxies is to compare the their correlations with the liquidity benchmarks, including the effective bid-ask spread and the price impact of *Lambda*.

The correlation analyses show strong evidence that our new liquidity measure, *Illiq_Zero*, is the best low-frequency liquidity proxy. It shows the highest cross-sectional correlations with the effective bid-ask spread and the price impact of *Lambda* in all the emerging markets. In the time-series, it is most correlated with the two liquidity benchmarks in most of the markets. This finding suggests that our new liquidity measure can facilitate the cross-country analysis on the effects of liquidity in emerging markets. Other than *Illiq_Zero*, *ZeroVol*, which is the percentage of zero-trading volume days in a month, and the Amihud measure are another better liquidity proxies and their relative performance depends on the trading activeness of the market. *ZeroVol* or the Zeros measure is more related to the effective bid-ask spread in markets with more no-trading days while the Amihud measure is a better spread proxy and price impact proxy in markets with fewer no-trading days. We also find that the Gibbs measure is a better spread proxy in the time-series than in the cross-section. Turnover, Zero2, Gamma and Amivest show relatively low correlations with the effective bid-ask spread and the price impact of *Lambda*.

In this paper, we also investigate the effects of country variables on market liquidity and expect that the same country variables have similar effects on the liquidity benchmarks as well as on the liquidity proxies. Consistent with our expectation, the effective bid-ask spread is smaller in markets with lower composite risk and more liberalization. Furthermore, these variables have the same effects on our new liquidity measure.

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Table 1: Descriptive statistics, January 1996 – December 2007

Trades and quotes data are retrieved from TAQTIC and all the other daily data are from Datastream. 'Start' is the year from which data are available for each market. PESPR is calculated as two times the difference between the transaction price and the mid-quote divided by the mid-quote. Lambda is constructed based on Hasbrouck (2009) and is the coefficient from regressing the stock return measured in percentage over a 30-minute interval onto the signed square-root of US dollar volume over the same interval with intercept omitted. The Roll measure equals to $2\times\sqrt{-Cov(\Delta P_t,\Delta P_{t-1})}_{\,t}$, where ΔP_t is the daily stock price change, and positive auto covariance is forced to be zero in order to make the formula meaningful. The Gibbs measure is the Gibbs estimate of effective cost and is formed base on Hasbrouck (2004). We divide the Gibbs measured in US cents by the average monthly price measured in US dollar in that month to get the Gibbs estimate measured in percentage. Turnover is defined as the share trading volume scaled by the number of shares outstanding at the beginning of the year. The Zeros measure represents the number of days with zero returns over one month scaled by the total number of valid trading days in that month. ZeroVol is constructed by dividing the number of days with zero trading volume over one month by the total number of available trading days in that month. LM1 is a standardized turnover-adjusted number of zero daily trading volume over the month, constructed based on Liu (2006). The Amihud measure is defined as $(1/D_m)\sum_{t=1}^{m}\left|r_{i,t}\right|/(volume\_USD_{i,t})$, where D_m is the number of valid trading days in each month and $volume\_USD_t$ is the stock *I*'s daily trading volume in US dollars. The value of 1 means that the trading volume of 1,000 US dollars moves return by 1%. The Amivest measure is defined as $(1/D_m)\sum_{t=1}^{m}(volume\_USD_{i,t})/\left|r_{i,t}\right|$ and daily return is measured in percentage and volume is in 1,000 US dollars. We truncate the upper and lower 1% of the distribution for the Amihud and the Amivest measures. Gamma is formed based on the regression of stock excess return at *t+1* measured in percentage on stock return at *t* and signed trading volume at *t* measured in 1,000 US dollars over the month. Gamma is the estimated coefficient of the signed trading volume. Illiq_Zero is defined as ln(Amihud)*(1+NT%) where return is measured in percentage and trading volume is measured in billions of US dollars in the Amihud measure and 'NT%' means the percentage of no-trading days in a month.

All measures are in monthly frequency. We use beginning-of-the-month exchange rate to convert local currency to US dollars in order to make a cross-market comparison. The summary statistics are first calculated for each firm over time and then average across all the firms. Within the braces are the median values.

		High-frequency Liquidity Benchmarks		Low-frequency Liquidity Proxies									
Market	**Start**	**PESPR** (%)	**Lambda**	**Roll** (%)	**Gibbs** (%)	**Turnover** (%)	**Zeros** (%)	**ZeroVol** (%)	**LM1**	**Amihud**	**Amivest**	**Gamma**	**Illiq_Zero**
Latin America													
Argentina	1999	2.552	0.003	0.966	1.686	0.077	37.983	23.868	4.845	0.772	0.204	-0.153	15.098
		[2.281]	[0.002]	[0.973]	[1.301]	[0.047]	[36.642]	[19.236]	[4.038]	[0.310]	[0.028]	[-0.023]	[14.626]
Brazil	1998	4.684	0.006	1.803	2.832	1.121	38.706	29.095	5.662	3.482	11.239	0.143	14.643
		[4.541]	[0.001]	[1.370]	[1.501]	[0.101]	[40.025]	[25.540]	[5.012]	[0.324]	[1.192]	[0.000]	[14.209]
Chile	2002	3.794	0.000	0.643	1.261	0.174	53.251	34.187	6.929	0.351	4.224	0.004	14.885
		[3.124]	[0.000]	[0.539]	[0.895]	[0.035]	[58.195]	[37.776]	[7.607]	[0.170]	[0.637]	[0.002]	[15.696]
Mexico	1996	2.834	0.001	0.943	1.939	0.165	31.263	20.854	4.311	3.805	12.027	0.128	13.587
		[2.307]	[0.000]	[0.803]	[1.083]	[0.068]	[20.499]	[11.199]	[2.323]	[0.214]	[1.589]	[0.000]	[11.877]
East Asia													
China	1996	0.313	0.001	1.166	1.098	1.310	5.811	2.554	0.534	0.009	5.711	-0.002	7.363
		[0.272]	[0.001]	[1.120]	[1.049]	[1.170]	[5.523]	[2.440]	[0.508]	[0.002]	[3.556]	[-0.001]	[7.346]
Korea	1996	1.391	0.001	1.643	1.439	3.155	11.440	4.140	0.852	0.132	1.767	-0.023	9.521
		[1.295]	[0.001]	[1.625]	[1.396]	[2.180]	[9.491]	[2.868]	[0.602]	[0.027]	[0.719]	[-0.004]	[9.360]
Philippines	1996	6.611	0.010	2.792	4.247	0.679	45.423	20.974	3.674	6.888	0.129	0.180	16.219
		[5.835]	[0.004]	[2.280]	[2.727]	[0.110]	[47.777]	[22.167]	[4.083]	[3.891]	[0.023]	[-0.001]	[16.666]
Taiwan	1996	0.629	0.017	0.982	0.955	1.319	11.614	0.478	0.083	0.043	4.695	-0.009	7.906
		[0.522]	[0.014]	[0.981]	[0.952]	[1.073]	[10.904]	[0.000]	[0.000]	[0.005]	[1.581]	[-0.002]	[7.766]
South Asia													
India	1996	1.900	0.009	1.661	1.420	0.429	7.096	3.626	0.705	6.556	2.993	-0.279	11.424
		[1.435]	[0.006]	[1.476]	[1.254]	[0.203]	[4.914]	[0.963]	[0.156]	[0.360]	[0.381]	[-0.008]	[11.287]
Indonesia	1996	6.174	0.003	2.955	3.335	0.437	48.959	21.658	4.526	22.033	0.407	0.107	16.107
		[5.577]	[0.001]	[2.718]	[3.020]	[0.250]	[51.798]	[19.770]	[4.091]	[7.995]	[0.056]	[0.000]	[16.428]
Malaysia	1996	2.427	0.005	1.782	1.545	0.341	27.908	8.668	1.810	0.879	0.431	-0.029	12.517
		[1.996]	[0.005]	[1.668]	[1.416]	[0.223]	[26.564]	[5.631]	[1.180]	[0.440]	[0.137]	[-0.008]	[12.500]
Singapore	1996	3.826	0.017	2.417	3.138	0.372	34.534	11.607	2.409	89.210	0.014	-0.815	17.137
		[2.600]	[0.010]	[2.093]	[1.906]	[0.257]	[35.713]	[5.804]	[1.179]	[21.802]	[0.002]	[-0.073]	[16.488]
Thailand	1996	2.583	0.019	1.797	1.778	1.025	30.531	13.394	2.770	2.225	0.928	0.015	12.857
		[1.876]	[0.007]	[1.659]	[1.477]	[0.416]	[25.075]	[4.674]	[0.982]	[0.454]	[0.189]	[0.000]	[11.870]

