MEASURING LIQUIDITY IN EMERGING MARKTES

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Contents

Summary

I propose a new liquidity measure, *Illiq_Zero*, which incorporates both the trading frequency and the price impact dimensions of liquidity. Based on the transaction-level data for 20 emerging markets from 1996 to 2007, I conduct a comparison analysis on the new liquidity measure and the other existing liquidity proxies. The results indicate that the new liquidity measure shows the highest correlations with the liquidity benchmarks. The Amihud illiquidity ratio of absolute stock returns to trading volume and the Zeros measure defined as the proportion of zero return days within a month are moderately correlated with the liquidity benchmarks and their performance is related to the trading activeness of the market.

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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 the 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 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 emerging markets.

To overcome this problem, a bunch of studies has proposed several low-frequency liquidity proxies.[1] Based on these measures, many studies have explored the effect of liquidity on various spectrum of finance. [2] 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

[1] For example, the Roll measure (Roll, 1984), Zeros measure (Lesmond, Ogden, and Trzcinka, 1999), the Amihud illiquidity ratio (Amihud, 2002), the Gibbs measure (Hasbrouck, 2009), the Liu's *LMx* measure (Liu, 2006), among others.
[2] See Acharya and Pedersen (2005), Pastor and Stambaugh (2003), Sadka (2006), Watanabe and Watanabe (2008), Goyenko (2006), and Bekaert, Harvey, and Lundblad (2007), among others, in asset pricing; Chordia, Goyal, Sadka, Sadka and Sivakumar (2008), and Tetlock (2008) in market efficiency; and Heflin and Shaw (2000), Lerner and Schoar (2004), Lipson and Mortal (2009), among others, in corporate finance.

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.

With the enhanced globalization of stock markets, emerging markets have grown 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. However, the characteristics of emerging markets could lead to liquidity being measured with more noise, if the existing liquidity proxies proposed based on the US market are used. Compared to the US market, emerging markets have more insider trading and weaker corporate governance. Investors, especially retail investors, have the expectation that they can be expropriated by the management or more informed investors. They also have relatively low disposable income to invest in the stock market and limited resource to obtain information. All these factors result in the on average low trading activity in the emerging markets. In other words, trading frequency becomes particularly important in emerging markets but the existing liquidity proxies rarely consider it. On the other hand, trading activeness vary across individual markets. There are a lot more trading in markets such as China and South Korea than in markets such as Indonesia and Philippines. Hence, some liquidity proxies designed to capture the trading costs could have different performance in different markets. As an example, the values the Zeros measure (proportion of zero-return days within a time period), become close to zero for all the stocks in an active market and therefore could not gauge the cross-sectional or the time-series variation in the underlying stock liquidity. A better liquidity proxy is expected to work well in all the emerging markets.

This study proposes a new liquidity proxy, *Illiq_Zero*, defined as the log transformation of the Amihud measure multiplied by the sum of 1 and *ZeroVol*, representing the proportion of no-trading days in a month. The new measure thus incorporates two dimensions of liquidity: price impact and trading frequency. The reason to combine the trading frequency with price impact rather than transaction cost is that emerging markets have relatively high information asymmetry. Both the theoretic models (Kyle, 1985; and Easley and O'Hara, 1987; Glosten, 1989) and the empirical analysis (Glosten and Harris, 1988) suggest that the liquidity effects of asymmetric information are most likely to be captured in the price impact of a trade. The new measure is also motivated by the complementariy between the Amihud measure and *ZeroVol*, that is, the Amihud measure does not deal with the non-trading issue while *ZeroVol* is incapable of capturing the price impact of transactions. On obtaining transactions and quoted data in 20 emerging markets from 1996 to 2007, I conduct a comparison analysis on my new liquidity measure and other low-frequency liquidity proxies such as Roll, Gibbs, turnover, Zeros, Amihud, Amivest and Gamma, in relation to the two high-frequency liquidity measures: the effective bid-ask spread and the price impact measure, *Lambda*.

The main comparison mechanism is the correlation between low-frequency liquidity proxies and the high-frequency liquidity benchmarks. Liquidity measures with higher correlations are considered more capable of capturing liquidity. I separate the correlation analyses into two parts: the cross-sectional and the time-series correlations. Amihud and Mendelson (1986), and Brennan and Subrahmanyam (1996), among others, suggest that illiquid stocks have higher expected returns. Hence the cross-sectional difference in stock liquidity is important and a good liquidity proxy should capture it. On the other hand, the covariance between stock liquidity and market return or liquidity over time is a priced factor as shown by Pastor and Stambaugh (2003), and Acharya and Pedersen (2005) in the U.S. markets and Lee (2011) in the global markets. So an important attribute of a good liquidity proxy is to gauge the time-series variation in liquidity. I find ample evidence that *Illiq_Zero* 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.

Among the widely-used low-frequency liquidity proxies, the Amihud measure and Zeros or *ZeroVol*, which is the proportion of zero trading volume days within a month, 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 shows higher correlations with liquidity benchmarks in markets with more no-trading days. This result also justifies my new liquidity measure, which is essentially a combination of them. Gibbs 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.

The high-frequency liquidity measures such as the effective bid-ask spread and the price impact measure might capture one specific aspect of the underlying liquidity. But liquidity is a multi-dimension concept. Hence, I perform a principal component analysis (PCA) on both the high- and low-frequency liquidity measures, with the assumption that the common factor(s) across all of them is the underlying liquidity factor. The results suggest that a large portion of the variation across liquidity measures can be explained by one single factor within each market. More importantly, the effective bid-ask spread and *Illiq_Zero* are significantly correlated with the dominant factor in 19 out of 20 markets. Further analysis indicates that the linear combination of all the low-frequency liquidity measures other than *Illiq_Zero* does not add additional value in explaining the underlying liquidity factor.

Prior studies suggest that stock liquidity is closely related to stock characteristics such as size and volatility. Smaller and more volatile stocks tend to have low liquidity. I expect that good liquidity measures should display this pattern. The cross-sectional analyses indicate that liquidity increases with firm size and decreases with volatility if the high-frequency liquidity measures are used as liquidity proxies. Among the low-frequency liquidity proxies, the new measure of *Illiq_Zero* generates the expected patterns in most markets. However, using the Zeros or *ZeroVol* measure produces the result in which volatility has negative effect on illiquidity in the majority of markets. This finding is as expected because volatility is associated with trading activity.

The main hypothesis in this study is that various liquidity proxies can capture the cross-sectional or time-series variation of the liquidity benchmarks. This study contributes to the literature in the following ways. First, it is among the first studies to examine 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 measure, *Lambda,* constructed from the intraday data as liquidity benchmarks. All of these measures are proposed based on the U.S. market. So this study provides an independent test of their performance. Furthermore, 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, I propose a new easily constructed liquidity measure, *Illiq_Zero*. The results show that it is the best liquidity proxy in capturing the cross-sectional and the time-series variations of the liquidity benchmarks in emerging markets. The better performance of the new measure suggests that trading frequency and price impact are two important facets of liquidity in the emerging markets. This new measure also facilitates the cross-country analysis focusing on the effects of liquidity in emerging markets, which needs a consistent liquidity proxy across countries.

The rest of the paper is organized as follows. Section 2 presents the related literature. Section 3 describes the data. Section 4 explains the methodology and empirical design. Construction of liquidity measures is shown in Section 5. Section 6 reports the results on the cross-sectional and the time-series correlation analyses. Section 7 produces the results of the principal component analysis. The examination of liquidity measures conditional on stock characteristics are shown in Section 8. Section 9 concludes the paper.

2. Related literature

The unavailability of high-frequency transaction data results in a bunch of studies proposing low-frequency liquidity proxies, which can be grouped into two categories.

Within the first category are more trading-based liquidity measures. 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 estimator of transaction costs. 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.

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 the 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 estimator, 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.

There is a growing literature with the focus on liquidity in emerging markets. However, different studies use different liquidity measures.[3] 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 (see Lesmond, Ogden, and Trzcinka, 1999), 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

[3] For example, 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 Bekaert, Harvey, and Lundblad (2007) and Lee (2011).

