What Are The Best Liquidity Proxies For Global Research?*

Kingsley Y. L. Fong — University of New South Wales
Craig W. Holden** — Indiana University
Charles A. Trzcinka — Indiana University

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** Corresponding author: Craig W. Holden, Kelley School of Business, Indiana University, 1309 E. Tenth St., Bloomington, IN 47405. Tel.: + 1-812-855-3383; fax: + 1-812-855-5875: email address: cholden@ indiana.edu

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Abstract

We compare both monthly and daily liquidity proxies constructed from low-frequency (daily) stock data to corresponding liquidity benchmarks computed from high-frequency (intraday) data on 43 exchanges. We find that for both monthly and daily frequencies Closing Percent Quoted Spread strongly dominates all other percent-cost proxies for global research. It provides enormous performance gains over the monthly proxies that global research has used-to-date. At both daily and monthly frequencies, Closing Percent Quoted Spread also does the best job of capturing the *level* of percent effective spread and percent quoted spread. At both frequencies, High-Low does the best job of capturing the *level* of percent realized spread and percent price impact. These are the first findings at the daily frequency that liquidity proxies can perform well. We find that five proxies are nearly equivalent as the best monthly cost-per-volume proxies: Closing Percent Quoted Spread Impact, LOT Mixed Impact, High-Low Impact, FHT Impact, and Amihud. We find that the daily version of Amihud is the best daily cost-per-volume proxy. All of these cost-per-volume proxies are highly correlated with lambda, but none of them captures the level of lambda at either frequency.

1. Introduction

Rapidly expanding global research analyzes the connection between *monthly* market liquidity and global asset pricing,[1] global corporate finance,[2] and global market microstructure.[3] Further global research analyzes *daily* liquidity,[4] including: (1) the pricing of daily liquidity risk, (2) the impact of firm announcements and regulatory changes on daily liquidity, (3) the interaction between daily market liquidity and daily funding liquidity, (4) the determinants of daily liquidity, and (5) the commonality of daily liquidity across countries. All of this literature faces great difficulty in trying to compute standard measures of liquidity for a global sample of stocks using intraday trade and quote data, because global intraday data: (1) is relatively expensive and (2) is very large and growing exponentially over time. As an example of the later point, the intraday sample used in this paper has 8.5 billion trades and 13.6 billion quotes and is growing at a 32.8% compound annual growth rate.[5] This exponential growth rate of intraday data has kept pace with the exponential growth rate of computer power.[6] Thus, it will continue to be very difficult to compute liquidity for a global sample based on intraday data for the foreseeable future.

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[1] See Stahel (2005), Liang and Wei (2006), Bekaert, Harvey, and Lundbland (2007), Chan, Jain, and Xia (2008), Griffin, Kelly, and Nardari (2010), Hearn, Piesse, and Strange (2010), Griffin, Hirschey, and Kelly (2011), Lee (2011), Asness, Moskowitz, and Pedersen (2013), and Bekaert, Harvey, Lundblad, Siegel (2014).

[2] See Bailey, Karolyi, and Salva, (2006), LaFond, Lang, and Skaife (2007), Lang, Lins, and Maffett (2012), and Hearn (2014).

[3] See Jain (2005), Levine and Schmukler (2006), Henkel, Jain, and Lundblad (2008), Henkel (2008), DeNicolo and Ivaschenko (2009), and Clark (2011).

[4] Bhattacharya, Daouk, Jorgenson, and Kehr (2000), Attig, Gadhoum, and Lang (2003), Gomez-Puig (2006), Gersl and Komarkov (2009), Erten and Okay (2012), Karolyi, Lee, and van Dijk (2012), Beber and Pagano (2013), and Lee, Tseng, and Yang, (2014).

[5] To determine the compound annual growth rate, we select the 20 most active stocks on the 37 exchanges for which we have data in 1996 and compare to the 20 most active stocks on the same exchanges in 2007. The quantity of trades and quotes is 22.7 times larger in 2007 than 1996, which translates into a 32.8% annual growth rate.

[6] Hennessy and Patterson (2012) report a 31.0% compound annual growth rate of computer power. Specifically, they report that CPU performance based on the SPECint benchmark for the fastest personal computer available each year grew at a 52% annual growth rate from 1986 to 2002 and then slowed to a 20% rate post-2002.

A recent literature proposes the use of low-frequency (monthly and daily) liquidity proxies that can be calculated from daily data. These liquidity proxies offer the (globally untested) potential benefit of being highly correlated with intra-day based liquidity benchmarks and an enormous savings in computational time compared to using intraday data. For example, the required data inputs for any low-frequency liquidity proxy are at most two data points[7] per stock-day, which yields approximately a 313-fold computational savings in our study. Looking at the pattern over time, the approximate computation savings in our sample has grown from 42-fold savings in 1996 to 962-fold savings in 2007. Undoubtedly, the computation savings will continue to grow in the years ahead as intraday data continues to grow exponentially versus a linear growth in daily data.

Given the enormous computational savings and the potential benefit, low-frequency liquidity proxies have been widely adopted by global research, including all of the studies mentioned in the introductory paragraph. Considering that "market liquidity" is a multi-dimensional concept, there are two major categories of low-frequency liquidity proxies. First are "percent-cost" liquidity proxies, which represent the transaction cost required to execute a small trade. Second are "cost-per-volume" liquidity proxies, which represent marginal transaction costs per currency unit of volume. They are useful for assessing the marginal cost of trading an additional quantity as part of a large trade.[8] Of the twenty papers using monthly proxies mentioned above, thirteen use percent-cost proxies and thirteen use cost-per-volume proxies.

[7] Depending on the particular liquidity proxy being used, the two data points might be price and volume, high and low, or closing bid and closing ask.

[8] The two categories are apples and oranges, because they are measured in different units and are on different numerical scales. Percent-cost proxies and benchmarks are unitless measures (i.e., they are measured in percent). Cost-per-volume proxies and benchmarks are denominated in percent-cost per local-currency-unit-of-volume (e.g., % / $). In our sample, all of the percent-cost benchmarks are relatively similar in magnitude and all of them are 10X to 10,000X larger than the cost-per-volume benchmark. Thus, we strictly compare proxies in one category against benchmarks in the same category.

New liquidity proxies continue to be developed. Corwin and Schultz (2012) develop the High-Low percent-cost proxy and find that it performs better in U.S. data than any other proxy that they test. Chung and Zhang (2014) develop the Closing Percent Quoted Spread percent-cost proxy and find that it generally, but not always,[9] performs better in U.S. data than any other proxy that they test. Neither paper tests these two proxies against each other. We develop a new percent-cost proxy, FHT, which simplifies the existing LOT Mixed measure. It is easy to implement yet retains the core elements of LOT Mixed. Our goal in this paper is to identify the best liquidity proxies for global research.

Our research design is to compare liquidity proxies to accurate liquidity benchmarks computed using more than a decade of global intraday data. Our sample contains 8.5 billion trades and 13.6 billion quotes representing 24,847 firms on 43 exchanges around the world from January 1996 to December 2007. Specifically, we evaluate 10 monthly percent-cost proxies relative to four monthly percent-cost benchmarks: percent effective spread, percent quoted spread, percent realized spread, and percent price impact. These benchmarks are standard measures of liquidity from the microstructure literature. We examine 13 monthly cost-per-volume proxies relative to a monthly cost-per-volume benchmark: the slope of the price function, which is often called "lambda" by reference to the same concept in Kyle (1985). While most liquidity proxies break down at the daily frequency, we are able to examine two *daily* percent-cost proxies relative to the *daily* version of the same four percent-cost benchmarks and four *daily* cost-per-volume proxies relative to *daily* lambda. In each case, we test the proxies using three performance dimensions: (1) higher average cross-sectional correlation with the benchmarks, (2) higher portfolio time-series correlation with the benchmarks, and (3) lower prediction error relative to the benchmarks.

We find that for both the monthly and daily frequencies Closing Percent Quoted Spread strongly dominates all other percent-cost proxies for global research. It has by-far the highest correlations with

[9] In sharp contrast to the rest of their results, they find that for NYSE/AMEX stocks from 1993-1996 the Closing Percent Quoted Spread has a -0.5073 time-series correlation with intraday effective spread. This result demonstrates there is no strictly mechanical reason why Closing Percent Quoted Spread *must* be highly correlated with intraday effective spread.

percent effective spread, percent quoted spread, percent realized spread, and percent price impact. It provides enormous performance gains over the monthly proxies that global research has used-to-date (Zeros, LOT Mixed, etc.). For example, the global average cross-sectional correlation between monthly Zeros and monthly percent effective spread is 0.404. The corresponding correlation for Closing Percent Quoted Spread is 0.802. At both daily and monthly frequencies, Closing Percent Quoted Spread also does the best job of capturing the *level* of percent effective spread and percent quoted spread. At both frequencies, High-Low does the best job of capturing the *level* of percent realized spread and percent price impact. These are the first findings at the daily frequency that liquidity proxies can perform well, which both validates existing research (see footnote 4) and lays the foundation for further daily liquidity studies. We find that Closing Percent Quoted Spread and High-Low are tied-for-best percent-cost proxies for US research, with the latter being available for a much longer time-series in US data. We find that five monthly proxies are nearly equivalent as the best monthly cost-per-volume proxies. They are Closing Percent Quoted Spread Impact, LOT Mixed Impact, High-Low Impact, FHT Impact, and Amihud. All five are highly correlated with monthly lambda, but none captures its level. We find that the daily version of Amihud is the best daily cost-per-volume proxy. It is highly correlated with daily lambda, but doesn't capture its level.

We extend previous liquidity proxy research such as Lesmond (2005) and Goyenko, Holden and Trzcinka (2009) by including new proxies that have not been tested against one another (High-Low, Closing Percent Quoted Spread, and FHT), by including the daily liquidity proxy that has never been examined, and by including new markets. We also contribute to the literature by examining the characteristics of a relatively new global intraday equity dataset: Thomson Reuters Tick History (TRTH). We examine how well our TRTH sample matches with Datastream (i.e., matching security identifiers and matching prices) and find that we can match 84.7% of Datastream stock-years from 1996-2007. We also compare TRTH's intraday data to Bloomberg's intraday data. For a random sample of 50 stocks per exchange in December 2011, we found the difference between Bloomberg and TRTH percent effective spreads to be 0.07% and the correlation between Bloomberg and TRTH percent effective spreads to be

99.19%. We also report the median ratio of the sum of intraday share volume reported by TRTH divided by the share volume reported by Datastream per stock per day. We find that 91% of the exchange-year ratios are exactly 100% and 97% of the exchange-year ratios are in the range [95%, 102%]. Combining all of this evidence, we conclude that TRTH is a high-quality, reliable dataset for global research.

The paper is organized as follows. Section 2 explains the high-frequency benchmarks. Section 3 introduces a new low-frequency proxy. Section 4 describes the data and our analysis of the TRTH dataset. Section 5 presents our empirical results. Section 6 concludes. The appendix summarizes the formulas for the low-frequency proxies from the existing literature.

2. High-Frequency Benchmarks

The liquidity benchmarks that we study include percent cost benchmarks, which measure the percent spread (i.e., the cost of trading as a percentage of the price), and a cost per volume benchmark, which captures the marginal transaction cost per unit of volume as measured in local currency. We analyze four high-frequency percent-cost benchmarks and one high-frequency cost per volume benchmark.