Europe													
Greece	1996	1.806	0.006	1.240	1.145	0.325	15.498	2.121	0.444	2.798	0.521	-0.047	11.805
		[1.693]	[0.005]	[1.176]	[1.067]	[0.260]	[13.793]	[0.253]	[0.053]	[0.892]	[0.076]	[0.012]	[11.534]
Poland	2000	1.416	0.003	1.439	1.292	1.199	15.349	4.937	0.999	1.869	0.393	0.137	12.100
		[1.340]	[0.003]	[1.317]	[1.088]	[0.272]	[13.440]	[0.903]	[0.190]	[0.215]	[0.084]	[0.000]	[11.737]
Portugal	1998	2.045	0.002	1.154	1.073	0.251	23.470	7.427	1.490	1.519	14.394	-0.058	9.764
		[0.650]	[0.000]	[0.787]	[0.675]	[0.187]	[15.652]	[0.317]	[0.064]	[0.008]	[1.340]	[0.000]	[8.164]
Russia	2000	3.167	0.001	1.216	6.389	0.146	42.700	40.059	7.508	4.433	24.325	0.033	15.038
		[2.029]	[0.000]	[0.761]	[1.682]	[0.006]	[41.371]	[38.946]	[6.812]	[0.099]	[0.164]	[0.000]	[14.909]
Turkey	1996	1.160	0.000	1.684	1.398	8.214	18.180	1.046	0.071	0.204	0.533	-0.046	10.001
		[1.091]	[0.000]	[1.677]	[1.438]	[6.275]	[17.320]	[0.063]	[0.011]	[0.050]	[0.119]	[-0.010]	[10.173]
Middle East/Africa													
Israel	1996	4.168	0.000	1.439	1.914	0.149	27.823	22.137	4.605	1.137	0.594	0.025	15.257
		[4.396]	[0.000]	[1.322]	[1.719]	[0.095]	[30.055]	[23.791]	[4.994]	[0.931]	[0.056]	[0.000]	[16.391]
South Africa	1996	4.137	0.000	1.815	2.039	0.159	37.243	18.438	3.721	6.037	4.083	-0.001	14.194
		[2.881]	[0.000]	[1.279]	[1.181]	[0.118]	[34.353]	[9.179]	[1.879]	[0.482]	[0.119]	[0.000]	[13.205]
All		2.157	0.006	1.613	1.739	1.729	20.118	8.884	1.780	7.928	3.225	-0.062	11.280
		[1.210]	[0.001]	[1.350]	[1.236]	[0.648]	[11.868]	[2.687]	[0.558]	[0.055]	[0.483]	[-0.001]	[9.973]

Table 2: Cross-sectional correlations between the effective bid-ask spread and alternative liquidity measures

This table shows the cross-sectional correlations between the liquidity benchmark of the effective bid-ask spread and liquidity proxies formed using low-frequency data. We sort all the markets by NT%, which is the percentage of no-trading days within a month, into three groups. Markets in NT% group 1 (3) have fewer (more) no-trading days, indicating high (low) level of trading volume. Roll is constructed based on the serial autovariance of change in daily stock prices. The Gibbs measure refers to the Gibbs estimate of the effective cost and is formed base on Hasbrouck (2004). Turnover measures the daily trading volume in shares divided by the number of shares outstanding. Zeros, Zeros2, and ZeroVol are defined as the number of days with zero returns, zero returns and non-zero trading volume, and zero trading volume divided by the total number of valid trading days within that month, respectively. LM1 is constructed based on Liu (2006). The Amihud measure is defined as $(1/D_m)\sum_{t=1}^{m}\left|r_{i,t}\right|/(volume\_USD_{i,t})$. The Amivest measure is defined as $(1/D_m)\sum_{t=1}^{m}(volume\_USD_{i,t})/\left|r_{i,t}\right|$. Gamma is formed based on Pastor and Stambaugh (2003). Illiq_Zero is defined as ln(Amihud)*(1+NT%).

We first calculate the Pearson correlation across all the stocks in each month. Then we average the correlation coefficients over time. We test the difference in correlations in a way similar to Fama-MacBeth where the standard errors are adjusted for autocorrelation with a Newey-West correction using four lags. The figures in bold represent the highest correlations in each country and the difference in correlations are tested at 1% of significance level. '% LC' shows the percentage of correlations larger than 0.55 across all the markets. '% Best' indicates the percentage of the highest correlation between each liquidity proxy and the effective bid-ask spread across all the markets and '% Second Best' presents the percentage of the highest correlations, assuming the best liquidity proxy does not exist. The last column shows the difference in correlations between Amihud with the liquidity benchmark and Zeros with the benchmark. *, **, and *** indicate the significance at the 0.05, 0.01 and 0.001 significance level, respectively, for the one-tail test.