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. The low-frequency liquidity proxies are also restricted. Fong, Holden and Trzcinka (2010) compare various liquidity proxies to the transaction costs constructed from the TAQTIC dataset in the global stock market. They introduce a new measure, FHT, which is based on the standard deviation of daily stock returns and the proportion of zero returns, and find that it is the best proxy for the bid-ask spread. But none of the price impact proxies does a good job in measuring the price impact of transactions. Their study separates the two important dimensions of liquidity, the spread and the price impact, and compares the liquidity proxies based on each of them. Even though FHT is a good spread proxy, it could not capture the price impact of a trade. I expect that a better defined liquidity measure should capture both aspects of liquidity.

3. Data construction

My sample spans from January 2nd, 1996 to December 31st, 2007. I retrieve the intraday data used to calculate the effective bid-ask spread and the price impact measure, *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. I only include common stocks from major exchanges defined as having the majority of listed stocks in that country. In my sample, all markets have one major exchange except China which has both Shenzhen and Shanghai stock exchanges. Based on data availability and the definitions of emerging markets in EMDB and MSCI, I include 20 emerging markets in this study[4].

I only include common stocks covered by both datasets. Due to the lack of a common identifier, different mechanisms are used to merge the two databases depending on the markets. For some markets such as China, stocks in the two datasets can be directly matched. For others, however, I have to merge them by hand using the company names as the main matching instrument. To improve the accuracy, I 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. This process leads to around 70% of stocks from the Datastream in each market being matched to the dataset of TAQTIC.

To make the data clean, I exclude a trade or quote if (1) the trading volume and/or quoted depth is negative or above the 99.5^{th} 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

[4] To include as many as emerging markets, I classify one market as an emerging market as long as either EMDB or MSCI defines it as an emerging market.

spread exceeds 30%. I further require stocks to have trades on at least 5 days within one month. I also follow Ince and Porter (2006) to set daily stock returns to be missing if

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

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, I require each market to have at least 10 stocks in a month and have at least 20 months over time. Finally, I only include stocks traded in local currency.

4. Empirical design

In this paper, I run a horserace among the low-frequency liquidity proxies using the effective bid-ask spread, the price impact measure, or the dominant factor across liquidity measures 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 and the price impact measure, *Lambda,* are assumed to more accurately capture the underlying liquidity. Then the correlation between various liquidity proxies constructed from low-frequency data and the benchmark is examined, with the higher correlation a sign of better performance of the liquidity proxy. Consistent with the literature, I also rely on the correlations as the main method in comparing the performance of liquidity proxies. Specifically, I employ three performance metrics. The first one is the average cross-sectional correlations between the high-frequency liquidity benchmarks and the low-frequency liquidity proxies. The correlation is calculated on individual stock basis. To test the difference in two correlations, I follow Goyenko, Holden and Trzcinka (2009) by running a *t*-test in a way similar to Fama-MacBeth. Specifically, in each month and for each liquidity proxy, I calculate its cross-sectional correlation with the liquidity benchmarks. To compare the performance of liquidity proxy *A* and *B*, I get the difference in their cross-sectional correlations with a liquidity benchmark in each month and obtain the time series of the difference in correlations. I 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, I 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 the second performance metric is the time-series correlation between the high-frequency liquidity benchmarks and the low-frequency liquidity proxies. In contrast to the stock level analysis when examining the cross-sectional correlations, I investigate the time-series correlations at the market portfolio level since the asset pricing research usually involves forming portfolios. Specifically, I 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. I then calculate the time-series correlations between the liquidity benchmarks and each liquidity proxy. To test the pair-wise difference in correlations, I 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}. The difference between r_{XY} and r_{VY} can be tested using the following t-statistic with n-3 degrees of freedom:

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

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 gauge illiquidity, I multiply these three measures by -1 when the correlations involve them.

To capture the underlying multi-dimensional liquidity in each market, a principal component analysis (PCA) is conducted. In this analysis, both the high- and low-frequency liquidity measures are used to extract the factors. The factor(s) is deemed as the dominant factor(s) if its eigenvalue is much larger than the eigenvalue of the following factor[5]. To increase the interpretability of factors, the orthogonally rotated factor loadings are used to determine the correlation between each liquidity measure and the factors. The factor loadings are significant if their absolute values are higher than or equal to 0.55, which corresponds to a R-square of 0.3 in the regression of the factors on the individual liquidity measure.

[5] The factors are retained until the sum of the eigenvalues is asymptotic. Some studies, i.e. Lesmond (2005), determine the dominant factors by the ratio of the first, largest eigenvalue and the next largest eigenvalue. If the ratio is larger than 1, the first factor is considered the dominant factor.

5. Liquidity measures

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

5.1 A new liquidity measure

The new measure is a combination of price impact and trading frequency and it is motivated by the importance of information asymmetry in the emerging market. In contrast to the more developed markets, emerging markets have weaker disclosure requirements, smaller number of analyst following and lower media penetration. Therefore, I expect that information asymmetry is more of an issue in emerging markets and this leads to low trading frequency or activity. To test this hypothesis, I include both the developed markets and the emerging markets.[6] Three proxies are used to measure a country's information environment: accounting standard index from La Porta et al. (1998), financial transparency factor from Bushman, Piotroski and Smith (2004), and disclosure requirements index from La Porta et al. (2006). While these proxies are highly

[6] The daily return and trading volume information are retrieved from CRSP for the U.S. market (NYSE/AMEX) and from Datastream for other markets for the sample period from 1996 to 2007. To clean the data, the following filters are used: (1) Only ordinary stocks are included; (2) Use both active and dead stocks to mitigate the survivor bias; (3) Stocks are traded in the local currency; (4) Days on which 90% or more of stocks in a given exchange have zero returns are excluded; (5) I set the daily return to be missing if any daily return above 100% (inclusive) is reversed the next day or it is above 200%; (6) I set daily return to be missing if either the total return index on the previous day or that on the current day is less than 0.01; (7) For all the markets in our sample, to exclude stocks with extreme price levels, I drop stocks over the month if their prices at the end of previous month are in the extreme 1% (inclusive) at the top and bottom of the cross-section in each market; and (8) I require each market to have at least 50 stocks. The classification of emerging markets and developed markets is based on the definitions of emerging markets in EMDB and MSCI. One market is classified as an emerging market as long as either EMDB or MSCI defines it as an emerging market. Based on the data availability on the information transparency of each market, I include 35 markets for this analysis.

correlated, they have their own focus in capturing the information environment in each market. To construct a composite measure, I first rank all the markets based on each of the three proxies and then obtain the average of the three ranks, $TRANS_c$. The trading (in)frequency, $NT\%$, is measured by the proportion of zero-volume days in a month. The market level $NT\%_c$ is the equal-weighted average of the stocks' time-series average trading (in)frequency. The scatter plot of the trading infrequency and information transparency is shown in Figure 1. Consistent with our expectations, emerging markets tend to have low information transparency and high trading infrequency. More importantly, the trading infrequency and information transparency is negatively related. The regression of trading infrequency on information transparency shows the following results:

$$NT\%_c = 34.441 - 0.556\ TRANS_c$$

$$(t =) \quad (6.46) \quad (1.95) \qquad\qquad R^2 = 0.10$$

These results support the hypothesis that trading frequency is low in markets with high information asymmetry, or low information transparency.

I construct the new liquidity measure, *Illiq_Zero*, as follows

$$Illiq\_Zero_{i,m} = [\ln(\frac{1}{N_{i,m}}\sum_{t=1}^{N_{i,m}}\frac{|R_{i,t}|}{VOL_{i,t}})]\times(1+NT\%_{i,m}) \qquad (3)$$

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, $VOL_{i,t}$ is the US dollar trading volume of stock i on day t, and $NT\%$ is the percentage of no-trading days within a month. I measure the trading volume in billions of US dollars so that the first part of the measure, which is essentially the log of the Amihud illiquidity ratio, is positive. This is because

Illiq_Zero is an illiquidity measure and larger values imply low liquidity.[7] In addition, I take the natural logarithm of the Amihud illiquidity measure to account for its extremely large values.[8]

The 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 the 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 trading, the Amihud measure may not work well for firms or countries with many zero trading days within certain period. 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; Goyenko and Sarkissian, 2008; and Lee, 2011, 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. The 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, I expect the new liquidity

[7] By deflating the trading volume by 1 billion U.S dollars, I lose 14 observations, accounting for less than 0.01% of the sample size.
[8] The average correlation between the Amihud measure and *NT%* is 0.343, with lower correlations in more active markets such as China (0.100), South Korea (0.233), Taiwan (0.281), Turkey (0.131).