Our first percent-cost benchmark is percent effective spread. For a given stock, the percent effective spread on the k^{th} trade is defined as

$$\textit{Percent Effective Spread}_k = 2D_k\,(\ln(P_k) - \ln(M_k)), \tag{1}$$

where D_k is an indicator variable that equals +1 if the k^{th} trade is a buy and -1 if the k^{th} trade is a sell, P_k is the price of the k^{th} trade and M_k is the midpoint of the consolidated BBO prevailing immediately prior to the time of the k^{th} trade (i.e., one second prior or one millisecond prior depending on the unit of time used by each exchange's time-stamp). Aggregating over period (day or month) i, a stock's *Percent Effective Spread*$_i$ is the local-currency-volume-weighted average of *Percent Effective Spread*$_k$ computed over all trades in period i.

Our second percent-cost benchmark is percent quoted spread. For a given time interval s, the percent quoted spread is defined as

$$Percent\ Quoted\ Spread_s = (Ask_s - Bid_s) / ((Ask_s + Bid_s)/2), \quad (2)$$

where Ask_s is the best ask quote Bid_s is the best bid quote in that time interval. Over period *i*, the stock's *Percent Quoted Spread*$_i$ is the time-weighted average of *Percent Quoted Spread*$_s$ computed over all time intervals in the period.

Our third percent-cost benchmark is the percent realized spread, which is the temporary component of the spread (see Huang and Stoll 1996). For a given stock, the percent realized spread on the k^{th} trade is

$$Percent\ Realized\ Spread_k = 2D_k\ (\ln(P_k) - \ln(M_{k+5})), \quad (3)$$

where $M_{(k+5)}$ is the midpoint five-minutes after the k^{th} trade and D_k is the buy-sell indicator variable as defined above. We follow the Lee and Ready (1991) method in that determines that a trade is a buy when $P_k > M_k$, is a sell when $P_k < M_k$, and the tick test is used when $P_k = M_k$. The tick test specifies that a trade is a buy (sell) if the most recent prior trade at a different price was at a lower (higher) price than P_k. Aggregating over period *i*, a stock's *Percent Realized Spread*$_i$ is the local-currency-volume-weighted average of *Percent Realized Spread*$_k$ computed over all trades in period *i*.

Our fourth percent-cost benchmark is percent price impact, which is the permanent component of the spread (see Huang and Stoll 1996). For a given stock, the percent price impact on the k^{th} trade is

$$Percent\ Price\ Impact_k = 2D_k\ (\ln(M_{k+5}) - \ln(M_k)). \quad (4)$$

For a given stock aggregated over a period *i*, the *Percent Price Impact*$_i$ is the local-currency-volume-weighted average of *Percent Price Impact*$_k$ computed over all trades in period *i*.

Our cost-per-volume benchmark is λ, which is the slope of the price function. We follow Goyenko, Holden, and Trzcinka (2009) and Hasbrouck (2009) and calculate λ as the slope coefficient of

$$r_n = \lambda \cdot S_n + u_n, \quad (5)$$

where for the n^{th} five-minute period, r_n is the stock return, $S_n = \sum_k Sign(v_{kn})\sqrt{|v_{kn}|}$ is the signed square-root local-currency-volume, v_{kn} is the signed local-currency-volume of the k^{th} trade in the n^{th} five-minute period, and u_n is the error term.

3. Low-Frequency Proxies

We analyze liquidity proxies computed from low-frequency (daily) data. Specifically, we analyze ten monthly percent-cost proxies and thirteen monthly cost-per-volume proxies. For each proxy, we require that the measure rely only on daily data and always produces a numerical result.[10] Nine of the percent-cost proxies that we analyze are from the prior literature: ‘‘Roll’’from Roll (1984); ‘‘LOT Mixed’’ and ‘‘Zeros” from Lesmond, Ogden, and Trzcinka (1999); “LOT Y-Split” and “Zeros2” from Goyenko, Holden, and Trzcinka (2009); “Effective Tick” from Goyenko, Holden, and Trzcinka (2009) and Holden (2009); “Extended Roll” from Holden (2009); “High-Low” from Corwin and Schultz (2012); and “Closing Percent Quoted Spread” from Chung and Zhang (2014).[11] Twelve of the cost-per-volume proxies are from the prior literature: ‘‘Amihud’’from Amihud (2002), ‘‘Pastor and Stambaugh’’ from Pastor and Stambaugh (2003), “Amivest,”and the Extended Amihud class of proxies from Goyenko, Holden, and Trzcinka (2009). We test ten versions of the Extended Amihud class of proxies by dividing ten different percent-cost proxies by the average daily currency value of volume in units of local currency. Nine of them are from the prior literature: Roll Impact, Extended Roll Impact, Effective Tick Impact, LOT Mixed Impact, LOT Y-split Impact, Zeros Impact, Zeros2 Impact, High-Low Impact, and Closing Percent Quoted Spread Impact. The tenth version, FHT Impact, is based on dividing our new percent-cost proxy FHT (discussed below) by the average daily local currency value of volume. The appendix summarizes the formulas for the low-frequency proxies from the existing literature.

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[10] If a measure cannot be computed we substitute a default value, such as zero.

[11] We analyze neither the Gibbs measure from Hasbrouck (2004), nor the Holden measure from Goyenko, Holden, and Trzcinka (2009) and Holden (2009), because both measures are *very* numerically-intensive. Given our large sample, they would be infeasible.

Most of the low-frequency proxies mentioned above *cannot* be computed on a daily basis, but a few can. We examine the daily version of two percent-cost proxies: High-Low and Closing Percent Quoted Spread. We examine the daily version of four cost-per-volume proxies: Amihud, Amivest, High-Low Impact, and Closing Percent Quoted Spread Impact.

We introduce a new percent-cost proxy, FHT, which is a simplification of the LOT Mixed model. We start by describing the setup of the LOT Mixed model.

3.1. The Setup of the LOT Mixed Model

Lesmond, Ogden, and Trzcinka (1999) develop a percent-cost proxy based on the idea that transaction costs cause a distortion in observed stock returns. The LOT Mixed model assumes that the unobserved "true return" R_{jt}^* of a stock *j* on day *t* is given by

$$R_{jt}^* = \beta_j R_{mt} + \varepsilon_{jt}, \tag{6}$$

where β_j is the sensitivity of stock *j* to the market return R_{mt} on day *t* and ε_{jt} is a public information shock on day *t*. They assume that ε_{jt} is normally distributed with mean zero and variance σ_j^2. Let $\alpha_{1j} \leq 0$ be the percent transaction cost of selling stock *j* and $\alpha_{2j} \geq 0$ be the percent transaction cost of buying stock *j*. Then the observed return R_{jt} on a stock *j* is given by

$$\begin{aligned}
R_{jt} &= R_{jt}^* - \alpha_{1j} \quad && \text{when } R_{jt}^* < \alpha_{1j} \\
R_{jt} &= 0 && \text{when } \alpha_{1j} < R_{jt}^* < \alpha_{2j} \\
R_{jt} &= R_{jt}^* - \alpha_{2j} && \text{when } \alpha_{2j} < R_{jt}^*.
\end{aligned} \tag{7}$$

The LOT Mixed liquidity measure is simply the difference between the percent buying cost and the percent selling cost:

$$LOT\ Mixed = \alpha_{j2} - \alpha_{j1}, \tag{8}$$

where the model's parameters are estimated by maximizing a likelihood function (see the appendix for details). Goyenko, Holden, and Trzcinka (2009) developed a new version of the measure, which they called *LOT Y-split*, by maximizing the same likelihood function over different spatial regions (see the appendix for details).

Both LOT measures contain two core elements: the proportion of zero returns (from the middle region of equation 7) and return volatility. This combination of core elements enables both LOT measures to outperform either Zeros or return volatility separately as shown by Goyenko, Holden, and Trzcinka (2009). However, the complexity and non-analytic character of LOT measures open the door to our new liquidity proxy.

3.2. FHT

We create a new percent-cost proxy, FHT, by simplifying the LOT model. First, we assume that transaction costs are symmetric. Let $\alpha_{j2} = S/2$ be the percent transaction cost of buying a stock and $\alpha_{j1} = -S/2$ be the percent transaction cost of selling the same stock, where S is the round-trip, percent transaction cost. Substituting this assumption into equation (7) and suppressing the subscripts, the observed return R on an individual stock is given by

$$\begin{aligned} &R = R^* + S/2 \quad \text{when } R^* < -S/2 \\ &R = 0 \qquad\qquad\ \text{when } -S/2 < R^* < S/2 \\ &R = R^* - S/2 \quad \text{when } S/2 < R^*. \end{aligned} \tag{9}$$

Secondly, we focus on the return distribution of an individual stock and provide no role for the market portfolio. Specifically, the unobserved "true return" R^* of an individual stock on a single day is assumed to be normally distributed with mean zero and variance σ^2. Thus, the theoretical probability of a zero return is the probability of being in the middle region, which is given by

$$N\left(\frac{S}{2\sigma}\right) - N\left(\frac{-S}{2\sigma}\right). \tag{10}$$

The empirically observed frequency of a zero return is given by the Zeros proxy:

$$z \equiv Zeros = \frac{ZRD}{TD + NTD}, \tag{11}$$

where ZRD = the number of zero returns days, TD = number of trading days, and NTD = number of no-trade days in a given stock-month. Equating the theoretical probability of a zero return to the empirically-observed frequency of a zero return, we obtain

$$N\left(\frac{S}{2\sigma}\right)-N\left(\frac{-S}{2\sigma}\right)=z \tag{12}$$

By the symmetry of the cumulative normal distribution, equation (12) can be rewritten as

$$N\left(\frac{S}{2\sigma}\right)-\left[1-N\left(\frac{S}{2\sigma}\right)\right]=z \tag{13}$$

Solving for *S*, we obtain

$$FHT \equiv S = 2\sigma N^{-1}\left(\frac{1+z}{2}\right), \tag{14}$$

where $N^{-1}(\ )$ is the inverse function of the cumulative normal distribution. The FHT measure is an analytic measure that can be computed 1,000 times faster than LOT, with a single line of SAS code,[12] and using only return data.[13] Researchers have already used the FHT measure in recent studies, including Bundgaard and Ahm (2012), Marshall, Nguyen, and Visaltanachoti (2012), and Edmans, Fang, and Zur (2013).

The intuition of the FHT measure follows from the simple idea that a zero return is the result of the true return being in-between the upper bound given by the transaction cost for buying and the lower bound given by the transaction cost for selling. Holding the volatility of the true return distribution constant, a greater proportion of zero returns implies wider bounds and thus a wider spread. Holding the proportion of zero returns constant, a higher volatility of the true return distribution implies that the transaction cost bounds and bid-ask spread must be larger in order to achieve the same proportion of zero

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[12] Sigma=Std(NonZeroReturns); Zeros=ZeroReturnDays/TotalDays; FHT = 2*Sigma*Probit((1+Zeros)/2).

[13] For example, Marshall, Nguyen, and Visaltanachoti (2012) are able to compute FHT in commodity markets using only commodity prices.

returns. In summary, the percent spread is an increasing function of both the proportion of zero returns and the volatility of the return distribution.