NT% Group	Market	Roll	Gibbs	Turnover	Zeros	Zero2	ZeroVol	LM1	Amihud	Amivest	Gamma	Illiq_Zero	Amihud - Zeros
1	Taiwan	0.066	0.132	-0.163	0.269	0.196	0.240	0.209	**0.399**	-0.156	-0.090	**0.448**	0.131**
	Turkey	0.195	0.170	-0.163	0.254	0.155	0.221	0.157	**0.514**	-0.154	-0.106	**0.488**	0.262***
	China	0.028	0.267	-0.190	0.369	0.352	0.229	0.234	0.604	-0.266	-0.169	**0.682**	0.235***
	Portugal	0.506	**0.787**	-0.089	0.581	0.114	0.748	0.723	**0.816**	-0.247	-0.074	**0.819**	0.101**
	Korea	0.187	0.193	-0.143	0.250	0.101	0.310	0.303	0.351	-0.275	-0.049	**0.585**	0.235***
	Greece	0.225	0.393	-0.269	0.403	0.049	0.499	0.501	0.602	-0.301	-0.022	**0.749**	0.199***
	India	0.384	0.580	-0.130	0.492	0.209	0.471	0.500	0.647	-0.202	-0.034	**0.789**	0.155***
2	Malaysia	0.219	0.401	-0.128	0.436	-0.046	0.600	0.607	0.575	-0.184	-0.021	**0.730**	0.139***
	Poland	0.298	0.393	0.132	0.347	-0.022	0.412	0.434	0.367	-0.225	0.053	**0.585**	0.019
	Mexico	0.226	0.471	-0.214	**0.585**	0.394	**0.593**	**0.588**	0.333	-0.165	0.073	**0.587**	-0.252***
	Singapore	0.345	0.519	-0.176	0.526	0.144	0.556	0.556	0.575	-0.199	-0.012	**0.746**	0.049***
	Thailand	0.257	0.499	-0.161	0.467	-0.058	0.620	0.623	0.459	-0.216	0.050	**0.724**	-0.009
	Israel	0.243	0.470	-0.193	0.622	0.184	0.595	0.598	0.548	-0.313	0.023	**0.711**	-0.074**
3	South Africa	0.445	0.721	-0.148	0.634	0.179	0.621	0.619	0.522	-0.215	0.015	**0.770**	-0.113***
	Indonesia	0.410	**0.706**	-0.147	0.532	0.028	0.485	0.484	0.459	-0.270	0.004	**0.664**	-0.073***
	Argentina	0.030	0.452	-0.145	0.595	0.145	0.590	0.591	0.523	-0.423	-0.052	**0.700**	-0.072**
	Philippines	0.279	0.409	0.007	0.504	-0.031	0.545	0.513	0.470	-0.261	0.027	**0.677**	-0.034
	Brazil	0.355	0.565	-0.091	**0.652**	0.331	0.560	0.558	0.330	-0.182	-0.002	**0.660**	-0.323***
	Chile	0.124	0.456	-0.028	0.542	0.189	0.535	0.531	0.357	-0.188	0.064	**0.593**	-0.185***
	Russia	0.147	0.372	-0.190	0.345	0.016	0.353	0.335	**0.486**	-0.215	-0.004	**0.537**	0.141*
	Average	0.248	0.448	-0.131	0.470	0.131	0.489	0.483	0.497	-0.233	-0.016	0.662	-
	% LC	0.00	25.00	0.00	30.00	0.00	45.00	45.00	30.00	0.00	0.00	90.00	-
	% Best	0.00	10.00	0.00	10.00	0.00	5.00	5.00	20.00	0.00	0.00	100.00	-
	% Second Best	0.00	15.00	0.00	30.00	0.00	50.00	40.00	50.00	0.00	0.00	-	-

Table 3: Cross-sectional correlations between the effective bid-ask spread and alternative liquidity measures: Subsample analysis

This table shows the cross-sectional correlations between the liquidity benchmark of the effective bid-ask spread and liquidity proxies formed using low-frequency data for the subsamples. In each subsample, we sort all the markets by NT%, which is the percentage of no-trading days within a month, into three groups. Markets in NT% group 1 (3) have fewer (more) no-trading days, indicating high (low) level of trading volume. Roll is constructed based on the serial autovariance of changes in daily stock prices. The Gibbs measure refers to the Gibbs estimate of effective cost and is formed base on Hasbrouck (2004). Turnover measures the daily trading volume in shares divided by the number of shares outstanding. Zeros, Zeros2, and ZeroVol are defined as the number of days with zero returns, zero returns and non-zero trading volume, and zero trading volume divided by the total number of valid trading days within that month, respectively. LM1 is constructed based on Liu (2006). The Amihud measure is defined as $(1/D_m)\sum_{t=1}^{m}\left|r_{i,t}\right|/(volume\_USD_{i,t})$. The Amivest measure is defined as $(1/D_m)\sum_{t=1}^{m}(volume\_USD_{i,t})/\left|r_{i,t}\right|$. Gamma is formed based on Pastor and Stambaugh (2003). Illiq_Zero is defined as ln(Amihud)*(1+NT%).

We first calculate the Pearson correlation across all the stocks in each month. Then we average the correlation coefficients over time. We test the difference in correlations in a way similar to Fama-MacBeth where the standard errors are adjusted for autocorrelation with a Newey-West correction using four lags. The figures in bold represent the highest correlations in each country and the difference in correlations are tested at 1% of significance level. '% LC' shows the percentage of correlations larger than 0.55 across all the markets. '% Best' indicates the percentage of the highest correlation between each liquidity proxy and the effective bid-ask spread across all the markets and '% Second Best' presents the percentage of the highest correlations, assuming the best liquidity proxy does not exist. The last column shows the difference in correlations between Amihud with the liquidity benchmark and Zeros with the benchmark. *, **, and *** indicate the significance at the 0.05, 0.01 and 0.001 significance level, respectively, for the one-tail test.

Panel A shows the correlations between the effective bid-ask spread in percentage and the liquidity proxies for the period from 1996 to 2001 while Panel B shows these correlations for the period from 2002 to 2007. We require each market to have at least 20 monthly cross-sectional correlations, which leaves 17 markets in Panel A and 20 markets in Panel B.

Panel A: From 1996 to 2001

NT% Group	Market	Roll	Gibbs	Turnover	Zeros	Zero2	ZeroVol	LM1	Amihud	Amivest	Gamma	Illiq_Zero	Amihud - Zeros
1	Taiwan	0.023	0.038	-0.132	**0.290**	0.296	0.004	0.015	0.110	-0.096	-0.046	**0.205**	-0.179***
	Turkey	0.194	0.161	-0.234	0.172	0.007	0.301	0.229	**0.555**	-0.138	-0.112	**0.463**	0.383***
	China	0.112	0.520	-0.160	0.613	0.502	0.462	0.470	**0.751**	-0.216	-0.205	**0.758**	0.138***
	Korea	0.188	0.249	-0.170	0.264	0.099	0.349	0.329	0.276	-0.235	-0.042	**0.477**	0.012
	Malaysia	0.116	0.258	-0.134	0.442	0.030	0.558	0.572	0.532	-0.191	-0.037	**0.694**	0.090***
	Singapore	0.251	0.426	-0.212	0.503	0.147	0.572	0.584	0.562	-0.218	-0.026	**0.771**	0.059**
2	Mexico	0.175	0.392	-0.091	**0.553**	0.389	**0.580**	0.400	0.192	-0.038	0.204	0.415	-0.361***
	Greece	0.128	0.306	-0.358	0.496	-0.055	0.616	0.612	**0.693**	-0.349	-0.040	**0.730**	0.197**
	India	0.468	**0.719**	-0.162	0.520	0.221	0.485	0.500	0.662	-0.214	-0.033	**0.763**	0.142***
	Thailand	0.289	0.578	-0.180	0.438	-0.037	0.550	0.557	0.421	-0.248	0.039	**0.701**	-0.016
	Israel	0.182	0.428	-0.116	0.569	0.233	0.495	0.495	0.469	-0.286	0.001	**0.632**	-0.100*
3	Indonesia	0.336	**0.643**	-0.146	0.549	0.071	0.474	0.473	0.407	-0.298	0.020	**0.637**	-0.142***
	Philippines	0.294	0.389	0.017	0.526	-0.024	0.572	0.558	0.430	-0.275	0.003	**0.708**	-0.096***
	South Africa	0.397	**0.725**	-0.117	0.610	0.134	0.600	0.599	0.556	-0.191	0.035	**0.766**	-0.055*
	Brazil	0.467	**0.641**	-0.037	0.566	0.446	0.389	0.376	0.328	-0.162	0.023	0.516	-0.239***
	Argentina	0.027	0.533	-0.066	0.496	0.099	0.513	0.514	0.500	-0.468	-0.010	**0.653**	0.004
	Russia	0.021	0.457	-0.255	0.595	0.139	0.594	0.604	0.507	-0.315	-0.060	**0.701**	-0.088
	Average	0.216	0.439	-0.150	0.483	0.159	0.477	0.464	0.468	-0.232	-0.017	0.623	-
	% LC	0.00	29.41	0.00	35.29	0.00	47.06	41.18	35.29	0.00	0.00	70.59	-
	% Best	0.00	23.53	0.00	11.77	0.00	5.88	0.00	17.65	0.00	0.00	88.24	-
	% Second Best	0.00	35.29	0.00	35.29	0.00	47.06	41.18	35.29	0.00	0.00	-	-