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 effectively.

5.2 Liquidity benchmarks constructed from high-frequency data[9]

5.2.1 Trade-based liquidity benchmark

In this study, two high-frequency liquidity benchmarks are employed. The first one is the effective bid-ask spread (*PESPR*)[10], 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. I use the share trade volume as the weight to get the daily *PESPR* and then average it over the month.

5.2.2 Price impact benchmark[11]

Bid-ask spread exists due to factors such as inventory carrying costs arising from risk aversion, or the transactions costs specialist must pay. These factors constitute the transitory component of the bid-ask spread. The spread also has an adverse-selection component because of the information asymmetry between the market makers and the traders. This component has a permanent impact on stock price movements. In an effort

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[9] I do not use depth as the liquidity measure because many of its values are missing in TAQTIC. Also, as Kang and Yeo (2009) suggest, depth is not a very good measure in capturing liquidity.

[10] As a robustness check, I 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.

[11] Bid-ask spread may be more appropriate for small or medium trades. Large orders, however, can be traded out of the bid-ask spread and the price impact measure might be able to measure liquidity in a better way.

to capture the price impact of transactions, Glosten and Harris (1988) propose a model in which the adverse selection component depends on the trade size, based on models of price formation such as Kyle (1985). Brennan and Subrahmanyam (1996) improve the model by adding a fixed cost component. Brennan, Chorida, Subrahmanyam and Tong (2009) propose variations of the Glosten and Harris's model to estimate the price impact for buys and sells separately.

To empirically estimate the price impact dimension of liquidity, I follow Hasbrouck (2009) by constructing our second high-frequency liquidity benchmark. 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. I run regression (5) over a month for each stock to get a monthly price impact measure.

The time-series variations of the two liquidity benchmarks averaged across all the emerging markets are shown in Figure 2. They show similar patterns over time. In down market such as the second half of 1997, there is a large increase in the effective bid-ask spread and the price impact measure. After 1999, the two liquidity benchmarks decreases gradually, indicating an improvement in liquidity over time in emerging markets.

[Insert Figure 2 here]

5.3 Liquidity proxies constructed from low-frequency data

5.3.1 Trade-based liquidity proxies

5.3.1.1 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 the effective spread can be estimated 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 can be estimated easily 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), I modify the Roll measure as follows:

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

5.3.1.2 Gibbs

Hasbrouck (2004) advocates a Bayesian estimation of the Roll model. In his 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

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

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 $p \equiv \{p_1, p_2, ..., p_T\}$, where T is the number of days in the time period, and the model parameters $\{c, \sigma_u^2\}$, the latent buy/sell indicators $q \equiv \{q_1, q_2, ..., q_T\}$, and the latent efficient prices $v \equiv \{v_1, v_2, ..., v_T\}$ are to be numerically estimated. The approach of the Gibbs sampler is an iterative process in which one sweep consists of three steps[12]. 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 estimator on his website. I use these codes directly without changing their main routines.

[12] 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.

The algorithm of constructing the Gibbs estimator 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. But there are many days with zero trading volume in emerging markets. To overcome the dependency problem, I follow Hasbrouck's suggestion by throwing out the days with zero trading volume in estimating the monthly Gibbs estimator in emerging markets. The daily price is converted to US dollar using the exchange rate at the end of previous month. I first use the raw daily price as the input and get Gibbs measured in US cents. Then I divide it by the monthly average of daily price to obtain the Gibbs estimator of transaction costs in percentage.

5.3.1.3 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, I propose another version of Zeros, *ZeroVol*[13], which is defined as

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

5.3.1.4 Liu's *LMx* 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

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

[13] Note that the value of *ZeroVol* is same as the value of *NT%* in the new liquidity measure.

for all sample stocks. I 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.

5.3.2 Price impact proxies

5.3.2.1 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*.

5.3.2.2 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*, $|R_{i,t}|$ 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, days with zero volume are excluded; but when the Amivest measure is constructed, days with zero returns are deleted. Therefore, the Amihud measure does not contain information on non-trading but does on noise trading. However, the Amivest measure captures neither of them.

5.3.2.3 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

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

where r_t^e is the stock's excess return above the value-weighted market return on day *t*, and Vol_t is the US dollar trading volume 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 0.313% 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. Hasbrouck (2009) find that the mean of the annual Gibbs estimator (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 monthly Gibbs in our sample is 2.096%, 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, I find that in most markets the Roll measure and the Gibbs estimator are smaller than the effective bid-ask spread. However, in relative more active markets such as China, South 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 Gibbs also results in the underestimation of the spread. In addition, the Gibbs estimator is closer to the effective bid-ask spread in magnitude than the Roll measure. The mean value of the price impact benchmark is 0.005, suggesting that a buy order of 10,000 in local currency would move the stock price by 0.5%. The mean 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.

6. Results on correlations

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

[Insert Table 2 here]

Using the effective bid-ask spread as the liquidity benchmark, I 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. I 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 I 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 South Korea. Nevertheless, the 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[14]. In the last column, I 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%*, I find mixed evidence of their performance. This finding justifies the new liquidity measure, which is a combination of the Amihud measure and *ZeroVol*, and is able to capture two dimensions of liquidity.

Most importantly, I find that the new liquidity measure, *Illiq_Zero*, is highly correlated with the effective bid-ask spread in all the emerging 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

[14] I also test the difference in correlations for the Amihud measure and *ZeroVol* and find similar pattern of complementarity between them.

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 the new liquidity measure in measuring bid-ask spread in the cross-section.

I also test the difference in correlations for other low-frequency liquidity measures. They are not indicated in Table 2 but can be 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 Goyenko, Holden and Trzcinka (2009), but also in markets with relatively thin trading. Second, focusing on the three zero measures, I 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 estimator, I 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[15]. Finally, turnover, Amivest and Gamma seem to be consistently dominated by other liquidity proxies.

[Insert Table 3 here]

It is possible that the above findings on the cross-sectional correlations are driven by the sample period. To deal with this issue, I break the sample into two equal time periods with each of them covering 6 years. I repeat the above analysis in each sub-sample period 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. I have 17 markets in the first time period because the 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, the 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. 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. I 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, I will not report the results for *LM1*.

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

6.2 Cross-sectional correlations with the price impact measure, *Lambda*

I report the cross-sectional correlations between the liquidity proxies and the price impact measure in Table 4. Here I 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 *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 the new liquidity measure, *Illiq_Zero*, is the best price impact measure: it shows the highest correlations with the price impact measure 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 I 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, the cross-sectional analyses in comparing the liquidity proxies in emerging markets suggest that: (1) The new liquidity measure, *Illiq_Zero*, is the best low-frequency liquidity measure using both the effective bid-ask spread and the price impact measure, *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 measure but the correlation is usually smaller in magnitude than its correlation with the effective bid-ask spread.

6.3 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 the time-series correlation is calculated at the market portfolio level and therefore, some measurement error affecting individual stocks might be diversified away. The other reason might be that liquidity proxies are more able to gauge the time series variation in liquidity benchmarks. However, I 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 stock 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. Nevertheless, 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 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 estimator is most correlated with the spread in time-series in 8 markets. This finding suggests that the Gibbs estimator 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. I also find some evidence that, in time-series, Amihud is more correlated with the effective spread in markets with more trading while *ZeroVol* or Zeros in markets with less trading, as indicated in the last column. Turnover, Amivest and Gamma show relatively low time-series correlations with the bid-ask spread.

6.4 Time-series correlations with the price impact measure, *Lambda*

I report the time-series correlations between the price impact measure, *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 *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. I 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 *Lambda* in 16 markets. The second best price impact proxy is Amihud and it is most correlated with *Lambda* in 14 markets, assuming the 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, I 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, the above 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, the 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 both the bid-ask spread and the price impact measure, *Lambda*, in time-series in more active markets.