4. Data

4.1. Thomson Reuters Tick History

We obtain US intraday trades and quotes data from TAQ and other data such as returns and market capitalization from CRSP and Compustat. We obtain intraday trades and quotes data of international markets from the Thomson Reuters Tick History (TRTH) database, and other international data such as returns, market capitalization, securities level information from Datastream. TAQ, CRSP, Compustat, and Datastream are widely used databases, but the TRTH database is relatively new. Hence, we focus on explaining the TRTH database and how we match the data to Datastream here.

The TRTH database is supplied by the Securities Industry Research Centre of Asia-Pacific (SIRCA). TRTH contains historical Reuters data feeds beginning January 1996 on over 5 million instruments from various exchanges.[14] We obtain equity trades and quotes which are time-stamped to whatever time unit an exchange uses and by Reuters to the millisecond.

The TRTH equity database is a survivor-bias-free database that covers both active and inactive stocks. It organizes data by the Reuters Instrument Code (RIC). A “RIC table” includes information such as asset class (e.g. equity), market, currency denomination, the first and the last data date, and the International Securities Identification Number (ISIN) where applicable.[15] A company may have a number of RICs that represent different classes of common shares, preference shares, depository receipts, cross-listings, and securities in special trading status such as deferred settlement after stock split. In order to

[14] Prior to July 10, 2009, the same underlying tick history data was supplied via the interface called TAQTIC, which was a more restricted version of the commercial TRTH. TAQTIC was decommissioned on July 17, 2009.

[15] The RIC for equity has the structure of company code (often, but not always, the same as the local ticker) plus a security class modifier called the brokerage character and the exchange code. The brokerage character varies by market and we obtain the brokerage character information from TRTH’s date sensitive market and securities reference system “Speedguide.”

create a representative sample of RICs of each stock market and to avoid multiple counting, we focus on one common stock per company, traded in the home country and in the local currency. TRTH however has limited historical coverage of some of these screening variables so we construct our sample by collecting the securities screening variables from Datastream and identify the matching RICs for the list of screened Datastream securities identifiers.

Datastream identifies each stock by its DSCODE, which is a unique identifier to a security-trading venue combination. Each DSCODE is associated with a comprehensive list of DSCODE information, including critically stock split information. We retain only the DSCODEs with an ISIN, in the local market, traded in the local currency and identified as "major security" and "primary quote." These screening criteria lead to one DSCODE per domestic company.

While the TRTH database covers all historically traded symbols on an exchange and their associated intraday data, matching RICs to other databases is not a trivial task. Our experience with the RIC table of the standard TRTH database indicates that comprehensive coverage of ISIN starts from June 2008. Hence many stocks that became inactive prior to June 2008 often do not have ISIN information from the RIC table. Our data period span from January 1996 to December 2007, so we need additional data and alternative methods to match RICs and DSCODEs. To this end, we obtain from SIRCA a RIC-DSCODE listing that SIRCA created upon our request from two sources of information. The first source of information is a RIC-DSCODE match list from another commercially available Thomson Reuter database. The second source of information is SIRCA's RIC-DSCODE matches based on their historical ISIN and SEDOL records. We validate each RIC-DSCODE match by checking two variables. First, we check that there are at least twelve month-end prices with positive monthly volume from the RIC firm in TRTH and from the DSCODE firm in Datastream. Second, we verify that these TRTH prices and corresponding Datastream prices match within a 10% range at least 90% of the time when stated in the original currency.[16]

The TRTH data have qualifiers in many markets that contain market specific codes denoting whether a trade is the first trade of the day, an auction trade, and an irregular trade (such as a off-market trade or a trade related to exercising an option). In computing intraday bid-ask spreads, effective spreads, intraday returns, and related measures, we exclude these irregular trades and quotes.

Trading hours differ across exchanges and over time. We determine each exchange's historical trading hour regime by examining for sharp increases and decreases in exchange-level aggregated trade frequency at 5 minute intervals in the time series. We cross-check the trading hour regimes based on aggregated trade frequency against the trading hour regimes listed in Reuter's Speedguide and the Handbook of World Stock, Derivative and Commodity Exchanges. The liquidity benchmarks that we compute are based on data during trading hours only.

4.2. Our Sample

Our sample covers 43 exchanges in 38 countries. We analyze the leading exchange by volume in 35 countries, plus two exchanges in Japan (the Tokyo Stock Exchange and the Osaka Securities Exchange), three exchanges in China (the Hong Kong Stock Exchange, Shanghai Stock Exchange, and Shenzhen Stock Exchange), and three exchanges in the U.S. (the New York Stock Exchange, American Stock Exchange, and NASDAQ). Given the large number of stocks and large amount of data in the U.S. market, we select a random sample of 400 firms out of the universe of all eligible U.S. firms in 1996,

[16] Specifically, we validate the match by comparing the Datastream price history to the TRTH price history after adjusting for currency reporting differences. TRTH prices are historical prices in the original currency. Datastream unadjusted prices are historical prices in the current currency unit, e.g. French stocks prior to 1999 were traded in French Franc but reported in Euro in Datastream. We convert Datastream prices to the original trading currency. Some differences are not avoidable due to noises. For instance, the bid-ask spread can be over 20% for illiquid stocks, and that Datastream's algorithm to sample end of day price is not stated for each market and over time.

replace any firms that are ineligible in 1997 with randomly drawn firms out of the universe of all eligible U.S. firms in 1997, and so on rolling forward to 2007.[17]

We impose several filters in order to have reliable and consistent proxy estimates. First, we require that a stock have at least 11 non-zero return days in the month (i.e., at least approximately 50% non-zero returns in the month). Second, for Datastream we follow the recommendation of Ince and Porter (2006) to remove any stock-month with extreme return reversal. Finally, we winsorize our data for each liquidity variable by replacing values above the 99th percentile with the 99th percentile value and replacing values below the 1st percentile with the 1st percentile value. Our final non-U.S. sample has 8.5 billion trades and 13.6 billion quotes. We compute the percent-cost benchmarks and proxies and cost-per-volume benchmark and proxies for 24,847 firms in 1,782,309 stock-months. For the proxies that require a market return we use the local country value-weighted market portfolio.

Table 1 examines how well our TRTH sample matches with Datastream. The third column lists the number of Datastream stock-years in the sample period 1996-2007. The fourth columns lists the number of stock-years where we could match TRTH and Datastream records (i.e., matching security identifiers RIC and ISIN and verifying that the month-end prices are within 10% at least 90% of the time). For the global sample, our percent matched was 84.7%.

We also compared TRTH's intraday data to Bloomberg's intraday data. Since Bloomberg only retains historical data for a few months to a few years, we checked a random sample of ten stocks per exchange in December 2011. For the global sample, we found that the Bloomberg percent effective spread was 1.16% and the TRTH percent effective spread was 1.08% yielding a difference of 0.07%. We

[17] Following the methodology of Hasbrouck (2009), a stock must meet five criteria to be eligible: (1) it has to be a common stock, (2) it has to be present on the first and last TAQ master file for the year, (3) it has to have the NYSE, AMEX or NASDAQ as the primary listing exchange, (4) it does not change primary exchange, ticker symbol or cusip over the year, and (5) has to be listed in CRSP. We use the sample of Goyenko, Holden, and Trzcinka (2009) for the years 1996 – 2005 and extend the sample through 2007. This had the additional advantage of facilitating comparison to the Goyenko, Holden, and Trzcinka (2009) results.

also found that the correlation between the Bloomberg percent effective spread and the TRTH percent effective spread was 99.19%. This high correlation implies that correlations between liquidity proxies and TRTH percent effective spread would be nearly identical to correlations between liquidity proxies and Bloomberg percent effective spread.[18]

As a further data integrity check, Table 2 reports the median ratio of the sum of intraday share volume reported by TRTH divided by the share volume reported by Datastream per stock per day. We find that 91% of the exchange-year ratios are exactly 100%. We also find that 97% of the exchange-year ratios are in the range [95%, 102%].[19] The exchanges with the most prolonged deviation from this range are Milan (4 years), Vienna (3 years), and Bombay (3 years). With full acknowledgement of these deviations, we note that the large majority of exchange-year volume ratios are close to or exactly equal to 100%.

Combining all the evidence above, we conclude that the TRTH intraday equity dataset is a high-quality, reliable dataset for global research. Our evidence does *not* imply anything about any other TRTH data (e.g. futures, options, commodities, foreign exchange, fixed income, etc.).

4.3. Descriptive Statistics

Table 3 provides the equally-weighted mean of the monthly percent-cost benchmarks and proxies. Each row represents a different exchange. For example, looking at the first row, the country is

[18] As an additional data integrity test, we checked the trades in our database against the Nordic Security Depository, which is the central clearing agency for all trading in Finland. It includes the complete, official trading records of all trading in securities listed on the Helsinki Stock Exchange. The random checks we performed showed the trades agree so that if a trade of 200 shares at 10kr shows in the TRTH database, we will see a purchase of 200 shares at 10kr and a corresponding sale of 200 shares in the Depository data. We performed the random trades across all twelve years of our data, not just the overlapping period with the BCP study and we believe that for this market the TRTH database exactly replicates trades reported in the central clearing agency.

[19] There are several reasons why TRTH and Datastream may differ. First, the basis of volume quotation on TRTH can change from rounding to the nearest 1000 or 100, although it is mostly in 1 share. When there is rounding, there is rounding down errors. Some of the larger differences may be due to the fact that Datastream includes afterhours trades, whereas our TRTH sample doesn't.

Argentina and the exchange is Buenos Ar., which is short for the Buenos Aires Stock Exchange. The last row is the global average of all 43 exchanges. Of particular importance, the global average of the *closing* percent quoted spread proxy is 0.021 (last column of the proxies) is relatively close to the global average of the (intraday) percent quoted spread benchmark of 0.022 (second column of the benchmarks) and to the global average of the percent effective spread benchmark of 0.017 (first column of the benchmarks).

Table 4 provides the equally-weighted mean of the monthly cost-per-volume benchmarks and proxies. Of particular importance, the global average for each of the cost-per-volume proxies is an order of magnitude larger than the global average of lambda at $0.033*10^{-3}$. The closest proxy is Roll Impact at $0.389*10^{-3}$, which off by more than a factor of 10X. None of the cost-per-volume proxies are on the same scale as lambda.

Figures 1 and 2 allow us to look at patterns in the data over time. Figure 1 presents the equally-weighted mean of the monthly percent effective spread for seven exchanges around the world during the sample period (January 1996 to December 2007). In general, percent effective spreads have declined over time, but the pattern and timing is idiosyncratic to each exchange. Bombay hovered around 7% for a long time and then decline by 50% during 2004 and 2005. Sao Paulo fluctuated around 3% for a long time and then declined by one-third in late 2005. Frankfurt more than doubled from 2000 to 2002, before dropping below the original level in 2003. NASDAQ decline by a one-third in 1997 and decline further from 2003 to 2007. Tokyo increased in 1997 and declined gradually from 2002 to 2005. New York increased in 2000, declined sharply in 2001, and declined gradually since then. Perhaps the most surprising is Shanghai, which has been one of the lowest in the world over the entire sample period. Not shown is Shenzhen, which has also been one of the lowest in the world over the entire sample period.