Panel B: From 2002 to 2007

NT% Group	Market	Roll	Gibbs	Turnover	Zeros	Zero2	ZeroVol	LM1	Amihud	Amivest	Gamma	Illiq_Zero	Amihud - Zeros
1	Taiwan	0.109	0.228	-0.195	0.248	0.095	0.404	0.404	**0.689**	-0.216	-0.135	**0.691**	0.441***
	Turkey	0.195	0.179	-0.093	0.335	0.303	0.141	0.084	**0.473**	-0.169	-0.100	**0.453**	0.137**
	India	0.303	0.448	-0.099	0.465	0.199	0.457	0.501	0.633	-0.190	-0.035	**0.813**	0.169***
	Greece	0.319	0.480	-0.179	0.313	0.134	0.390	0.391	0.512	-0.254	-0.004	**0.767**	0.199***
	China	-0.057	0.017	-0.220	0.125	0.203	-0.004	-0.003	0.457	-0.316	-0.134	**0.606**	0.333***
	Korea	0.186	0.136	-0.116	0.235	0.102	0.277	0.277	0.427	-0.315	-0.055	**0.696**	0.192***
	Portugal	0.506	**0.787**	-0.089	0.581	0.114	0.748	0.723	**0.816**	-0.247	-0.074	**0.819**	0.235***
2	Poland	0.299	0.397	0.135	0.384	-0.013	0.454	0.456	0.390	-0.237	0.062	**0.614**	0.006
	Thailand	0.225	0.419	-0.143	0.497	-0.080	0.689	0.689	0.496	-0.184	0.061	**0.747**	-0.001
	Malaysia	0.321	0.543	-0.121	0.430	-0.121	0.642	0.642	0.618	-0.177	-0.004	**0.765**	0.188***
	Mexico	0.267	0.540	-0.317	0.612	0.399	0.602	0.602	0.457	-0.276	-0.042	**0.738**	-0.155***
	Singapore	0.439	0.613	-0.139	0.548	0.141	0.539	0.528	0.587	-0.181	0.003	**0.721**	0.039
	South Africa	0.501	**0.715**	-0.184	0.662	0.231	0.646	0.642	0.483	-0.242	-0.008	**0.776**	-0.179***
3	Argentina	0.031	0.410	-0.185	0.645	0.168	0.630	0.629	0.534	-0.400	-0.073	**0.724**	-0.111***
	Israel	0.305	0.514	-0.271	0.676	0.135	0.694	0.700	0.627	-0.339	0.046	**0.789**	-0.049**
	Indonesia	0.483	**0.768**	-0.148	0.514	-0.015	0.496	0.495	0.510	-0.242	-0.013	**0.703**	-0.004
	Brazil	0.289	0.521	-0.123	**0.702**	0.264	0.659	0.663	0.331	-0.195	-0.017	**0.743**	-0.371***
	Philippines	0.263	0.427	-0.003	0.483	-0.038	0.518	0.471	0.508	-0.248	0.049	**0.647**	0.026
	Chile	0.124	0.456	-0.028	0.542	0.189	0.535	0.531	0.357	-0.188	0.064	**0.593**	-0.185***
	Russia	0.186	0.346	-0.169	0.265	-0.021	0.275	0.249	**0.480**	-0.183	0.012	**0.485**	0.214***
	Average	0.265	0.447	-0.134	0.463	0.120	0.490	0.484	0.519	-0.240	-0.020	0.693	-
	% LC	0.00	20.00	0.00	30.00	0.00	40.00	40.00	30.00	0.00	0.00	90.00	-
	% Best	0.00	15.00	0.00	5.00	0.00	0.00	0.00	20.00	0.00	0.00	100.00	-
	% Second Best	0.00	20.00	0.00	20.00	0.00	40.00	35.00	50.00	0.00	0.00	-	-

Table 4: Cross-sectional correlations between the price impact of *Lambda* and alternative liquidity measures

This table shows the cross-sectional correlations between the price impact measure of Lambda, and liquidity proxies formed using low-frequency data. Lambda is formed based on Hasbrouck (2009 Turnover measures the daily trading volume in shares divided by the number of shares outstanding. Zeros, Zeros2, and ZeroVol are defined as the number of days with zero returns, zero returns and non-zero trading volume, and zero trading volume divided by the total number of trading days in that month, respectively. Amihud is defined as $(1/D_m)\sum_{t=1}^{m}\left|r_{i,t}\right|/(volume\_USD_{i,t})$. The Amivest measure is defined as $(1/D_m)\sum_{t=1}^{m}(volume\_USD_{i,t})/\left|r_{i,t}\right|$. Gamma is formed based on Pastor and Stambaugh (2003). Illiq_Zero is defined as ln(Amihud)*(1+NT%).

We first calculate the Pearson correlation across stocks in each month and then average it over time. We test the difference in correlations in a way similar to Fama-MacBeth where the standard errors are adjusted for autocorrelation with a Newey-West correction using four lags. For each country, the highest correlation(s) between *Lambda* and liquidity proxies are indicated in bold. '% LC' shows the percentage of correlations larger than 0.55 across all the markets. '% Best' indicates the percentage of the highest correlation between each liquidity proxy and *Lambda* across all the markets and '% Second Best' presents the percentage of the highest correlations assuming the best liquidity proxy does not exist.