7. Principal component analysis

Although the bid-ask spread and the price impact measure, *Lambda*, are treated as traditional liquidity measures, one would not expect one single measure could gauge all the different dimensions of liquidity, as suggested by Amihud (2002) and Amihud, Mendelson and Pedersen (2005). To capture the underlying liquidity factor, I do a principal component analysis (PCA) on the selected liquidity proxies including the effective bid-ask spread, *Lambda*, Gibbs, turnover, *ZeroVol*[16], Amihud, Amivest and *Illiq_Zero*.[17] The PCA requires the units across different liquidity measures to be comparable. So I standardize each of the eight liquidity measures so that their sample mean and standard deviation are 0 and 1, respectively, during the sample period within each market. I multiply the turnover measure and the Amivest measure by -1 for the purpose of easier interpretation of the results.

The eigenvalues of the first three factors are presented in column 2 to 4 in Table 7. The results show that the first eigenvalue is much larger than the second one in all the markets. For example, in Argentina, the first factor has an eigenvalue of 3.30 which is more than 300% of the eigenvalue of the second factor. On the other hand, the second eigenvalue is usually slightly larger than the third one in most of the markets. For instance, it decreases from 1.20 to 1.05 in South Korea. These patterns suggest that there is one dominant factor which is sufficient to explain the eight liquidity measures. Indeed, as shown in the last column of Table 7, at least 30% of total variation in the eight liquidity measures is explained by the first factor, indicating that different facets of liquidity comove.

To see the correlations between each liquidity measure and the factors, I report its rotated factor loadings on the three factors in Table 7. The significant factor loadings

[16] Replacing *ZeroVol* with Zeros or LM1 generates similar results.
[17] The dominant factors are sensitive to the number of variables measuring the same aspect of the underlying liquidity in the PCA. For instance, if I include all the four proxies of Zeros, *ZeroVol*, Zero2 and LM1, the dominant factor will be highly correlated with the spread. Therefore, when selecting the liquidity proxies in the PCA, I concentrate on those representing different aspects of liquidity. It is possible that the principal component analysis overweights the illiquidity ratio of Amihud if both Amihud and Amivest are included as one is the inverse of the other. Dropping the Amivest measure gives us similar results.

with absolute value larger than 0.55 are indicated in bold type. The most important finding is that the effective bid-ask spread and *Illiq_Zero* are significantly correlated with the dominant factor in 19 markets, as shown in the last row of Table 7. This indicates that the new liquidity measure is highly correlated with both the high-frequency liquidity benchmarks and the common variation across different liquidity measures. Another consistent evidence is that Gibbs, *ZeroVol*, and Amihud are more correlated with the dominant factor while *Lambda*, turnover and the Amivest measure are more related to the second or the third factor, supporting the relative better performance of the first three measures. In addition, *ZeroVol* has larger factor loadings on the dominant factor in less active markets such as Brazil and Chile while Amihud is more correlated with the dominant factor in more active markets such as China, Taiwan and South Korea. Overall, the PCA delivers similar results as the correlation analysis.

One would argue that, compared to other liquidity measures such as Zeros, Amihud, and Gibbs, the new measure *Illiq_Zero* combines the two dimensions of liquidity. As a result, it is natural to expect that it have higher correlation with liquidity benchmarks. And one way to construct a better liquidity proxy is simply to combine all the (low-frequency) liquidity proxies. To see the incremental value of combining all the liquidity proxies, I do a two-step PCA. In the first step, I perform a PCA on all the low-frequency liquidity measures other than *Illiq_Zero*, that is, Gibbs, turnover, *ZeroVol*, Amihud and Amivest, and obtain the first factor[18]. This factor, denoted as *LowFreq Factor*, is the linear combination of the five liquidity measures. In step two, a new PCA is performed on the two high-frequency liquidity measures, the new liquidity measure of *Illiq_Zero*, and the *LowFreq Factor* measure.

[18] Turnover and the Amivest measure are multiplied by -1.

The first three eigenvalues and the factor loadings are reported in Table 8. As before, the larger value of the first eigenvalue indicates that there is one dominant factor in most of the markets. Furthermore, the effective bid-ask spread and the *Illiq_Zero* measure are more correlated with the dominant factor. The factor loadings of *Illiq_Zero* are significant in 19 markets. Surprisingly, *LowFreq Factor* has significant correlations with the dominant factor in only 8 markets. This result indicates that there is no incremental value of combining all the other low-frequency liquidity proxies, compared to a single measure of *Illiq_Zero*. Instead, the combined measure is less correlated with the dominant factor of liquidity. One possible reason is that some liquidity proxies are noisy and a simple combination of them would increase the measurement noise.

8. Liquidity and stock characteristics

As an important stock attribute, liquidity is closely related with other stock characteristics such as firm size and volatility. Although it is not a direct liquidity measure, firm size, or the market value of the stock, is correlated with many variables which are related to liquidity, including trading volume, stock price continuity, number of market makers trading the stock (See Garbade, 1982; Stoll, 1985). Amihud (2002) suggests that size is related to liquidity because a larger stock issue usually has smaller price impact for a given order flow and a small bid-ask spread. So I sort stocks in each market into five portfolios based on their beginning-of-year market capitalization and examine the patterns of the liquidity measures across these portfolios. The hypothesis is that liquidity increases with firm size. Based on the above analyses, I include five liquidity proxies: the effective bid-ask spread, *Lambda*, *ZeroVol*, Amihud and the new measure of *Illiq_Zero*.

Results in Table 9 indicate that a negative size-illiquidity relationship generally holds in the emerging markets. The effective bid-ask spread and the price impact measure, *Lambda,* measure decreases monotonically with firm size in all the markets and the differences between the small and the large stocks are statistically positive. Take Malaysia as an example, the effective bid-ask spread for size quintile 1, 3 and 5 is 3.33%, 2.15% and 1.01%, respectively, and the difference between quintile 1 and 5 is 2.32%, which is statistically significant. The values of *ZeroVol* and Amihud decrease with firm size in most markets. But we do not find such a relationship in China, Greece, Russia and Turkey (Greece, Portugal, Poland and South Korea) for the *ZeroVol* (Amihud) measure. On the other hand, the difference in *Illiq_Zero* between the small quintile and the large quintile is significantly positive in all the markets other than Russia.

As a measure of stock risk, volatility and illiquidity are positively correlated. Stoll (1978) suggests that bid-ask spread set by a risk-averse market maker increases with stock risk. Constantinides (1986) proposes that stock variance positively affects its required return because of the higher trading costs as a consequence of more frequent portfolio rebalancing. O'Hara and Oldfield (1986) indicate that volatility increases the inventory value uncertainty and therefore has a positive effect on stock illiquidity. I group stocks based on their volatility estimated using monthly return in the past year within each market and examine the cross-sectional variation in liquidity measures. The expectation is that liquidity becomes low for highly volatile stocks.

The equal-weighted portfolio liquidity measures for the 1st (high), 3rd (medium) and 5th (low) volatility quintiles are shown in Table 10. The effective bid-ask spread and *Lambda* increase with volatility in most of the emerging markets. However, in markets such as Argentina, Malaysia and Thailand, the difference in the two measures between the high and low volatility quintile are insignificant or significantly negative. Among the three low-frequency liquidity measures, the Amihud measure and *Illiq_Zero* have significantly larger values in high volatility quintile than in low volatility quintile in 14 markets. But the positive illiquidity-volatility holds in only 4 markets if *ZeroVol* is used to measure liquidity. A similar result is obtained using the Zeros or the LM1 measure. This result suggests that *ZeroVol* may not be able to capture the high transaction costs and inventory risk associated with the stock volatility.

Overall, examining the cross-sectional variation in liquidity measures conditional on size and stock volatility suggests that liquidity, constructed from high-frequency data, tend to be low for small and highly volatile stocks. Among the low-frequency liquidity measures, the new measure *Illiq_Zero* shows the expected pattern in the majority of markets. In a contrast, the positive effect of volatility on illiquidity rarely holds for the *ZeroVol* measure.