Figure 2 presents the equally-weighted mean of the monthly lambda for seven exchanges around the world during the sample period (January 1996 to December 2007). The y-axis is on a log-scale because the values of lambda by exchange differ by many orders of magnitude. Again the pattern and timing of lambda is idiosyncratic to each exchange. Bombay declined sharply in 2004 and 2005. Sao Paulo declined sharply in 2006. Frankfurt increased to a peak in 2002 and then declined gradually through

2007. Both NASDAQ and New York declined gradually from 2003 to 2007. Tokyo increased in 1997 and declined from 2003 to 2007. Shanghai and Shenzhen (not shown) have both been among the lowest in the world over the sample period and both declined in 2006 and 2007.

Table 5 describes the availability of closing bid and ask prices in Datastream, which is the information that is required to computing the Closing Percent Quoted Spread proxy. We find that global average availability of closing bid and ask data in Datastream rises from 72.7% in 1996 to 95.1% in 2007. Seven exchanges have less than 70% availability in 1996 and this declines to zero in 2007. Seventeen exchanges have less than 90% availability in 1996 and this declines to five in 2007. For the most part, the data inputs required to compute the Closing Percent Quoted Spread are widely available in Datastream.

5. Results

5.1. Global Overview of Monthly Percent-Cost Proxies

Table 6 provides a global overview. Panels A-C report the global performance of ten monthly percent-cost proxies compared with four monthly percent-cost benchmarks (percent effective spread, percent quoted spread, percent realized spread, and percent price impact). The three panels report three performance dimensions: average cross-sectional correlations, portfolio time-series correlations, and average root mean squared errors.

Panel A reports the average cross-sectional correlation[20] for each monthly percent-cost proxy compared to the four monthly percent-cost benchmarks. The convention that we will use throughout the rest of the paper is to place a solid box around the highest correlation in the row and a dashed box around any correlations that are statistically indistinguishable from the highest correlation in the row at the 5% level.[21] The idea is to identify the best proxy relative to a particular benchmark and the full "leadership

[20] The average cross-sectional correlations are computed in the spirit of Fama and MacBeth (1973) by: (1) calculating for each month the cross-sectional correlation across all firms and then (2) calculating the average correlation value over all months.

[21] In all tables with cross-sectional correlations, we test if the correlations are different between proxies on the same row by t-tests on the time-series of correlations in the spirit of Fama-MacBeth. Specifically, we calculate the cross-

group" that statistical indistinguishable from the best proxy. For example in the first row, the proxy Closing Percent Quoted Spread has the highest average cross-sectional correlation with percent effective spread at 0.802 and there are no dashed boxes – so all of the rest of the correlations in the first row are significantly lower than 0.802. Boldfaced correlations are statistically different from zero at the 5% level.[22] All correlations in this panel are statistically different from zero.

Closing Percent Quoted Spread dominates all of the row comparisons for the four percent-cost benchmarks in Panel A. Closing Percent Quoted Spread has the highest correlation (solid box) on all four rows and the Closing Percent Quoted Spread correlation is statistically higher than the correlation of any other proxy on all four rows. FHT has the second best correlations on the first three rows and the third best in the fourth row. High-Low has the third best correlations on the first three rows and the second best in the fourth row. This is evidence that Closing Percent Quoted Spread, FHT, and High-Low are the *top three* percent-cost proxies. This paper is the first to test any of these top three proxies against the others.

Closing Percent Quoted Spread is the winner by a wide margin. It provides enormous performance gains over the proxies that global research has used-to-date (Zeros, LOT Mixed, etc.). For instance, Panel A's results imply that it's mean cross-sectional correlation is 1.9-2.2 times the correlation of Zeros and 1.4-1.6 times the correlation of LOT Mixed. Interestingly, Closing Percent Quoted Spread

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sectional correlation of each proxy for each month and then regress the correlations of one proxy on the correlations of another proxy. We assume that the time series of correlations of each proxy is *i.i.d.* over time, and test if the regression intercept is zero and the slope is one. Standard errors are adjusted for autocorrelation with a Newey-West correction using four lags.

[22] In all tables with correlations, we test if the correlations in all tables to see if they are statistically different from zero and highlight the correlations that are significant in boldface. For an estimated correlation σ, Swinscow (1997, Ch. 11) gives the appropriate test statistic as

$$t = \sigma\sqrt{\frac{D-2}{1-\sigma^2}},$$

where D is the sample size.

has relatively higher correlations with percent effective spread (0.802) and percent quoted spread (0.920) and relatively lower correlations with percent realized spread (0.592) and percent price impact (0.562).

Figure 3 plots the global average of the cross-sectional correlations of six percent-cost proxies with percent effective spread over time. The global average of the cross-sectional correlation for Closing Percent Quoted Spread stays primarily in the range 0.65 – 0.85 range over the entire sample period. It is typically 0.15-0.20 above FHT and High-Low. It is typically 0.30-0.40 above Zeros. In other words, the large increase in performance occurs throughout the sample period.

Table 6, Panel B is based on equally-weighted portfolios across all stocks for month *i*. That is, we compute a portfolio percent-cost proxy (benchmark) in month *i* by taking the average of that percent-cost proxy (benchmark) over all stocks in month *i*. Then, Panel B reports the time-series correlation between each portfolio percent-cost proxy and the portfolio percent-cost benchmarks. Closing Percent Quoted Spread dominates all of the row comparisons for the four percent-cost benchmarks. Closing Percent Quoted Spread has the highest correlation (solid box) on all four rows and the Closing Percent Quoted Spread correlation is statistically higher than the correlation of any other proxy on three rows and higher than all but Extended Roll on the fourth row.[23] As in panel A, Closing Percent Quoted Spread, FHT, and High-Low are the top three percent-cost proxies on all four rows. Once again, Closing Percent Quoted Spread provides enormous performance gains over Zeros, LOT Mixed, etc. Again we find that Closing Percent Quoted Spread has relatively higher correlations with percent effective spread (0.827) and percent quoted spread (0.871) and relatively lower correlations with percent realized spread (0.627) and percent price impact (0.634).

Panel C reports the average root mean squared error (RMSE) between each percent-cost proxy and percent-cost benchmarks based on individual firms. The average RMSE tells us whether a particular proxy does a good job of capturing the *level* of a benchmark, not just whether it is correlated with the benchmark. The root mean squared error is calculated every month for a given exchange and then

[23] We test whether time-series correlations are statistically different from each other using Fisher's Z-test.

averaged over all sample months. In this case, a solid box identifies the *lowest* average RMSE in the row and a dashed box indicates RMSEs that are statistically indistinguishable from the *lowest* average RMSE in the row.[24] Boldfaced RMSE indicates that the predictive power of the variation in the proxy is statistically different from zero at the 5% level.[25]

Closing Percent Quoted Spread has the lowest average RMSE (solid box) on the first two rows. It is statistically indistinguishable from High-Low relative to percent effective spread and significantly better than all other proxies relative to percent quoted spread. Again, Closing Percent Quoted Spread, FHT, and High-Low are the top three percent-cost proxies on both rows. As in panels A and B, Closing Percent Quoted Spread provides enormous performance gains over Zeros, LOT Mixed, etc.

High-Low has the lowest average RMSE (solid box) on the last two rows. It significantly better than all other proxies relative to percent realized spread and percent price impact. Overall, Closing Percent Quoted Spread is closest to the level of percent effective spread and percent quoted spread, whereas High-Low is closest to the level of percent realized spread and percent price impact.

Figure 4 graphs the global average level of the top three percent-cost proxies (Closing Percent Quoted Spread, FHT, and High-Low) and four percent-cost benchmarks over the sample period. Closing Percent Quoted Spread is very close in both level and pattern to the Percent Quoted Spread Benchmark throughout the sample period. And both of them follow a relatively similar pattern to the Percent Effective Spread Benchmark, except that the level of the latter is approximately 0.5% lower. FHT follows the pattern of Percent Effective Spread well, except that the level is sometimes lower. The Percent Realized Spread Benchmark and the Percent Price Impact Benchmark, which by definition sum up to the Percent Effective Spread Benchmark, are typically nearly equal (except in the year 2000). Thus, their

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[24] We test whether RMSEs are statistically different from each other using a paired t-test.

[25] We test whether RMSEs are statistically significant using the U-statistic developed by Theil (1966). Here, if $U^2 = 1$, then the proxy has zero predictive power (i.e., it is no better at predicting the benchmark than the sample mean). If $U^2 = 0$, then the proxy perfectly predicts the benchmark. We test if U^2 is significantly less than 1 based on an F distribution where the number of degrees of freedom for both the numerator and the denominator is the sample size.

level is approximately half the level of the Percent Effective Spread Benchmark. High-Low is typically much closer to the level of the Percent Realized Spread Benchmark and the Percent Price Impact Benchmark than to the level of Percent Effective Spread Benchmark.

To summarize Table 6, Panels A-C, Closing Percent Quoted Spread strongly dominates all other monthly percent-cost proxies and provides enormous performance gains over Zeros, LOT Mixed, etc. It is highly correlated with all four percent-cost benchmarks – both in the cross-section and in the time-series. It does the best job of capturing the level of percent effective spread and percent quoted spread, whereas High-Low does the best job of capturing the level of percent realized spread and percent price impact.

5.2. Global Overview of Monthly Cost-Per-Volume Proxies

The global overview continues with Panels D-F, which report the global performance of thirteen monthly cost-per-volume proxies compared with the single monthly cost-per-volume benchmark (lambda). Panel A reports the average cross-sectional correlation for each monthly cost-per-volume proxy compared to monthly lambda. Closing Percent Quoted Spread Impact has the highest correlation (0.563) and that is statistically higher than the correlation of any other proxy.

Figure 5 plots the global average of the cross-sectional correlations of five cost-per-volume proxies with lambda over time (January 1996 to December 2007). The global average of the cross-sectional correlations of all five proxies (Closing Percent Quoted Spread Imapct, FHT Impact, High-Low Impact, LOT Mixed Impact, and Amihud) are very close over the entire sample. The correlations are typically in the 0.45 – 0.60 range over the entire sample period. In other words, the performance of these five proxies is very similar throughout the sample period.

Table 6, Panel E reports the time-series correlation between each portfolio cost-per-volume proxy and the portfolio lambda. LOT Mixed Impact has the highest correlation (0.645) but that is statistically indistinguishable from Roll Impact and High-Low Impact.

Panel F reports the *ratio* of the average root mean squared error (RMSE) between each cost-per-volume proxy and lambda divided by the mean of lambda. The lowest ratio is Paster and Stambaugh at 3.4. The rest of the cost-per-volume proxies have a ratio of 51 or greater. In other words, the average error is an order of magnitude larger than the mean of lambda itself. Thus, we conclude that none of the cost-per-volume proxies capture the level of lambda.

Figure 6 graphs the global average level of five cost-per-volume proxies and lambda over the sample period. It is visually clear that all five proxies are correlated with lambda. However, considering that the y-axis is on a log-scale, it is immediately clear that none of the proxies is on the same order of magnitude as lambda. In other words, there is more than a 10X difference in level between the proxies and lambda throughout the sample period.

To summarize Table 6, Panels D-F we find that five monthly proxies do nearly as well economically on *both* Panels D and E. They are LOT Mixed Impact, FHT Impact, High-Low Impact, Closing Percent Quoted Spread Impact, and Amihud. All five are highly correlated with monthly lambda, but none captures its level.