NT% Group	Market	Turnover	Zeros	Zero2	ZeroVol	Amihud	Amivest	Gamma	Illiq_ Zero	Amihud - Zeros
1	Taiwan	-0.198	0.043	0.028	0.073	0.302	-0.253	-0.114	**0.539**	0.259***
	Turkey	-0.074	0.008	-0.017	0.077	0.255	-0.164	-0.061	**0.340**	0.247***
	China	-0.131	0.277	0.300	0.106	**0.667**	-0.266	-0.190	**0.699**	0.390***
	Korea	-0.065	0.018	0.003	0.027	0.168	-0.179	-0.055	**0.354**	0.150***
	Portugal	-0.019	0.269	0.213	0.281	**0.655**	-0.253	0.151	**0.593**	0.386***
	Greece	-0.180	0.111	0.047	0.148	0.438	-0.273	-0.030	**0.481**	0.327***
	India	-0.099	0.232	0.070	0.070	0.423	-0.138	-0.043	**0.504**	0.191***
2	Malaysia	-0.104	0.121	-0.121	0.285	0.423	-0.200	-0.037	**0.512**	0.302***
	Poland	0.023	0.081	-0.014	0.137	0.171	-0.201	0.018	**0.363**	0.090*
	Mexico	-0.010	0.286	0.094	0.294	0.326	-0.020	-0.032	**0.402**	0.040
	Singapore	-0.086	0.194	-0.023	0.310	0.306	-0.103	-0.020	**0.397**	0.112***
	Thailand	-0.044	0.098	-0.026	0.148	0.127	-0.070	-0.011	**0.202**	0.029*
	Israel	-0.097	0.283	0.043	0.289	0.355	-0.176	-0.001	**0.395**	0.072*
3	South Africa	-0.068	0.220	0.109	0.229	0.357	-0.119	0.004	**0.419**	0.137***
	Indonesia	-0.045	0.109	-0.117	**0.225**	0.149	-0.057	-0.005	**0.237**	0.040*
	Argentina	-0.063	0.223	0.037	0.239	0.300	-0.244	-0.067	**0.363**	0.077**
	Philippines	0.046	0.085	-0.049	0.132	0.128	-0.060	-0.014	**0.161**	0.043*
	Brazil	-0.055	0.168	0.104	0.141	0.225	-0.079	0.017	**0.267**	0.057
	Chile	-0.023	**0.094**	0.053	**0.084**	**0.073**	-0.024	0.056	**0.101**	-0.021
	Russia	-0.106	0.193	0.012	0.199	0.334	-0.140	-0.021	**0.385**	0.141*
	Average	-0.070	0.156	0.037	0.175	0.309	-0.151	-0.023	0.386	-
	% LC	0.00	0.00	0.00	0.00	10.00	0.00	0.00	10.00	-
	% Best	0.00	5.00	0.00	10.00	15.00	0.00	0.00	100.00	-
	% Second Best	0.00	5.00	0.00	30.00	90.00	15.00	0.00	-	-

Table 5: Time-series correlations: Effective bid-ask spread as the benchmark

This table shows the time-series correlations between the liquidity benchmark of the effective bid-ask spread and the liquidity proxies formed using low-frequency data at the market portfolio level. Roll is constructed based on the serial autovariance of changes in daily stock prices. The Gibbs measure refers to the Gibbs estimate of effective cost and is formed base on Hasbrouck (2004). Turnover measures the daily share trading volume divided by the number of shares outstanding. Zeros, Zeros2, and ZeroVol are defined as the number of days with zero returns, zero returns and non-zero trading volume, and zero trading volume divided by the total number of valid trading days within that month, respectively. The Amihud measure is defined as $(1/D_m)\sum_{t=1}^{m}\left|r_{i,t}\right|/(volume\_USD_{i,t})$. The Amivest measure is defined as $(1/D_m)\sum_{t=1}^{m}(volume\_USD_{i,t})/\left|r_{i,t}\right|$. Gamma is formed based on Pastor and Stambaugh (2003). Illiq_Zero is defined as ln(Amihud)*(1+NT%).

The time-series correlation is calculated at the market portfolio level. We calculate the Pearson correlation using panel data. The difference in correlations is tested following Cohen and Cohen (1983). For each country, the highest correlation(s) between the effective bid-ask spread and liquidity proxies are indicated in bold. '% LC' shows the percentage of correlations larger than 0.55 across all the markets. '% Best' indicates the percentage of the highest correlation between each liquidity proxy and the effective bid-ask spread across all the markets and '% Second Best' presents the percentage of the highest correlations, assuming the best liquidity proxy does not exist.

NT% Group	Market	Roll	Gibbs	Turnover	Zeros	Zero2	ZeroVol	Amihud	Amivest	Gamma	Illiq_Zero	Amihud - Zeros
1	Taiwan	-0.050	0.037	-0.544	0.438	0.416	0.153	0.361	**-0.699**	-0.287	0.559	-0.077
	Turkey	0.622	**0.848**	0.541	0.067	0.011	0.419	0.762	-0.103	-0.447	0.635	0.695***
	China	0.320	0.526	0.264	0.349	0.528	0.035	**0.844**	-0.265	-0.226	0.414	0.495***
	Korea	0.198	0.426	-0.159	0.604	0.409	0.528	**0.743**	-0.344	-0.446	**0.719**	0.139**
	Portugal	**0.330**	**0.408**	-0.079	-0.074	-0.181	0.170	0.248	-0.154	-0.012	**0.396**	0.322***
	Greece	0.394	0.396	-0.172	**0.727**	0.245	**0.788**	0.577	-0.203	-0.147	0.463	-0.150***
	India	0.811	0.901	-0.161	0.772	0.602	0.853	0.883	-0.872	-0.278	**0.955**	0.111***
2	Malaysia	0.249	0.612	-0.694	0.612	0.290	0.796	**0.848**	-0.737	-0.278	**0.888**	0.236***
	Poland	0.734	0.832	-0.726	0.816	0.459	0.889	**0.903**	-0.837	0.308	**0.918**	0.087***
	Mexico	0.115	0.393	-0.378	0.601	0.038	0.733	0.491	0.327	0.058	**0.816**	-0.110*
	Singapore	0.670	**0.935**	-0.266	0.850	0.648	**0.911**	**0.936**	-0.578	0.004	0.879	0.086***
	Thailand	0.745	**0.918**	-0.290	0.422	-0.227	0.837	0.799	-0.507	0.048	**0.872**	0.377***
	Israel	0.311	0.494	0.322	0.651	-0.435	**0.792**	0.661	0.178	0.115	**0.743**	0.010
3	South Africa	0.512	**0.711**	-0.510	0.567	0.223	**0.681**	**0.770**	-0.510	-0.100	**0.740**	0.203***
	Indonesia	0.873	**0.967**	-0.144	0.592	0.631	0.194	0.462	-0.637	0.090	0.602	-0.130**
	Argentina	0.098	**0.748**	-0.130	0.399	0.064	0.434	0.143	-0.187	-0.041	0.353	-0.256*
	Philippines	0.285	0.432	-0.411	0.578	-0.428	0.849	0.791	-0.749	0.132	**0.896**	0.213***
	Brazil	**0.599**	**0.609**	0.424	**0.567**	0.286	**0.568**	0.018	0.062	-0.018	0.169	-0.549***
	Chile	0.088	0.549	0.110	0.568	0.290	**0.616**	0.469	-0.256	0.200	**0.633**	-0.099*
	Russia	0.210	0.313	-0.083	**0.424**	0.185	**0.417**	0.238	-0.312	-0.225	0.329	-0.186**
	Average	0.406	0.603	-0.154	0.527	0.203	0.583	0.597	-0.369	-0.078	0.649	-
	% LC	35.00	50.00	10.00	65.00	15.00	60.00	60.00	35.00	0.00	70.00	-
	% Best	10.00	40.00	0.00	15.00	0.00	35.00	30.00	5.00	0.00	55.00	-
	% Second Best	10.00	45.00	0.00	15.00	0.00	50.00	40.00	15.00	0.00	-	-