9. 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, I examine the various existing liquidity proxies plus a new measure, *Illiq_Zero*, which can be interpreted as a no-trading-day adjusted Amihud measure. This measure is motivated by the hypothesis that trading frequency is low in emerging markets because of high information asymmetry. So liquidity proxies which do not incorporate the trading frequency information could measure the underlying liquidity with more noise. 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. The main mechanism to compare the performance of liquidity proxies is to compare their correlations with the liquidity benchmarks, including the effective bid-ask spread and the price impact measure, *Lambda*.

The correlation analyses show strong evidence that the new liquidity measure, is the best low-frequency liquidity proxy. It shows the highest cross-sectional correlations with the effective bid-ask spread and *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 the 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. I also find that the Gibbs estimator 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 high-frequency liquidity benchmarks

I also do a principal component analysis (PCA) on the main low-frequency liquidity proxies as well as the two high-frequency liquidity measures. I find that the effective bid-ask spread and the new measure of *Illiq_Zero* are significantly correlated with the dominant factor in 19 markets. Furthermore, a simple linear combination of all the low-frequency measures other than *Illiq_Zero* does not add any incremental value in capturing the underlying liquidity. In addition, the cross-sectional analyses of liquidity measures conditional on firm size and volatility indicate that liquidity, measured by the high-frequency liquidity proxies and *Illiq_Zero*, tend to be low for smaller and more volatile firms but this pattern is not pronounced for other measures such as *ZeroVol*.

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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. Gibbs is the Gibbs estimate of effective cost and is formed base on Hasbrouck (2004). I scale 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. I 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. I 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.

		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]
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]
South 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]
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]

(To be continued)

		High-frequency Liquidity Benchmarks		Low-frequency Liquidity Proxies									
Market	**Start**	**PESPR** (%)	**Lambda**	**Roll** (%)	**Gibbs** (%)	**Turnover** (%)	**Zeros** (%)	**ZeroVol** (%)	**LM1**	**Amihud**	**Amivest**	**Gamma**	**Illiq_Zero**
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]
Average													
		2.881	0.005	1.577	2.096	1.052	28.239	14.563	2.897	7.719	4.481	-0.035	12.871

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. I sort all the markets by *NT%*, which is the percentage of no-trading days within a month, into three groups. Market NT% is calculated as the time-series average of cross-sectional mean of *NT%*. Markets in NT% group 1 (3) have fewer (more) no-trading days, indicating high (low) level of trading volume. I first calculate the Pearson correlation across all the stocks in each month. Then the correlation coefficients are averaged over time. The difference in correlations is tested 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 '% 2nd 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 the Amihud measure 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**
	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***
1	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**
	South 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***
	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
2	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**
	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**
3	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	-
	% 2nd 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. I 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. I first calculate the Pearson correlation across all the stocks in each month. Then the correlation coefficients are averaged over time. I 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 '% 2nd 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 the Amihud measure 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. I 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***
	South 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	-
	% 2nd 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***
	South 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	-
	% 2nd 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 measure (*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. I 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. I first calculate the Pearson correlation across all the stocks in each month. Then the correlation coefficients are averaged over time. I 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 '% 2nd 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	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***
	South 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	-
	% 2nd 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. The time-series correlation is calculated at the equal-weighted market portfolio level. 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 '% 2nd 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***
	South 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	-
	% 2nd Best	10.00	45.00	0.00	15.00	0.00	50.00	40.00	15.00	0.00	-	-

Table 6: Time-series correlations: the price impact measure (*Lambda)* as the benchmark

This table shows the time-series correlations between the price impact measure, *Lambda,* and the liquidity proxies formed using low-frequency data at the market portfolio level. The time-series correlation is calculated at the equal-weighted market portfolio level. The difference in correlations is tested following Cohen and Cohen (1983). 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 '% 2nd 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
	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***
1	South 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***
	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***
2	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*
	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***
3	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	-
	% 2nd Best	15.00	15.00	5.00	30.00	70.00	40.00	10.00	-	-

Table 7: Principal component analysis

This table shows the results of principal component analysis (PCA) using standardized PESPR, *Lambda*, Gibbs, turnover, *ZeroVol*, Amihud, Amivest and *Illiq_Zero*. The eigenvalues of first three factors are reported in column 2 to 4. Then the factor loadings of each liquidity proxy on the first, second and third factors are reported column 5 to 12. Finally, the percent of variance explained by each factor is reported in the last column. Factor loading is significant if it is larger than 0.55 and these factor loadings are shown in bold. '% LF' in the last row indicates, for each liquidity proxy, the percentage of significant factor loadings on the first factor across all the countries.