5.3. Developed vs. Emerging Countries

Next we examine the robustness of our results in developed countries vs. emerging countries. Table 7, Panels A-C report monthly percent-cost proxies compared with monthly percent effective spread and Panels D-F report monthly cost-per-volume proxies compared with monthly lambda.

In Panels A and B, we find that Closing Percent Quoted Spread has the highest correlation and is significantly higher than the correlation of any other proxy in both developed and emerging countries. In Panel C, we find that Closing Percent Quoted Spread has the lowest average RMSE, is significantly lower than any other proxy in developed countries except for High-Low, and is significantly lower than any other proxy in emerging countries.

In Panel D, we find that Closing Percent Quoted Spread Impact has the highest correlation and is significantly higher than the correlation of any other proxy in both developed and emerging countries. In Panel E, we find Amihud has the highest correlation in Developed Countries, LOT Mixed Impact has the highest in Emerging Countries, and several other proxies are insignificantly different to the leaders in both cases. In all cases in Panels D and E, the five cost-per-volume proxies LOT Mixed Impact, FHT Impact, High-Low Impact, Closing Percent Quoted Spread Impact, and Amihud are essentially economically equivalent to the leader. Panel F reports the *ratio* of the average root mean squared error (RMSE) between each cost-per-volume proxy and lambda divided by the mean of lambda. All of the ratios are larger than one (i.e., the average error is larger than the mean of lambda itself) in both developed and emerging countries. Thus, none of the monthly cost-per-volume proxies captures the level of monthly lambda.

5.4. Overview of Daily Liquidity Proxies

Table 8 provides an overview of daily liquidity proxies. Panels A compares two daily percent-cost proxies with four daily percent-cost benchmarks on a global basis and Panel B compares both daily proxies with daily percent effective spread in developed and emerging countries. We find the same pattern as the monthly results. Daily Closing Percent Quoted Spread strongly dominates daily High-Low. Its correlations with all four daily percent-cost benchmarks are surprisingly high (i.e., they are only modestly diminished compared to the analogous monthly proxy correlations). It does the best job of capturing the level of daily percent effective spread and daily percent quoted spread, whereas daily High-Low does the best job of capturing the level of daily percent realized spread and daily percent price impact.

Panels C and D analyze four daily cost-per-volume proxies relative to daily lambda. Daily Amihud dominates the other daily cost-per-volume proxies. Like the monthly version, daily Amihud is strongly correlated with daily lambda, but doesn’t capture its level.

5.5. By Exchange

Table 9, Panel A reports the average cross-sectional correlation for each percent-cost proxy with percent effective spread by exchange. Closing Percent Quoted Spread strongly dominates. It has the highest correlation on 42 out of 43 exchanges and is statistically higher than the correlation of any other proxy on all 42 exchanges. It consistently provides enormous performance gains over Zeros, LOT Mixed, etc. Similarly, Panel B reports the average cross-sectional correlation for the US as a whole. It is a weighted average over the three US exchanges, where the weights are based on the number of stocks on each exchange in the sample. Closing Percent Quoted Spread has the highest correlation and is statistically higher than any other proxy. High-Low has the second highest correlation.

Table 10, Panel A reports the time-series correlation between each portfolio percent-cost proxy and portfolio percent effective spread by exchange. Closing Percent Quoted Spread dominates these comparisons, but not quite as strongly as before. Closing Percent Quoted Spread has the highest portfolio time-series correlation on 31 out of 43 exchanges. It has the highest correlation or is insignificantly different from the highest on 35 exchanges. Remarkably, it yields correlations of 95% or above on 14 exchanges and yields correlations of 80% or above on 35 exchanges. Panel B reports the time-series correlation for the US as a whole weighted by the number of stocks on each exchange. Closing Percent Quoted Spread has the highest time-series correlation.

Table 11, Panel A reports the average RMSE between each percent-cost proxy and percent-cost benchmarks by exchange. Closing Percent Quoted Spread dominates these comparisons too. It has the lowest RMSE on 30 exchanges. It has the lowest RMSE or is insignificantly different from the lowest on 34 exchanges. Panel B reports the average RMSE for the US as a whole. High-Low has the lowest average RMSE and is statistically higher than any other proxy. Closing Percent Quoted Spread has the second lowest average RMSE.

Table 12, Panel A reports the average cross-sectional correlation for each cost-per-volume proxies with lambda by exchange. Five proxies do better than the rest. Closing Percent Quoted Spread Impact, LOT Mixed Impact, High-Low Impact, Amihud, and FHT Impact have the highest average cross-sectional correlation on 18 exchanges, 12 exchanges, 8 exchanges, 2 exchanges, and 1 exchange, respectively. The same five has the highest correlation or is insignificantly different from the highest on 22 exchanges, 17 exchanges, 10 exchanges, 6 exchanges, and 6 exchanges, respectively. Panel B reports the average cross-sectional correlation for the US as a whole. High-Low Impact has the highest correlation and is statistically higher than any other proxy. Closing Percent Quoted Spread Impact and LOT Mixed Impact are close behind.

Table 13, Panel A compares daily liquidity proxies with daily liquidity benchmarks by exchange and Panel B does the same for the US as a whole. In both panels, daily Closing Percent Quoted Spread dominates the daily percent-cost results and daily Amihud dominates the daily cost-per-volume results.

In summary, Panel A of Tables 9-11 and 13 show that Closing Percent Quoted Spread robustly dominates most exchanges as the best proxy for percent effective spread at both frequencies. It is highly correlated with and captures the level of percent effective spread. In the US context, Panel B of Tables 9-11 show that Closing Percent Quoted Spread and High-Low are essentially tied as the best monthly proxies for the US as a whole. For researchers who need a long time-series, monthly High-Low has the advantage of being available for a much longer period of time in US data.[26] Table 12 shows that five monthly cost-per-volume proxies, Closing Percent Quoted Spread Impact, LOT Mixed Impact, High-Low Impact, FHT Impact, and Amihud, are nearly equivalent in being highly correlated with monthly lambda. Table 13 shows that daily Closing Percent Quoted Spread and daily Amihud are the best daily liquidity proxies. However, the prior sections showed that none of proxies capture the level of lambda at either frequency.

6. Conclusion

We examine a relatively new global intraday equity dataset, Thomson Reuters Tick History (TRTH). We find that we can match a relatively high percentage of Datastream stock-years to TRTH and the database does well on several data integrity checks. Using TRTH data, we compare both monthly and daily liquidity proxies constructed from low-frequency (daily) stock data to corresponding liquidity benchmarks computed from high-frequency (intraday) data for 24,847 firms on 43 exchanges around the world on three performance dimensions: average cross-sectional correlation with the benchmarks,

[26] Specifically, High-Low measure can be computed from CRSP High and Low prices that are available for all US stocks on all exchanges from 1926 – present. By contrast, the Daily Percent Quoted spread can be computed from CRSP Closing Bid and Ask prices, which are only available on NYSE/AMEX from 1926 – 1941 and 1993 – present, on the NASDAQ Global Market and Global Select Market (formerly National Market) 1982 – present, and on the NASDAQ Capital Market (formerly SmallCap) 1992 – present.

portfolio correlations with the benchmarks, and prediction accuracy. We find that for both monthly and daily frequencies Closing Percent Quoted Spread strongly dominates all other percent-cost proxies for global research. It has by-far the highest correlations with percent effective spread, percent quoted spread, percent realized spread, and percent price impact. It provides enormous performance gains over the monthly proxies that global research has used-to-date. At both daily and monthly frequencies, Closing Percent Quoted Spread also does the best job of capturing the *level* of percent effective spread and percent quoted spread. At both frequencies, High-Low does the best job of capturing the *level* of percent realized spread and percent price impact. These are the first findings at the daily frequency that liquidity proxies can perform well. We find that five proxies are nearly equivalent as the best monthly cost-per-volume proxies: Closing Percent Quoted Spread Impact, LOT Mixed Impact, High-Low Impact, FHT Impact, and Amihud. We find that the daily version of Amihud is the best daily cost-per-volume proxy. All of these cost-per-volume proxies are highly correlated with lambda, but none of them captures the level of lambda at either frequency.

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Appendix: Existing Low-Frequency Proxies.

$$Roll = 2\sqrt{-Cov\left(\Delta P_t, \Delta P_{t-1}\right)} \Big/ \overline{P} \text{ when } Cov\left(\Delta P_t, \Delta P_{t-1}\right) < 0 \text{ or } 0 \text{ when } Cov\left(\Delta P_t, \Delta P_{t-1}\right) \geq 0.$$

$$Extended\ Roll = 2\sqrt{-Cov\left(\Delta P_t^*, \Delta P_{t+1}^*\right)} \Big/ \overline{P} \text{ when } Cov\left(\Delta P_t^*, \Delta P_{t+1}^*\right) < 0 \text{ or } 0 \text{ when } Cov\left(\Delta P_t^*, \Delta P_{t+1}^*\right) > 0,$$

where $\Delta P_t^* = z_t \cdot P_{t-1}$ and z_t is the residual from $ar_t - r_f = \alpha + \beta\left(r_{mt} - r_f\right) + z_t$.

$$Effective\ Tick = \frac{\sum_{j=1}^{J} \hat{\gamma}_j s_j}{\overline{P}_i} \text{ on a \$1/8th price grid is:}$$

$$F_j = \frac{N_j}{\sum_{j=1}^{J} N_j} \text{ for } j = 1, 2, \ldots, J; \qquad U_j = \begin{cases} 2F_j & j = 1 \\ 2F_j - F_{j-1} & j = 2, 3, \ldots, J-1; \\ F_j - F_{j-1} & j = J. \end{cases}$$

$$\hat{\gamma}_j = \begin{cases} Min\left[Max\left\{U_j, 0\right\}, 1\right] & j = 1 \\ Min\left[Max\left\{U_j, 0\right\}, 1 - \sum_{k=1}^{j-1} \hat{\gamma}_k\right] & j = 2, \ldots, J; \end{cases}$$

where F_j is the probability of trades on prices corresponding to the jth spread, U_j be the unconstrained probability of the jth spread, $\hat{\gamma}_j$ be the *constrained* probability of the jth spread, and s_j is the jth spread. The decimal price grid formula is in Appendix A of Holden (2009). Detailed examples are at: www.kelley.iu.edu/cholden/examples.pdf.

$LOT\ Mixed = \alpha_2 - \alpha_1,$ where $\alpha_2\left(\alpha_1\right)$ is the trans cost to buy (sell) and is estimated using:

$$\underset{\alpha_1,\alpha_2,\beta,\sigma}{Max}\begin{cases}\prod_1 \frac{1}{\sigma} n\left[\frac{R_t+\alpha_1-\beta R_{mt}}{\sigma}\right] \\ \times\prod_0 \left[N\left(\frac{\alpha_2-\beta R_{mt}}{\sigma}\right)-N\left(\frac{\alpha_1-\beta R_{mt}}{\sigma}\right)\right] \\ \times\prod_2 \frac{1}{\sigma} n\left[\frac{R_t+\alpha_2-\beta R_{mt}}{\sigma}\right]\end{cases}$$

where $R_t\left(R_{mt}\right)$ is the own return (market return), σ is the return volatility, and β is the stock's market sensitivity, $S.T.\quad \alpha_1 \le 0, \alpha_2 \ge 0, \beta \ge 0, \sigma \ge 0$. $LOT\ Mixed$ is capped at a max value of 1.5.