Table 6: Time-series correlations: *Lambda* as the benchmark

This table shows the time-series correlations between the price impact measure of Lambda and liquidity proxies formed using low-frequency data at the market portfolio level. Lambda is formed based on Hasbrouck (2009). Turnover measures the daily share trading volume divided by the number of shares outstanding. Zeros, Zeros2, and ZeroVol are defined as the number of days with zero returns, zero returns and non-zero trading volume, and zero trading volume divided by the total number of valid trading days within that month, respectively. The Amihud measure is defined as $(1/D_m)\sum_{t=1}^{m}|r_{i,t}|/(volume\_USD_{i,t})$. Amivest is defined as $(1/D_m)\sum_{t=1}^{m}(volume\_USD_{i,t})/|r_{i,t}|$. Gamma is formed based on Pastor and Stambaugh (2003). Illiq_Zero is defined as ln(Amihud)*(1+NT%).

The time-series correlation is calculated at the market portfolio level. We calculate the Pearson correlation using panel data. The difference in correlations is tested following Cohen and Cohen (1983). For each country, the highest correlation(s) between the price impact of *Lambda* and liquidity proxies are indicated in bold. '% LC' shows the percentage of correlations larger than 0.55 across all the markets. '% Best' indicates the percentage of the highest correlation between each liquidity proxy and the liquidity benchmark across all the markets and '% Second Best' presents the percentage of the highest correlations assuming the best liquidity proxy does not exist.

NT% Group	Market	Turnover	Zeros	Zero2	ZeroVol	Amihud	Amivest	Gamma	Illiq_ Zero	Amihud - Zeros
1	Taiwan	-0.504	0.151	0.062	0.279	0.735	-0.586	-0.613	**0.828**	0.584***
	Turkey	**-0.520**	-0.308	-0.270	-0.363	-0.351	0.080	0.251	-0.345	-0.043
	China	0.062	0.206	0.347	0.013	0.549	-0.449	-0.156	**0.709**	0.343***
	Korea	**-0.437**	0.015	-0.123	0.119	**0.515**	-0.165	**-0.465**	**0.409**	0.500***
	Portugal	-0.346	-0.109	-0.163	0.066	**0.896**	-0.360	0.083	0.801	1.005***
	Greece	**-0.189**	-0.156	-0.060	-0.162	**0.181**	**-0.252**	0.039	**0.240**	0.337***
	India	-0.021	0.660	0.517	0.728	0.842	-0.867	-0.263	**0.902**	0.182***
2	Malaysia	-0.243	0.059	-0.229	0.345	0.345	-0.465	-0.386	**0.506**	0.286***
	Poland	-0.706	0.858	0.507	**0.922**	**0.940**	-0.812	0.230	**0.932**	0.082***
	Mexico	-0.172	0.547	0.139	**0.588**	0.243	0.295	-0.096	**0.625**	-0.304***
	Singapore	-0.134	-0.143	-0.352	0.106	0.337	**-0.555**	0.117	**0.459**	0.480***
	Thailand	-0.303	0.307	-0.290	**0.737**	0.559	-0.287	-0.038	**0.732**	0.252***
	Israel	0.147	0.585	-0.503	**0.733**	**0.691**	0.058	0.084	**0.700**	0.106*
3	South Africa	0.274	0.481	0.368	0.466	0.162	**-0.754**	0.085	**0.700**	-0.319***
	Indonesia	-0.139	0.196	0.205	0.033	0.343	-0.346	0.005	**0.452**	0.147**
	Argentina	0.064	-0.354	-0.328	-0.255	**0.708**	**-0.702**	-0.193	**0.661**	1.062***
	Philippines	0.291	-0.375	0.025	-0.421	-0.199	-0.213	-0.052	-0.362	0.176***
	Brazil	0.095	**0.176**	**0.215**	0.095	**0.207**	0.028	-0.130	0.099	0.031
	Chile	0.034	0.167	0.069	0.190	**0.313**	-0.142	0.043	**0.279**	0.146
	Russia	-0.214	**0.354**	0.207	**0.340**	**0.315**	-0.184	-0.037	**0.382**	-0.039
	Average	-0.148	0.166	0.017	0.228	0.417	-0.334	-0.075	0.485	-
	% LC	5.00	15.00	0.00	25.00	40.00	30.00	5.00	50.00	-
	% Best	15.00	10.00	5.00	25.00	45.00	20.00	5.00	80.00	-
	% Second Best	15.00	15.00	5.00	30.00	70.00	40.00	10.00	-	-

Table 7: Descriptive statistics of country-level variables

Composite risk measure is obtained from the International Country Risk Guide (ICRG), with high values indicating low level of risk. Market liberalization is measured following Bekaert, Harvey and Landblad (2007) by the ratio of the market capitalization of the constituent firms comprising the S&P-IFC Investable Index to that of firms comprising the S&P-IFC Global Index for each country. Data on shareholder rights, enforcement and disclosure are from LLSV (1998) and LLSV (2006), with high values indicating high protection of shareholder rights, high quality of enforcement and high level of disclosure, respectively. Annual GDP per capita measured in 1,000 USD is retrieved from the Economist Intelligence Unit (EIU). Total market capitalization and trading volume are measured in billions of USD and millions of USD, respectively. Average stock price in the market is in USD. Market volatility is constructed based on French, Schwert and Stambaugh (1987). Composite risk, market liberalization, market capitalization, market volatility, trading volume and market price are measured at the monthly frequency while GDP per capita is an annual measure. Shareholder rights index, enforcement and disclosure have one value for each market.

Panel A presents the mean values of the country-level variables with the median values, if available, in the braces.

Panel B shows the Pearson correlations between the country-level variables. Within the the parentheses are the corresponding *p*-values. Correlations which are significantly different from zero at the 0.01 significance level are indicated in bold.