	Eigenvalues			Factor loadings								% of var.
Market	**First**	**Second**	**Third**	**PESPR**	**Lambda**	**Gibbs**	**Turnover**	**ZeroVol**	**Amihud**	**Amivest**	**Illiq_Zero**	**explained**
Argentina	3.30	1.05	0.88	**0.72**	0.06	0.25	0.02	**0.93**	0.37	0.36	**0.90**	41.25
				0.36	**0.82**	0.51	-0.07	0.05	**0.60**	0.29	0.32	13.13
				0.07	0.19	-0.27	**0.87**	0.00	-0.01	0.45	0.15	11.00
Brazil	3.06	1.28	0.98	**0.87**	-0.01	0.53	-0.01	**0.86**	0.34	0.13	**0.87**	38.25
				0.01	0.04	-0.05	**0.82**	0.06	0.04	**0.79**	0.24	16.00
				0.15	**0.84**	0.40	0.03	-0.03	**0.59**	0.02	0.23	12.25
Chile	2.94	1.45	0.99	**0.79**	0.07	**0.64**	-0.03	**0.82**	**0.56**	0.14	**0.90**	36.75
				0.02	0.00	-0.07	**0.87**	0.06	0.04	**0.85**	0.23	18.13
				0.06	**0.99**	-0.13	0.01	0.05	0.09	-0.01	0.09	12.38
China	3.10	1.45	1.20	**0.84**	**0.83**	0.23	0.01	-0.11	**0.83**	0.23	**0.67**	38.75
				0.13	0.18	-0.32	**0.82**	0.14	-0.04	**0.78**	**0.56**	18.13
				0.03	0.02	0.64	-0.09	0.88	0.01	0.00	0.36	15.00
Greece	2.61	1.27	1.07	**0.82**	0.04	**0.57**	0.13	**0.73**	0.07	0.36	**0.65**	32.63
				0.08	**0.82**	0.04	0.02	-0.03	**0.79**	0.23	**0.64**	15.88
				0.06	0.05	-0.47	**0.91**	0.12	-0.03	-0.03	0.01	13.38
India	3.63	1.26	0.84	**0.77**	**0.84**	**0.69**	-0.01	0.18	**0.73**	0.09	**0.58**	45.38
				0.47	-0.05	0.21	0.01	0.94	0.24	0.10	**0.65**	15.75
				0.16	0.15	-0.08	**0.79**	0.01	-0.01	**0.78**	0.35	10.50
Indonesia	3.16	1.18	0.98	**0.87**	0.03	**0.89**	-0.14	0.34	**0.56**	0.24	**0.56**	39.50
				0.15	-0.14	-0.01	**0.74**	0.41	0.04	**0.69**	0.54	14.75
				0.11	**0.82**	-0.01	0.05	**0.63**	0.25	0.06	0.51	12.25
Israel	3.70	1.03	0.92	**0.73**	**0.65**	**0.66**	0.01	**0.64**	**0.76**	-0.02	**0.69**	46.25
				0.45	-0.03	0.01	0.02	0.54	0.18	**0.88**	**0.65**	12.88
				0.08	0.03	-0.14	**0.98**	0.14	0.08	-0.03	0.14	11.50
Malaysia	3.51	1.26	0.91	**0.80**	0.44	0.11	0.11	**0.88**	**0.67**	0.08	**0.88**	43.88
				0.11	0.15	-0.06	**0.78**	0.05	-0.01	**0.81**	0.32	15.75
				0.36	**0.59**	**0.87**	-0.16	-0.05	0.27	0.20	0.18	11.38
Mexico	3.45	1.21	0.81	**0.74**	0.16	0.49	0.18	**0.80**	**0.75**	0.02	**0.81**	43.13
				0.25	0.10	-0.17	**0.76**	0.15	-0.07	**0.77**	0.40	15.13
				0.33	**0.84**	0.49	-0.20	0.18	-0.02	0.26	0.27	10.13
Philippines	3.14	1.11	0.96	**0.83**	0.07	0.19	0.21	**0.88**	**0.64**	0.43	**0.95**	39.25
				0.20	**0.66**	**0.65**	-0.35	0.04	0.24	-0.27	0.05	13.88
				-0.05	-0.08	0.00	**0.75**	-0.03	0.18	**-0.64**	-0.15	12.00
Poland	3.09	1.31	0.96	0.54	0.21	0.38	0.21	**0.78**	**0.75**	-0.05	**0.76**	38.63
				0.58	**0.67**	0.07	0.05	0.21	-0.05	**0.77**	**0.56**	16.38
				-0.29	-0.16	**-0.66**	**0.86**	-0.03	-0.03	0.20	0.06	12.00
Portugal	3.23	1.42	0.96	**0.71**	**0.55**	0.45	0.24	**0.67**	0.05	**0.64**	**0.93**	40.38
				-0.49	-0.31	**-0.74**	**0.84**	-0.02	-0.02	0.22	-0.03	17.75
				0.33	0.04	0.23	0.10	0.05	**0.98**	-0.09	0.16	12.00
Russia	2.59	1.60	1.22	**0.77**	**0.82**	0.45	0.04	-0.07	**0.75**	0.03	0.33	32.38
				0.31	0.08	0.00	0.10	**0.96**	-0.06	0.05	**0.83**	20.00
				0.01	-0.03	0.14	**0.84**	-0.03	-0.02	**0.83**	0.33	15.25
Singapore	3.46	1.14	0.87	**0.84**	0.54	**0.63**	0.11	**0.79**	**0.74**	0.10	**0.87**	43.25
				-0.09	0.24	-0.44	**0.80**	0.27	-0.09	0.17	0.28	14.25
				0.18	-0.26	0.24	0.19	0.03	0.00	**0.90**	0.19	10.88
South Africa	3.45	1.13	0.92	**0.76**	**0.67**	**0.75**	0.04	0.41	**0.68**	-0.13	**0.55**	43.13
				0.49	0.15	0.22	0.09	**0.63**	-0.09	**0.80**	**0.77**	14.13
				-0.01	0.00	-0.05	**0.98**	-0.08	0.11	0.14	0.05	11.50
South Korea	2.81	1.20	1.05	**0.79**	**0.76**	0.10	-0.03	0.04	**0.67**	0.33	**0.73**	35.13
				0.14	0.07	-0.28	**0.83**	0.25	-0.01	**0.62**	0.49	15.00
				0.17	-0.13	0.69	-0.02	**0.80**	0.08	-0.01	0.30	13.13
Taiwan	2.81	1.43	0.93	**0.77**	**0.71**	0.06	0.06	0.11	**0.77**	0.15	**0.69**	35.13
				0.13	0.12	-0.23	**0.78**	0.15	-0.01	**0.80**	**0.59**	17.88
				0.15	-0.09	**0.72**	-0.12	**0.81**	0.16	0.02	0.14	11.63
Thailand	3.09	1.23	0.92	**0.78**	0.13	**0.58**	0.03	**0.78**	**0.65**	0.20	**0.84**	38.63
				0.09	0.02	-0.39	**0.76**	0.24	0.03	**0.67**	0.41	15.38
				0.32	**0.98**	0.04	0.03	0.05	0.00	0.02	0.10	11.50
Turkey	2.38	1.51	0.98	**0.80**	-0.05	0.40	0.11	0.10	**0.74**	0.48	**0.83**	29.75
				-0.30	**0.55**	-0.48	**0.72**	0.04	0.01	0.52	0.39	18.88
				0.02	0.04	0.08	0.06	**0.97**	0.09	-0.20	0.08	12.25
% LF				95.00	40.00	40.00	0.00	60.00	80.00	5.00	95.00	-

Table 8: 2-step principal component analysis

This table shows the results of a two-step principal component analysis (PCA). In the first step, I do a PCA on all the standardized low-frequency liquidity measures other than *Illiq_Zero*, that is, Gibbs, turnover, *ZeroVol*, Amihud and Amivest, and obtain the first factor, *LowFreq Factor.* In step two, a new PCA is performed on standardized PESPR, *Lambda*, *Illiq_Zero* and *LowFreq Factor.* The eigenvalues of first three factors are reported in column 2 to 4. Then the factor loadings of each liquidity proxy on the first, second and third factors are reported column 5 to 8. The percent of variance explained by each factor is reported in the last column. Factor loading is significant if it is larger than 0.55 and these factor loadings are shown in bold. '% LF' in the last row indicates, for each liquidity proxy, the percentage of significant factor loadings on the first factor across all the countries.

	Eigenvalues			Factor loadings				% of var.
Market	**First**	**Second**	**Third**	**PESPR**	**Lambda**	**Illiq_Zero**	**LowFreq Factor**	**explained**
Argentina	2.48	0.77	0.48	**0.93**	0.16	**0.64**	0.25	62.00
				0.23	0.14	**0.61**	**0.94**	19.25
				0.15	**0.98**	0.21	0.12	12.00
Brazil	1.87	0.98	0.90	**0.94**	0.11	**0.90**	-0.08	46.75
				-0.05	0.01	0.21	**0.99**	24.50
				0.05	**0.99**	0.14	0.01	22.50
Chile	1.73	0.99	0.94	**0.92**	0.07	**0.89**	0.08	43.25
				-0.06	0.00	0.20	**0.99**	24.75
				0.05	**1.00**	0.06	0.00	23.50
China	2.47	0.89	0.42	0.31	**0.94**	**0.62**	0.10	61.75
				0.09	0.08	0.53	**0.98**	22.25
				0.94	0.28	0.44	0.07	10.50
Greece	2.26	0.92	0.53	0.23	0.09	**0.56**	**0.95**	56.50
				0.05	**0.97**	0.53	0.08	23.00
				0.96	0.03	0.47	0.21	13.25
India	2.94	0.58	0.32	**0.75**	0.27	**0.90**	0.38	73.50
				0.44	0.18	0.31	**0.90**	14.50
				0.38	**0.94**	0.23	0.19	8.00
Indonesia	2.39	0.91	0.42	0.34	0.11	**0.92**	**0.75**	59.75
				0.92	0.07	0.23	0.50	22.75
				0.08	**0.99**	0.12	0.09	10.50
Israel	2.73	0.74	0.33	**0.90**	0.18	**0.73**	0.38	68.25
				0.29	0.15	**0.56**	**0.90**	18.50
				0.22	**0.97**	0.15	0.18	8.25
Malaysia	2.83	0.68	0.29	0.39	0.18	**0.72**	**0.93**	70.75
				0.86	0.24	0.52	0.27	17.00
				0.29	**0.95**	0.28	0.13	7.25
Mexico	2.66	0.76	0.38	**0.92**	0.18	**0.78**	0.37	66.50
				0.25	0.14	0.49	**0.91**	19.00
				0.18	**0.97**	0.17	0.15	9.50
Philippines	2.56	0.97	0.36	0.44	0.05	**0.88**	**0.94**	64.00
				0.89	0.05	0.40	0.27	24.25
				0.07	**1.00**	0.06	0.05	9.00
Poland	2.55	0.80	0.38	**0.90**	0.25	**0.65**	0.24	63.75
				0.24	0.11	**0.61**	**0.95**	20.00
				0.28	**0.96**	0.22	0.08	9.50
Portugal	2.55	0.76	0.46	**0.63**	0.22	**0.94**	0.24	63.75
				0.53	0.10	0.22	**0.95**	19.00
				0.41	**0.96**	0.19	0.08	11.50
Russia	1.97	1.11	0.57	**0.70**	**0.96**	0.15	0.00	49.25
				0.55	0.07	**0.92**	0.16	27.75
				-0.09	0.05	0.23	**0.98**	14.25
Singapore	2.68	0.77	0.31	0.46	0.17	**0.87**	**0.85**	67.00
				0.17	**0.98**	0.20	0.14	19.25
				0.87	0.13	0.30	0.36	7.75
South Africa	2.79	0.66	0.35	**0.72**	0.21	**0.92**	0.36	69.75
				0.51	0.18	0.28	**0.90**	16.50
				0.30	0.96	0.18	0.19	8.75
South Korea	2.33	0.88	0.53	**0.93**	0.27	**0.72**	0.13	58.25
				0.05	0.09	0.51	**0.97**	22.00
				0.24	**0.96**	0.25	0.07	13.25
Taiwan	2.25	0.84	0.66	0.09	0.12	**0.61**	**0.97**	56.25
				0.97	0.17	**0.56**	0.07	21.00
				0.15	**0.97**	0.40	0.07	16.50
Thailand	2.46	0.91	0.38	0.38	0.08	**0.80**	**0.93**	61.50
				0.90	0.14	0.44	0.22	22.75
				0.18	**0.99**	0.09	0.07	9.50
Turkey	2.02	1.10	0.65	0.19	0.09	**0.84**	**0.95**	50.50
				0.97	-0.06	0.40	0.04	27.50
				-0.08	**0.99**	0.07	0.07	16.25
% LF				55.00	10.00	95.00	40.00	-