Region 0 is $R_{jt} = 0$, region 1 is $R_{jt} \neq 0$ and $R_{mt} > 0$, and region 2 is $R_{jt} \neq 0$ and $R_{mt} < 0$.

$LOT\ Y\text{-}split = \alpha_2 - \alpha_1$ where everything is the same as *LOT Mixed*, except that region 0 is $R_{jt} = 0$, region 1 is $R_{jt} > 0$, and region 2 is $R_{jt} < 0$ and no upper bound cap is imposed. $Zeros = \frac{ZRD}{TD+NTD}$, where ZRD = the number of zero returns days, TD = number of trading days, and NTD = number of no-trade days in a given stock-month.

$High - Low = Average\left(\frac{2\left(e^{\alpha_t}-1\right)}{1+e^{\alpha_t}}\right)$; where $\alpha_t = \frac{\sqrt{2\beta_t}-\sqrt{\beta_t}}{3-2\sqrt{2}} - \sqrt{\frac{\gamma_t}{3-2\sqrt{2}}}$, β_t is the sum over two days of the squared daily log(high/low), and γ_t is the squared log(High/Low) where the High (Low) value is over two days.

$$Daily\ Percent\ Quoted\ Spread\ = Average\left(\frac{Closing\ Ask_t - Closing\ Bid_t}{\left(Closing\ Ask_t + Closing\ Bid_t\right)/2}\right)$$

$Amihud\ = Average\left(\frac{\left|r_t\right|}{Volume_t}\right)$, where r_t is the stock return on day *t* and $Volume_t$ is the currency value of volume on day *t* in units of local currency.

$Extended\ Amihud\ Proxy_i = \frac{\text{Percent Cost Proxy}_\text{i}}{\text{Average Daily Currency Volume}_\text{i}}$. We test ten versions of this class of cost-per-volume measures based on ten corresponding percent-cost proxies.

$Pastor\ and\ Stambaugh = \Gamma$, from the regression: $r_{t+1}^{e} = \theta + \phi r_t + \Gamma sign\left(r_t^e\right)\left(Volume_t\right) + \varepsilon_t$, where r_t^e is the stock's excess return above the CRSP VWMR on day *t*, θ is the intercept, ϕ and Γ are regression coefficients, and ε_t is the error term.

$Amivest\ = Average\left(\frac{Volume_t}{|r_t|}\right)$. All dollar spread proxies above are converted to percent spread proxies by dividing by the average price $\overline{P}$ in a given stock-month.

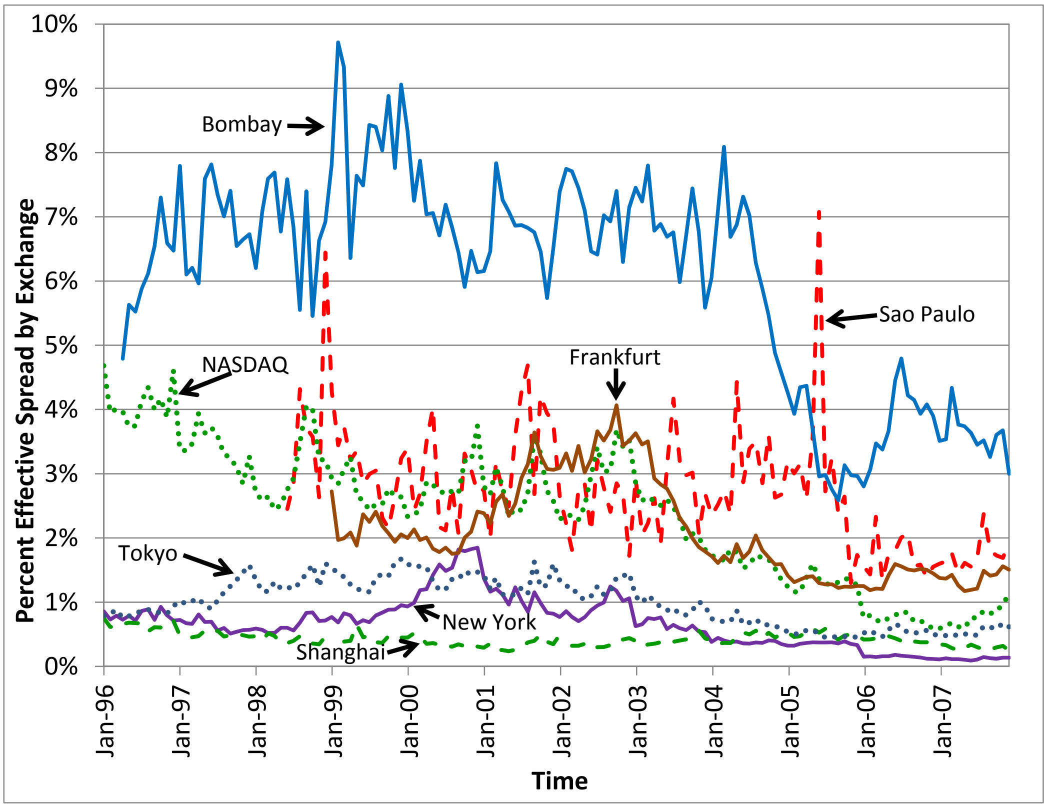

Figure 1 Percent Effective Spread By Exchange Over Time.

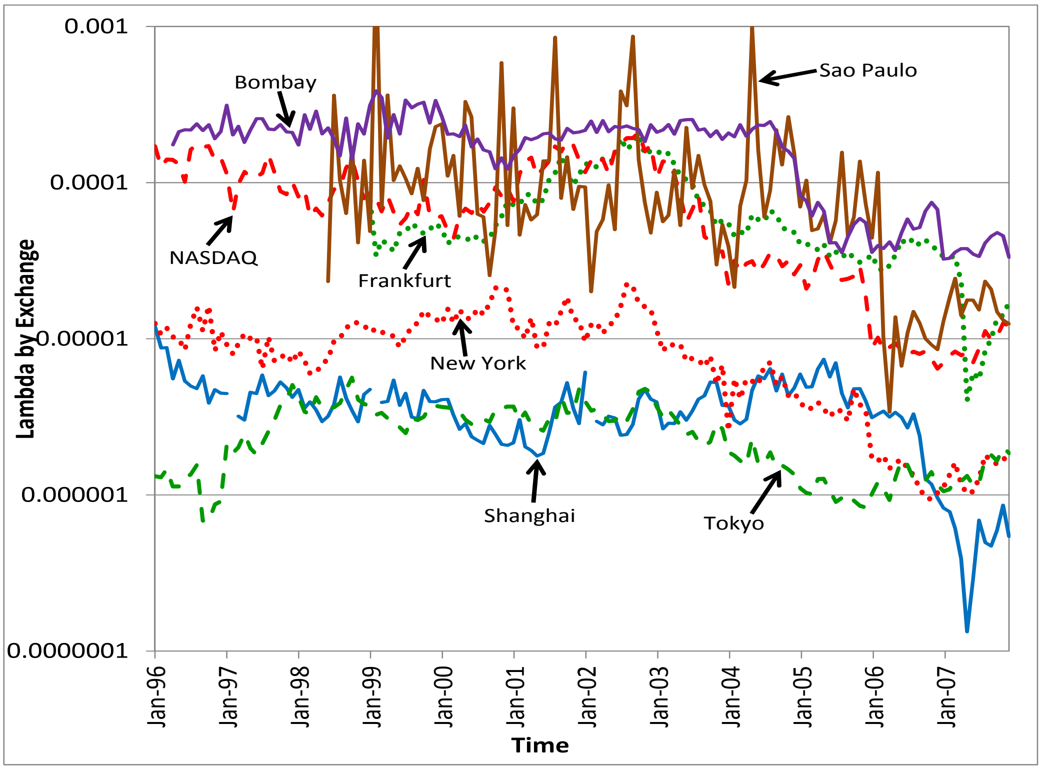

Figure 2 Lambda By Exchange Over Time.

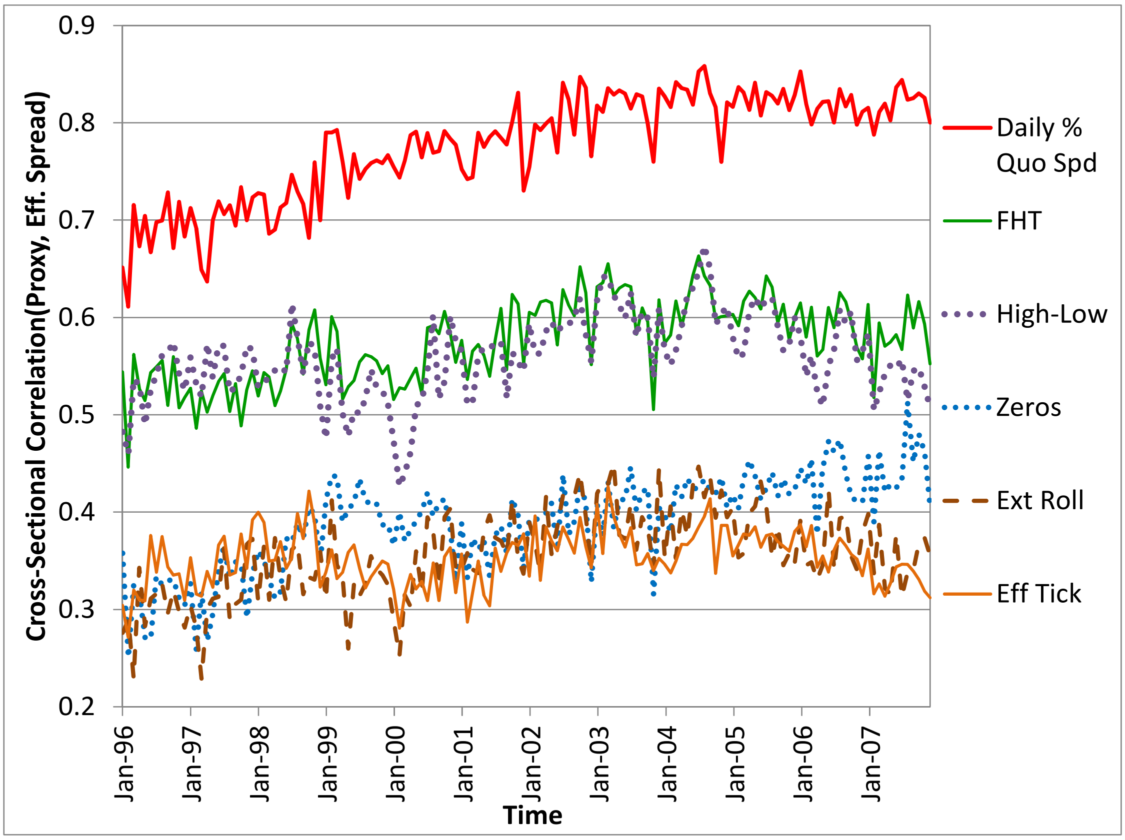

Figure 3 Global Average of Cross-Sectional Correlations(Proxy, Percent Effective Spread) Over Time.