Panel A: Summary statistics

Country	Composite Risk	Market Liberalization	Shareholder Rights Index	Enforcement	Disclosure	GDP Per Capita	Market Cap.	Market Volatility	Trading Volume	Market Price
Argentina	67.71	0.94	4	5.64	0.50	10.11	88.41	0.07	0.23	2.52
	[69.50]	[0.97]				[9.20]	[66.26]	[0.06]	[0.17]	[2.46]
Brazil	66.01	0.94	4	6.46	0.25	8.14	145.22	0.07	6.79	24.12
	[65.65]	[0.95]				[7.81]	[81.80]	[0.06]	[5.94]	[24.56]
Chile	79.86	0.94	6	6.77	0.58	11.84	69.53	0.04	8.04	8.86
	[80.50]	[0.96]				[12.21]	[67.44]	[0.04]	[4.68]	[3.44]
China	75.52	0.38	-	-	-	3.11	384.70	0.07	5.06	1.32
	[75.00]	[0.37]				[2.87]	[183.65]	[0.06]	[2.90]	[1.33]
Greece	74.76	1.00	3	6.84	0.33	23.09	28.06	0.07	0.53	3.69
	[74.80]	[1.00]				[22.69]	[28.28]	[0.06]	[0.42]	[4.61]
India	67.80	0.44	5	6.12	0.92	1.81	157.20	0.08	3.46	4.18
	[67.80]	[0.41]				[1.69]	[65.97]	[0.07]	[2.56]	[3.63]
Indonesia	60.70	0.86	2	4.38	0.50	2.74	56.16	0.09	1.20	0.32
	[61.30]	[0.88]				[2.63]	[48.68]	[0.07]	[0.87]	[0.17]
Israel	69.79	0.99	3	7.79	0.67	21.44	40.93	0.05	0.71	7.88
	[70.00]	[0.99]				[20.50]	[33.32]	[0.05]	[0.68]	[7.04]
Korea	78.83	0.89	3	6.71	0.75	18.69	326.39	0.09	4.71	13.88
	[79.80]	[0.95]				[18.66]	[221.56]	[0.08]	[2.81]	[11.69]
Malaysia	77.23	0.93	5	7.71	0.92	9.83	100.37	0.06	0.92	1.03
	[77.00]	[0.93]				[9.40]	[98.60]	[0.04]	[0.49]	[0.63]

Mexico	72.72	0.98	1	5.99	0.58	11.35	265.05	0.06	8.07	2.66
	[72.50]	[0.99]				[11.02]	[310.66]	[0.05]	[7.51]	[2.49]
Philippines	69.81	0.52	3	4.08	0.83	2.47	63.46	0.06	0.35	1.11
	[69.50]	[0.49]				[2.38]	[44.61]	[0.05]	[0.21]	[1.06]
Poland	75.69	0.98	-	-	-	12.95	20.95	0.05	0.62	6.15
	[75.80]	[0.98]				[12.69]	[12.94]	[0.05]	[0.35]	[6.67]
Portugal	78.22	-	3	7.81	0.42	21.11	69.09	0.04	12.11	6.44
	[78.30]	-				[20.84]	[59.37]	[0.04]	[11.99]	[6.64]
Russia	78.84	0.78	-	-	-	12.96	388.81	0.08	1.90	61.80
	[78.00]	[0.90]				[13.23]	[442.06]	[0.07]	[0.73]	[42.03]
Singapore	87.98	-	5	8.99	1.00	29.17	1.31	0.06	0.02	0.01
	[89.00]	-				[27.46]	[0.88]	[0.05]	[0.02]	[0.01]
South Africa	71.80	1.00	5	6.70	0.83	7.26	225.55	0.06	2.80	4.92
	[72.00]	[1.00]				[6.77]	[115.41]	[0.05]	[2.20]	[4.17]
Taiwan	82.05	0.60	3	8.08	0.75	24.60	272.26	0.07	11.31	0.98
	[83.00]	[0.57]				[22.69]	[242.69]	[0.06]	[6.90]	[0.91]
Thailand	72.73	0.53	2	5.93	0.92	5.76	62.82	0.09	1.54	1.22
	[73.90]	[0.55]				[5.32]	[49.25]	[0.07]	[1.35]	[0.91]
Turkey	60.35	0.98	2	5.46	0.50	9.03	10.98	0.12	1.71	9.29
	[58.00]	[0.99]				[8.32]	[5.20]	[0.10]	[1.40]	[5.35]
Average	73.42	0.82	3.47	6.56	0.67	12.37	138.86	0.07	3.60	8.12
	[73.75]	[0.93]	[3.00]	[6.70]	[0.67]	[10.73]	[78.97]	[0.07]	[1.81]	[3.94]

Panel B: Pearson correlations

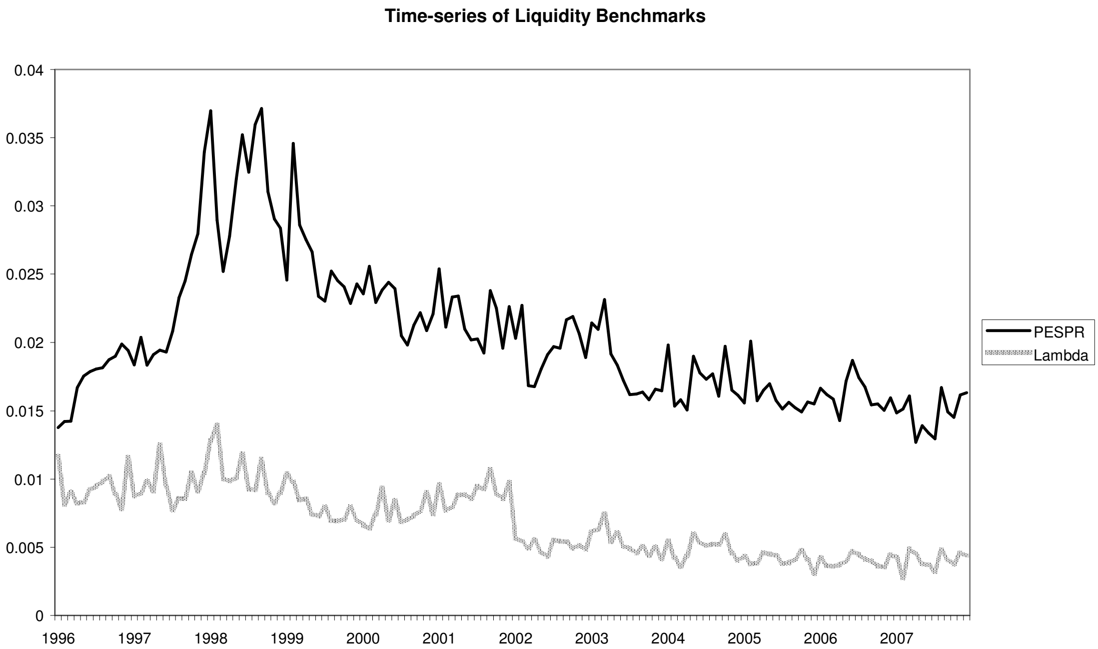
	Market Liberalization	Shareholder Rights Index	Enforcement	Disclosure	GDP Per Capita	Market Cap.	Market Volatility	Trading Volume	Market Price
Composite Risk	**-0.132**	**0.335**	**0.665**	**0.421**	**0.564**	**0.209**	**-0.309**	0.154	-0.018
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.33)	(0.40)
Market Liberalization		0.004	**0.190**	**-0.506**	**0.394**	0.045	**-0.059**	**-0.119**	**0.166**
		(0.87)	(0.00)	(0.00)	(0.00)	(0.05)	(0.01)	(0.00)	(0.00)
Shareholder Rights Index			**0.465**	**0.361**	**0.091**	-0.032	**-0.190**	**-0.064**	0.039
			(0.00)	(0.00)	(0.00)	(0.16)	(0.00)	(0.00)	(0.08)
Enforcement				**0.298**	**0.775**	0.069	**-0.169**	**0.142**	0.001
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.97)
Disclosure					0.021	0.051	**-0.067**	**-0.133**	**-0.353**
					(0.34)	(0.02)	(0.00)	(0.00)	(0.00)
GDP Per Capita						0.040	**-0.179**	**0.060**	0.029
						(0.06)	(0.00)	(0.00)	(0.17)
Market Cap.							**-0.088**	**0.303**	**0.185**
							(0.00)	(0.00)	(0.00)
Market Volatility								0.018	0.042
								(0.39)	(0.05)
Market Price									**0.158**
									(0.00)