Table 9: Firm size and liquidity measures

Stocks are sorted into 5 portfolios based on the year-beginning market capitalization in each market. The time-series averages of monthly liquidity measures for the 1st (small), 3rd (medium) and 5th (large) size quintile portfolio are reported. 'Small – Large' refers to the difference between the small size quintile and the large size quintile for each liquidity proxy. Statistically significant and positive values with t-stats larger than 1.645 are indicated in bold type. T-statistics are based on the time-series standard deviation. All the liquidity proxies are defined as before.

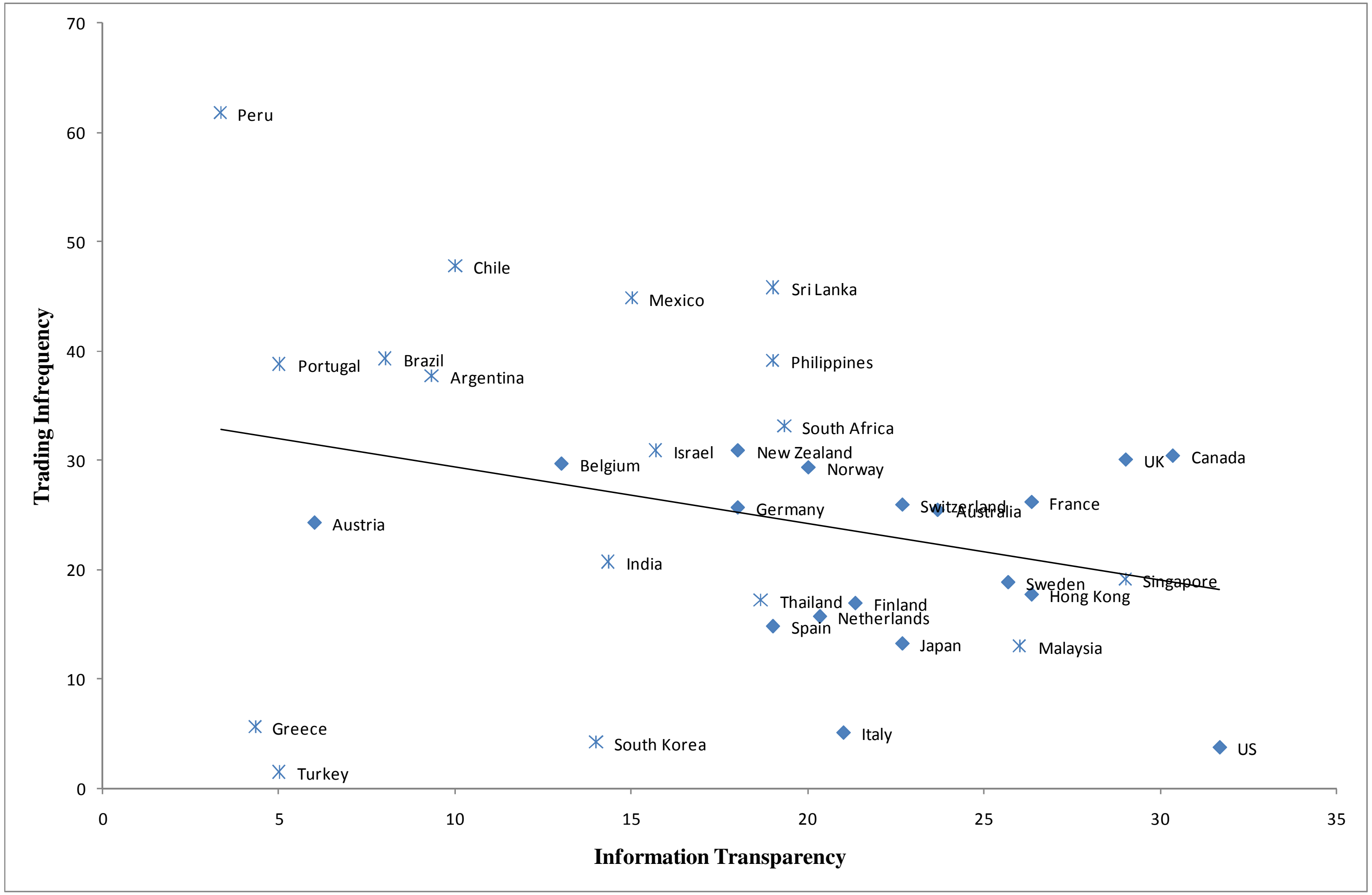
	Small (Quin 1)					Medium (Quin 3)					Large (Quin 5)					Small - Large				
Market	PESPR	Lambda	ZeroVol	Amihud	Illiq_Zero	PESPR	Lambda	ZeroVol	Amihud	Illiq_Zero	PESPR	Lambda	ZeroVol	Amihud	Illiq_Zero	PESPR	Lambda	ZeroVol	Amihud	Illiq_Zero
Argentina	3.44	0.42	30.39	0.84	17.02	2.13	0.20	12.02	0.27	12.91	1.26	0.09	6.86	0.12	10.68	**2.19**	**0.34**	**23.53**	**0.72**	**6.34**
Brazil	6.30	0.62	26.43	2.66	13.13	3.51	1.19	14.31	0.93	11.76	1.68	0.39	3.90	1.47	9.07	**4.62**	**0.24**	**22.54**	**1.19**	**4.06**
Chile	3.77	0.02	25.00	0.36	14.19	2.73	0.00	17.15	0.26	13.28	1.16	0.00	4.52	0.06	8.54	**2.61**	**0.02**	**20.49**	**0.31**	**5.65**
China	0.36	0.10	1.67	0.00	7.54	0.31	0.08	1.64	0.00	7.66	0.25	0.05	1.74	0.00	6.91	**0.11**	**0.05**	-0.07	**0.00**	**0.64**
Greece	2.47	1.06	1.87	4.86	13.70	1.50	0.61	0.47	2.89	12.42	1.00	0.32	1.41	5.13	10.91	**1.47**	**0.74**	**0.46**	-0.27	**2.79**
India	3.58	2.03	7.97	8.38	14.81	2.18	1.16	4.07	6.11	13.27	0.85	0.35	1.17	1.06	9.43	**2.72**	**1.68**	**6.79**	**7.32**	**5.38**
Indonesia	7.03	0.46	23.80	28.52	17.69	5.06	0.24	16.23	10.25	15.15	3.23	0.04	3.88	5.99	10.51	**3.80**	**0.42**	**19.92**	**22.54**	**7.17**
Israel	5.59	0.08	25.41	1.86	17.07	4.36	0.03	22.44	0.93	15.77	0.85	0.01	1.10	0.05	8.64	**4.74**	**0.07**	**24.31**	**1.81**	**8.43**
Malaysia	3.33	0.83	12.63	1.19	13.65	2.15	0.56	7.19	0.66	12.76	1.01	0.16	2.14	0.10	9.63	**2.32**	**0.67**	**10.49**	**1.09**	**4.02**
Mexico	5.20	0.23	27.78	9.07	18.31	1.87	0.06	4.46	0.30	9.82	1.09	0.02	0.92	0.01	7.93	**4.12**	**0.20**	**26.86**	**9.06**	**10.37**
Philippines	6.86	1.89	20.93	6.42	17.27	5.04	0.45	18.95	4.22	16.25	1.94	0.10	4.39	1.65	11.06	**4.92**	**1.78**	**16.55**	**4.77**	**6.20**
Poland	2.07	0.73	5.61	1.74	12.56	1.59	0.60	4.63	2.07	13.09	0.74	0.14	2.14	0.17	10.06	**1.33**	**0.59**	**3.47**	**1.57**	**2.49**
Portugal	3.48	0.37	10.97	2.06	14.28	0.82	0.04	2.95	0.04	9.17	0.23	0.00	0.00	0.00	3.28	**3.26**	**0.37**	**10.97**	2.06	**11.00**
Russia	2.81	0.08	15.24	7.18	9.07	1.34	0.02	22.98	0.06	12.88	0.59	0.01	4.80	0.04	8.89	**2.22**	**0.07**	**10.44**	**7.14**	0.18
Singapore	5.45	4.15	18.64	172.94	20.72	2.58	1.62	6.89	38.59	16.65	1.02	0.40	1.25	6.13	12.75	**4.43**	**3.75**	**17.39**	**166.81**	**7.97**
South Africa	5.53	0.04	12.99	7.50	15.70	2.58	0.01	7.77	1.01	12.81	0.86	0.00	1.04	0.38	7.35	**4.67**	**0.04**	**11.95**	**7.11**	**8.35**
South Korea	1.94	0.21	3.17	0.10	9.67	1.36	0.13	2.21	0.09	9.57	0.81	0.05	1.94	0.11	8.45	**1.12**	**0.15**	**1.23**	-0.01	**1.22**
Taiwan	0.75	3.31	0.37	0.07	9.59	0.52	1.52	0.09	0.01	7.72	0.42	0.62	0.04	0.01	5.88	**0.33**	**2.68**	**0.33**	**0.06**	**3.71**
Thailand	3.37	3.93	11.79	2.63	13.34	2.44	2.23	8.85	1.69	12.77	1.34	0.74	2.66	0.39	9.32	**2.03**	**3.19**	**9.14**	**2.24**	**4.02**
Turkey	1.41	0.05	0.19	0.32	10.79	1.24	0.03	0.23	0.18	10.33	1.08	0.01	0.19	0.08	8.68	**0.32**	**0.03**	0.00	**0.24**	**2.12**