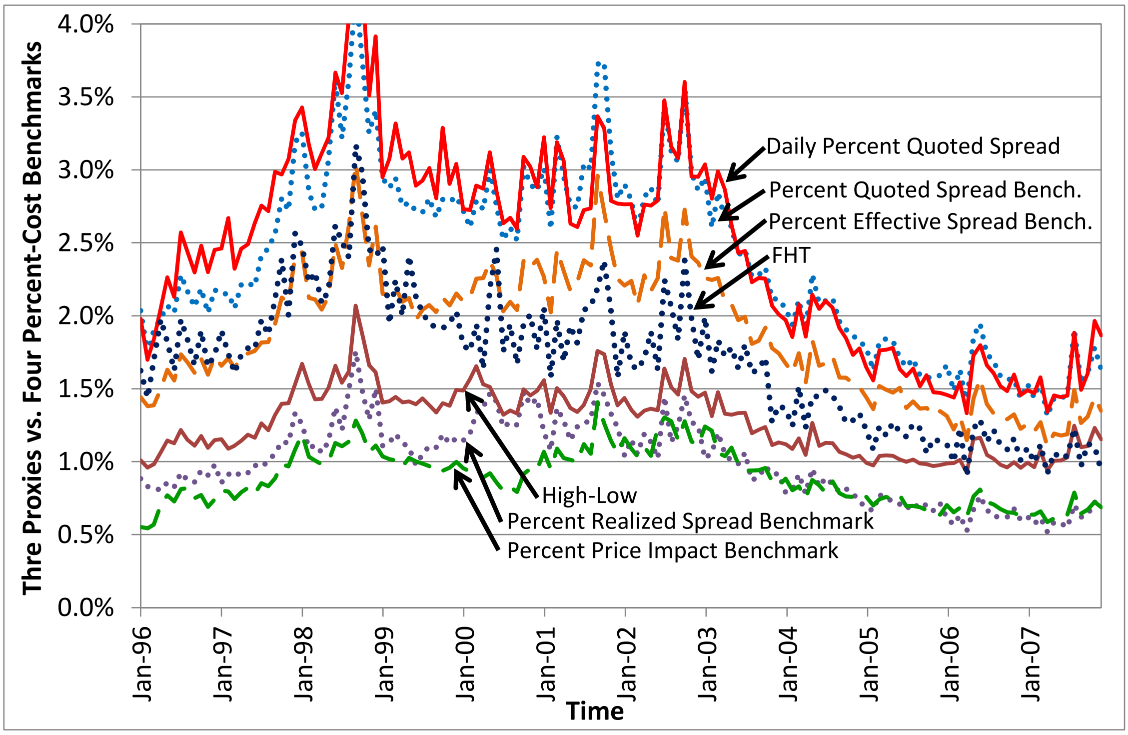

Figure 4 Global Average of Three Percent-Cost Proxies and Four Percent-Cost Benchmarks over Time.

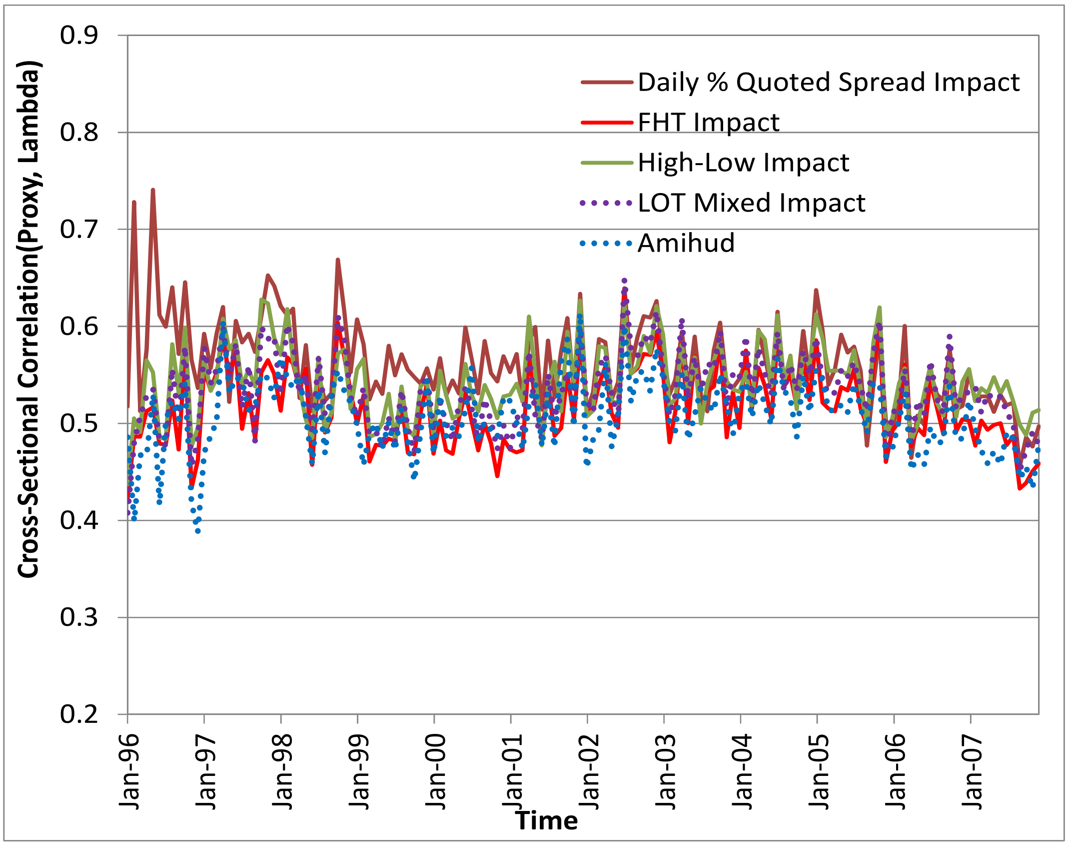

Figure 5 Global Average of Cross-Sectional Correlations(Proxy, Lambda) Over Time Figure.

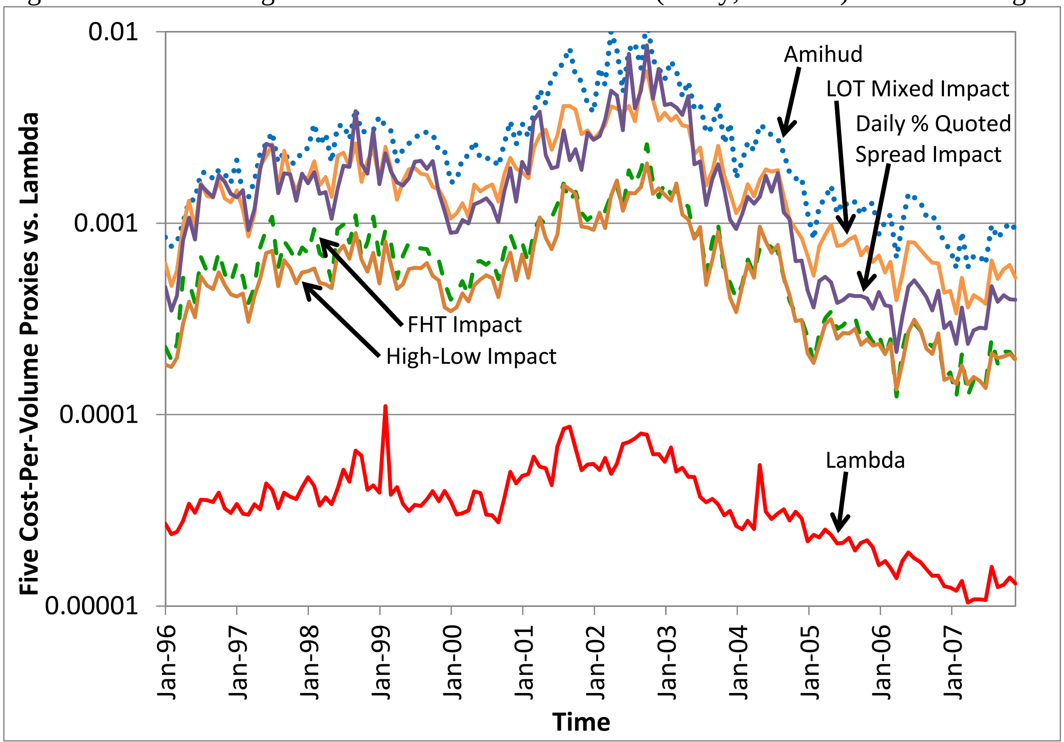

Figure 6 Global Average of Five Cost-Per-Volume Proxies and Lambda Over Time.

Table 1

Thompson Reuters Tick History (TRTH) Trade and Quote Count, Match With Datastream and Comparison With Bloomberg

per day. 2007 daily average is the average across all stock-days in 2007. 2007/1996 relative average is the average daily value in 2007 divided by the average stock-day in 1996. Blank value is due to the sample starts after 1996. 2011/2007 relative daily average is defined analogously. Match with Datastream is the percentage of Datastream stock-years in 1996-2007 where we could match TRTH and Datastream records (i.e., matching security identifiers RIC and ISIN and verifying that the month-end prices are within 10% at least 90% of the time). The median TRTH to Datastream Volume is the median daily ratio of the sum of intraday share volume reported by TRTH divided by share volume reported by Datastream. The TRTH comparison with Bloomberg is the difference in the TRTH and Bloomberg percent effective spreads and the correlation of the TRTH and Bloomberg percent effective spreads based on a random sample of 10 stocks per exchange in December