Table 8: Determinants of market liquidity

We use a random effects specification in each model. The dependent variable is the monthly market liquidity measures listed in the second row. Data on composite risk is from the International Country Risk Guide (ICRG), with high values indicating low level of risk. Market liberalization is measured following Bekaert, Harvey and Landblad (2007) by the ratio of the market capitalization of the constituent firms comprising the S&P-IFC Investable Index to that of firms comprising the S&P-IFC Global Index for each country. Data on shareholder rights, enforcement and disclosure are from LLSV (1998) and LLSV (2006), with high values indicating high protection of shareholder rights, high quality of enforcement and high level of disclosure, respectively. GDP per capita measured in 1,000 USD is retrieved from the Economist Intelligence Unit (EIU). Market volatility is constructed based on French, Schwert and Stambaugh (1987). Price, trading volume, market capitalization and GDP per capita are log scaled. For the ease of presentation, we also adjust the scale of the estimated coefficients based on the magnitude of the dependent variable. Within the parentheses are the White (1980) *t*-statistics. *, **, and *** indicate the significance at the 0.05, 0.01 and 0.001 level, respectively.

	Dependent Variables											
	PESPR	**Lambda**	**Roll**	**Gibbs**	**Turnover**	**Zeros**	**Zeros2**	**ZeroVol**	**Amihud**	**Amivest**	**Gamma**	**Illiq_Zero**
Intercept	0.122***	0.055**	0.910***	0.883***	0.180***	1.030***	0.601***	0.447***	33.741***	-0.029	-0.010	27.819***
	(4.65)	*(4.86)*	*(7.09)*	*(4.07)*	*(4.26)*	*(5.30)*	*(4.80)*	*(4.46)*	*(3.91)*	*(-0.39)*	*(-1.92)*	*(11.54)*
Composite Risk	-0.001***	0.000	-0.003***	-0.001**	-0.001***	-0.000	-0.001***	0.000	-0.058*	-0.239	0.001**	-0.032***
	(-9.88)	*(1.14)*	*(-9.59)*	*(-2.89)*	*(-5.84)*	*(-1.56)*	*(-3.98)*	*(1.05)*	*(-2.35)*	*(-1.37)*	*(2.69)*	*(-4.90)*
Market Liberalization	-0.011***	-0.010***	0.017	-0.002	0.048***	-0.108***	-0.031***	-0.074***	-1.692	-10.900	0.003*	-2.600***
	(-4.37)	*(-5.35)*	*(1.14)*	*(-0.69)*	*(7.29)*	*(-7.82)*	*(-3.57)*	*(-7.15)*	*(-1.50)*	*(-1.37)*	*(2.17)*	*(-8.78)*
Shareholder Rights	0.004	-0.003**	-0.011	0.000	-0.005	0.052*	0.019	0.032**	0.418	-6.595	-0.000	0.223
	(1.44)	*(-2.92)*	*(-0.78)*	*(0.03)*	*(-1.34)*	*(2.22)*	*(1.25)*	*(2.82)*	*(0.46)*	*(-0.81)*	*(-0.86)*	*(1.18)*
Enforcement	-0.007	0.009***	0.023	-0.003	-0.010	-0.088**	-0.054**	-0.031*	-0.134	3.906	-0.001	-0.508
	(-1.88)	*(5.54)*	*(1.23)*	*(-1.16)*	*(-1.79)*	*(-3.02)*	*(-2.87)*	*(-2.11)*	*(-0.11)*	*(0.37)*	*(-0.92)*	*(-1.47)*
Disclosure	0.021	-0.011	0.044	0.016	0.089***	0.151	0.148	-0.008	-6.678	-10.500*	0.002	-0.483
	(1.11)	*(-1.57)*	*(0.50)*	*(1.27)*	*(3.43)*	*(1.04)*	*(1.58)*	*(-0.12)*	*(-1.16)*	*(-2.03)*	*(0.79)*	*(-0.30)*
log (GDP per capita)	-0.003	-0.010***	-0.076***	-0.002	0.009	0.036**	0.017*	0.014	-2.134*	8.096	0.001	-0.137
	(-1.20)	*(-6.43)*	*(-5.48)*	*(-0.60)*	*(1.51)*	*(2.73)*	*(2.03)*	*(1.42)*	*(-2.03)*	*(1.07)*	*(0.22)*	*(-0.49)*
Market Cap.	-0.002***	-0.001***	-0.003	-0.001	-0.015***	-0.023***	-0.014***	-0.008***	0.180	1.241	0.000	-0.129**
	(-5.51)	*(-5.78)*	*(-1.44)*	*(-1.89)*	*(-17.29)*	*(-11.86)*	*(-11.13)*	*(-5.69)*	*(1.15)*	*(1.10)*	*(1.14)*	*(-3.12)*
Market Volatility	0.072***	0.032***	0.215***	0.066***	0.010	-0.324***	-0.318***	-0.012	-1.122	-6.750***	0.012***	3.704***
	(12.54)	*(7.88)*	*(6.59)*	*(9.17)*	*(0.65)*	*(-10.61)*	*(-16.28)*	*(-0.51)*	*(-0.44)*	*(3.81)*	*(3.37)*	*(5.61)*
Trading Volume	-0.003***	-0.002***	0.008***	-0.002***	0.009***	-0.036***	-0.012***	-0.024***	-0.328*	9.139***	-0.000	-0.900***
	(-8.62)	*(-8.25)*	*(4.07)*	*(-4.65)*	*(10.25)*	*(-19.64)*	*(9.76)*	*(-17.39)*	*(-2.16)*	*(8.53)*	*(-1.44)*	*(-22.60)*
Price	-0.003**	-0.001	-0.022***	-0.001	0.012***	-0.003	0.000	-0.003	-2.939***	4.455***	0.000	-0.729***
	(-6.32)	*(-0.81)*	*(-8.68)*	*(-1.70)*	*(11.01)*	*(-1.23)*	*(0.19)*	*(-1.60)*	*(-15.08)*	*(3.23)*	*(1.19)*	*(14.25)*
R-square (%)	24.20	33.00	39.01	25.62	47.21	22.90	30.15	10.95	41.82	38.49	3.03	48.26
Number of Observation	1,728	1,695	1,834	1,827	1,827	1,728	1,728	1,728	1,728	1,728	1,728	1,728

Figure 1



Time-series of Liquidity Benchmarks
0.04
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
PESPR
Lambda