Table 10: Volatility and liquidity measures

Stocks are sorted into 5 portfolios based on the stock volatility estimated using the monthly return in the past year. The time-series averages of monthly liquidity measures for the 1st (high), 3rd (medium) and 5th (low) volatility quintile portfolio are reported. 'High – Low' refers to the difference between the high volatility quintile and the low volatility quintile for each liquidity proxy. Statistically significant and positive values with t-stats larger than 1.645 are indicated in bold type. T-statistics are based on the time-series standard deviation. All the liquidity proxies are defined as before.

	High (Quin 1)					High (Quin 3)					Low (Quin 5)					High - Low				
Market	PESPR	Lambda	ZeroVol	Amihud	Illiq_Zero	PESPR	Lambda	ZeroVol	Amihud	Illiq_Zero	PESPR	Lambda	ZeroVol	Amihud	Illiq_Zero	PESPR	Lambda	ZeroVol	Amihud	Illiq_Zero
Argentina	2.20	0.24	9.83	0.40	12.50	2.19	0.20	13.01	0.40	13.21	2.05	0.24	16.01	0.31	13.66	0.14	0.00	-6.18	0.08	-1.16
Brazil	3.58	2.69	7.96	1.57	11.98	2.00	0.60	6.91	1.21	9.37	2.60	0.32	10.44	1.29	10.01	**0.98**	**2.36**	-2.47	0.28	**1.96**
Chile	2.57	0.01	13.94	0.29	12.57	1.81	0.00	11.47	0.09	10.81	2.03	0.00	14.66	0.08	11.56	**0.55**	**0.01**	-0.72	**0.21**	**1.01**
China	0.31	0.08	1.68	0.00	7.58	0.31	0.08	1.72	0.00	7.65	0.29	0.07	2.03	0.00	7.41	**0.02**	**0.01**	-0.35	**0.00**	**0.17**
Greece	1.74	0.79	0.94	3.21	12.25	1.69	0.71	0.86	4.24	12.38	1.45	0.44	1.68	1.98	11.69	**0.29**	**0.35**	-0.74	**1.23**	**0.56**
India	2.49	1.56	2.97	8.29	13.29	2.07	1.12	3.89	5.10	12.74	1.76	0.76	3.86	3.36	12.07	**0.74**	**0.79**	-0.88	**4.93**	**1.22**
Indonesia	6.17	0.20	13.43	15.97	14.90	4.37	0.17	11.53	10.16	13.61	3.57	0.16	14.05	6.94	13.37	**2.60**	0.04	-0.62	**9.03**	**1.53**
Israel	4.40	0.05	17.32	1.19	14.73	3.89	0.03	19.07	0.80	14.52	2.57	0.02	12.46	0.46	11.95	**1.83**	**0.03**	**4.86**	**0.74**	**2.77**
Malaysia	1.28	0.13	2.22	0.10	9.39	1.24	0.13	1.92	0.07	9.11	1.50	0.14	2.57	0.08	9.56	-0.22	-0.02	-0.35	**0.02**	-0.17
Mexico	2.13	0.56	4.90	0.64	11.78	2.07	0.53	6.37	0.62	12.08	1.77	0.37	7.48	0.45	11.96	**0.36**	**0.20**	-2.58	**0.18**	-0.18
Philippines	2.41	0.08	10.27	2.00	11.85	1.29	0.04	4.29	0.46	8.19	1.64	0.06	3.16	0.57	8.42	**0.78**	**0.02**	**7.11**	**1.43**	**3.44**
Poland	5.18	0.84	17.03	5.40	16.02	3.70	0.30	11.78	2.79	13.94	3.13	0.12	12.90	1.74	13.50	**2.06**	**0.72**	**4.12**	**3.66**	**2.52**
Portugal	1.48	0.53	2.81	1.68	11.98	1.28	0.40	2.91	1.48	11.79	1.14	0.31	3.28	0.81	11.64	**0.34**	**0.22**	-0.48	**0.87**	**0.34**
Russia	0.98	0.15	3.86	0.10	8.59	0.51	0.02	0.68	0.01	6.75	0.58	0.05	1.96	0.07	6.76	**0.39**	**0.10**	1.90	0.03	**1.83**
Singapore	2.16	0.05	16.62	0.38	11.70	0.87	0.01	10.39	0.03	9.39	0.83	0.02	15.78	0.04	10.57	**1.33**	**0.03**	0.84	**0.33**	**1.13**
South Africa	3.24	2.00	6.67	69.53	16.54	2.66	1.94	7.65	53.65	16.51	1.93	1.39	7.14	33.14	16.06	**1.31**	**0.61**	-0.47	**36.39**	**0.48**
South Korea	3.96	0.03	7.54	4.36	14.13	1.82	0.01	4.32	0.78	10.41	1.46	0.00	5.07	0.37	9.87	**2.49**	**0.02**	**2.48**	**3.99**	**4.26**
Taiwan	0.57	1.87	0.20	0.03	7.59	0.54	1.71	0.08	0.02	7.71	0.55	1.63	0.19	0.03	8.01	**0.02**	**0.24**	0.01	0.00	-0.42
Thailand	2.19	2.32	4.67	1.63	11.31	2.27	2.36	7.38	1.54	11.88	2.54	2.25	13.16	1.62	13.42	-0.35	0.06	-8.49	0.01	-2.10
Turkey	1.23	0.03	0.30	0.15	9.85	1.20	0.03	0.09	0.15	10.01	1.24	0.03	0.19	0.20	10.22	-0.02	**0.00**	0.11	-0.05	-0.36

Figure 1 Information transparency and trading frequency



'*' refers to emerging markets and '◆' stands for developed markets.

Figure 2 Time-series variation in high-frequency liquidity benchmarks