		Match With Datastream (1996-2007)				Comparison With Bloomberg (December 2011)			
Country	Exchange	Number of Datastream Stock-Years	Match With Datastream (Stock-Years)	Percent Matched	Median TRTH to Datastream Volume	Bloomberg % Effective Spread	TRTH % Effective Spread	Difference in % Effective Spread	Correlation of Bloomberg & TRTH %EffSpd
Argentina	Buenos Ar.	794	679	85.5%	100%	1.53%	1.36%	0.17%	97.85%
Australia	Australian	14,072	11,855	84.2%	100%	0.44%	0.51%	-0.07%	99.69%
Austria	Vienna	999	785	78.6%	100%	0.32%	0.33%	-0.01%	98.98%
Belgium	Brussels	1,480	1,361	92.0%	100%	0.08%	0.09%	-0.01%	98.38%
Brazil	Sao Paulo	910	740	81.3%	100%	0.72%	1.06%	-0.34%	99.99%
Canada	Toronto	12,466	7,254	58.2%	100%	1.17%	0.43%	0.74%	95.30%
Chile	Santiago	1,993	905	45.4%	100%	1.15%	0.95%	0.20%	99.75%
China	Hong Kong	8,986	7,945	88.4%	100%	0.21%	0.23%	-0.02%	99.96%
China	Shanghai	7,263	7,042	97.0%	99%	0.18%	0.20%	-0.02%	99.54%
China	Shenzhen	5,437	5,287	97.2%	105%	0.20%	0.20%	0.00%	99.99%
Denmark	Copenhag.	2,208	1,912	86.6%	100%	0.65%	0.63%	0.02%	99.97%
France	Paris	9,662	7,527	77.9%	100%	0.24%	0.26%	-0.02%	99.99%
Finland	Helsinki	1,411	1,313	93.1%	100%	1.35%	1.31%	0.04%	99.95%
Germany	Frankfurt	1,996	1,546	77.5%	100%	6.51%	3.83%	2.68%	99.14%
Greece	Athens	3,174	2,940	92.6%	100%	3.35%	3.26%	0.09%	99.99%
India	Bombay	12,811	10,929	85.3%	100%	1.45%	1.52%	-0.07%	97.52%
Indonesia	Jakarta	3,360	3,325	99.0%	100%	2.55%	2.73%	-0.18%	99.99%
Ireland	Irish	422	345	81.8%	100%	2.16%	2.34%	-0.18%	95.41%
Israel	Tel Aviv	4,957	3,996	80.6%	100%	2.07%	1.79%	0.28%	99.91%
Italy	Milan	2,872	2,735	95.2%	100%	0.17%	0.16%	0.01%	99.40%
Japan	Tokyo	25,834	23,220	89.9%	100%	0.24%	0.25%	-0.01%	99.98%
Japan	Osaka	2,940	2,885	98.1%	100%	1.17%	1.06%	0.11%	95.14%
Malaysia	Kuala Lum.	8,490	8,076	95.1%	100%	4.40%	4.71%	-0.31%	100.00%
Mexico	Mexican	1,303	1,093	83.9%	100%	0.50%	0.53%	-0.03%	99.96%
Netherland	AEX	1,885	1,353	71.8%	100%	0.10%	0.11%	-0.01%	99.99%
New Zealand	New Zea.	923	720	78.0%	100%	1.60%	1.64%	-0.04%	96.74%
Norway	Oslo	2,215	2,059	93.0%	100%	0.39%	0.39%	0.00%	99.73%
Philippines	Phillipine	2,289	2,141	93.5%	100%	---	---	---	---
Poland	Warsaw	992	837	84.4%	100%	1.54%	1.39%	0.15%	99.15%
Portugal	Lisbon	883	158	17.9%	100%	0.36%	0.38%	-0.02%	99.78%
Singapore	Singapore	4,528	4,281	94.5%	100%	3.06%	3.23%	-0.17%	99.92%
South Africa	Johannes.	4,894	4,403	90.0%	100%	1.10%	1.13%	-0.03%	99.79%
South Korea	Korea	7,738	7,097	91.7%	100%	0.22%	0.24%	-0.02%	98.68%
Spain	Barcelona	1,498	1,406	93.9%	100%	0.49%	0.48%	0.01%	99.99%
Sweden	Stockholm	3,768	3,164	84.0%	100%	0.34%	0.36%	-0.02%	99.89%
Switzerland	SWX Swiss	2,872	2,366	82.4%	108%	0.71%	0.73%	-0.02%	99.86%
Taiwan	Taiwan	6,986	6,156	88.1%	100%	0.32%	0.34%	-0.02%	99.30%
Thailand	Thailand	4,536	4,273	94.2%	100%	0.94%	0.95%	-0.01%	100.00%
Turkey	Istanbul	3,020	2,958	97.9%	100%	0.74%	0.74%	0.00%	99.98%
UK	London	18,650	13,382	71.8%	100%	0.38%	0.43%	-0.05%	100.00%
Global		203,517	172,449	84.7%	100.28%	1.16%	1.08%	0.07%	99.19%

Table 2

TRTH and Datastream Trading Volume Comparison

This table reports the median ratio of TRTH to Datastream Volume, which is the median ratio of the sum of intraday share volume reported by TRTH divided by share volume reported by Datastream per stock per day.

Country	Exchange	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	All Years
Argentina	Buenos Ar.			100%	101%	101%	103%	102%	100%	100%	100%	100%	100%	100%
Australia	Australian	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Austria	Vienna				50%	50%	56%	100%	100%	100%	100%	100%	100%	100%
Belgium	Brussels				100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Brazil	Sao Paulo			100%	100%	93%	100%	100%	100%	100%	65%	100%	100%	100%
Canada	Toronto	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Chile	Santiago							100%	100%	100%	100%	100%	100%	100%
China	Hong Kong	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
China	Shanghai	99%	99%	100%	100%	100%	100%	100%	100%	100%	100%	100%	97%	100%
China	Shenzhen	97%	95%	97%	98%	97%	98%	99%	100%	100%	100%	100%	100%	99%
Denmark	Copenhag.	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	101%	100%
France	Paris				95%	96%	97%	97%	100%	100%	100%	100%	100%	100%
Finland	Helsinki				100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Germany	Frankfurt				100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Greece	Athens						100%	100%	100%	100%	100%	100%	100%	100%
India	Bombay	100%	100%	100%	100%	100%	100%	100%	74%	51%	61%	100%	100%	100%
Indonesia	Jakarta	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Ireland	Irish					100%	100%	100%	100%	100%	100%	100%	100%	100%
Israel	Tel Aviv			100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Italy	Milan				77%	71%	75%	73%	100%	102%	102%	100%	100%	100%
Japan	Tokyo	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Japan	Osaka	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Malaysia	Kuala Lum.	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Mexico	Mexican			100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Netherland	AEX				100%	100%	99%	97%	100%	100%	100%	101%	100%	100%
New Zealand	New Zea.	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Norway	Oslo	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Philippines	Phillipine	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Poland	Warsaw					100%	100%	100%	100%	100%	100%	100%	100%	100%
Portugal	Lisbon										100%	100%	100%	100%
Singapore	Singapore	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
South Africa	Johannes.	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
South Korea	Korea								100%	100%	100%	100%	100%	100%
Spain	Barcelona				100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Sweden	Stockholm	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Switzerland	SWX Swiss	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Taiwan	Taiwan	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Thailand	Thailand	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Turkey	Istanbul										100%	100%	100%	100%
UK	London	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Global Median		100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

Table 3

Mean of the Monthly Percent Cost Benchmarks and Proxies

The percent cost benchmarks (percent effective spread, percent quoted spread, percent realized spread, and percent price impact) are calculated from every trade and corresponding BBO quote in the SIRCA Thomson Reuters Tick History database for a sample stock-month. All percent cost proxies are calculated from daily stock price data for a sample stock-month. The sample spans 43 exchanges around the world from 1996-2007. It consists of all stock-months with at least five positive-volume days and eleven non-zero return days. This results in 1,531,162 stock-months from 24,847 firms. All variables are winsorized at 1st and 99th percentile in each exchange-year.

		Percent Cost Benchmarks				Percent Cost Proxies												
Country	Exchange	% Effective Spread	% Quoted Spread	% Realized Spread	% Price Impact	Roll	Extended Roll	Effective Tick	LOT Mixed	LOT Y-split	FHT	Zeros	Zeros2	High -Low	Closing % Quo Sprd	Stocks	Stock-Months	Start Date
Argentina	Buenos Ar.	0.017	0.025	0.009	0.008	0.002	0.010	0.021	0.035	0.020	0.017	0.203	0.146	0.009	0.017	75	3,965	7/98
Australia	Australian	0.024	0.029	0.012	0.012	0.009	0.025	0.036	0.064	0.034	0.031	0.238	0.191	0.018	0.031	1,922	84,495	1/96
Austria	Vienna	0.016	0.016	0.009	0.007	0.004	0.011	0.004	0.021	0.009	0.008	0.117	0.084	0.009	0.015	106	4,459	1/99
Belgium	Brussels	0.012	0.013	0.006	0.006	0.004	0.012	0.003	0.022	0.009	0.008	0.131	0.104	0.009	0.013	151	8,721	1/99
Brazil	Sao Paulo	0.023	0.035	0.009	0.014	0.005	0.016	0.008	0.034	0.016	0.013	0.124	0.082	0.013	0.028	139	2,893	6/98
Canada	Toronto	0.025	0.029	0.011	0.014	0.012	0.026	0.023	0.050	0.022	0.020	0.161	0.124	0.017	0.020	1,235	73,105	1/96
Chile	Santiago	0.017	0.021	0.011	0.005	0.001	0.006	0.003	0.025	0.014	0.011	0.195	0.154	0.006	0.027	101	3,256	6/02
China	Hong Kong	0.022	0.029	0.013	0.009	0.006	0.021	0.022	0.055	0.029	0.024	0.211	0.158	0.017	0.027	925	66,075	1/96
China	Shanghai	0.004	0.003	0.000	0.004	0.001	0.008	0.003	0.015	0.005	0.003	0.045	0.031	0.010	0.002	812	77,271	1/96
China	Shenzhen	0.004	0.003	0.000	0.004	0.001	0.008	0.003	0.014	0.004	0.003	0.044	0.029	0.010	0.003	677	57,488	1/96
Denmark	Copenhag.	0.015	0.022	0.010	0.006	0.005	0.013	0.011	0.032	0.016	0.014	0.209	0.149	0.010	0.020	253	12,158	1/96
France	Paris	0.016	0.018	0.009	0.007	0.004	0.012	0.004	0.025	0.010	0.008	0.120	0.091	0.011	0.017	915	41,098	1/99
Finland	Helsinki	0.013	0.017	0.011	0.003	0.006	0.016	0.013	0.032	0.016	0.013	0.168	0.123	0.010	0.018	161	10,209	1/99
Germany	Frankfurt	0.022	0.033	0.008	0.014	0.008	0.020	0.013	0.042	0.019	0.015	0.140	0.092	0.014	0.032	893	46,246	1/99
Greece	Athens	0.019	0.019	0.009	0.010	0.004	0.012	0.011	0.034	0.014	0.011	0.138	0.127	0.013	0.019	356	23,603	1/01
India	Bombay	0.052	0.060	0.029	0.023	0.015	0.036	0.013	0.070	0.032	0.027	0.123	0.047	0.030	0.073	1,667	82,624	4/96
Indonesia	Jakarta	0.026	0.041	0.012	0.014	0.010	0.028	0.031	0.081	0.050	0.044	0.290	0.236	0.023	0.038	380	14,278	1/96
Ireland	Irish	0.017	0.023	0.008	0.010	0.007	0.017	0.018	0.059	0.044	0.017	0.182	0.135	0.012	0.022	55	2,708	6/00
Israel	Tel Aviv	0.030	0.042	0.009	0.021	0.003	0.012	0.002	0.036	0.020	0.014	0.150	0.048	0.014	0.026	580	22,686	12/98
Italy	Milan	0.007	0.008	0.004	0.004	0.007	0.015	0.005	0.022	0.008	0.007	0.087	0.075	0.009	0.009	371	23,976	1/99
Japan	Tokyo	0.009	0.012	0.003	0.006	0.004	0.014	0.010	0.026	0.010	0.008	0.114	0.096	0.008	0.011	2,803	270,518	1/96
Japan	Osaka	0.013	0.021	0.006	0.007	0.007	0.021	0.020	0.048	0.025	0.021	0.231	0.154	0.012	0.021	306	22,212	1/96
Malaysia	Kuala Lum.	0.017	0.028	0.005	0.012	0.007	0.020	0.020	0.043	0.023	0.020	0.223	0.182	0.013	0.025	960	79,565	1/96
Mexico	Mexican	0.015	0.029	0.005	0.010	0.002	0.010	0.006	0.028	0.014	0.010	0.122	0.078	0.008	0.026	116	5,042	5/98
Netherlands	AEX	0.013	0.013	0.005	0.009	0.004	0.012	0.007	0.026	0.011	0.009	0.115	0.095	0.010	0.014	190	11,620	1/99
New Zealand	New Zea.	0.017	0.015	0.012	0.005	0.003	0.009	0.022	0.030	0.017	0.015	0.260	0.229	0.007	0.015	99	5,052	1/96
Norway	Oslo	0.019	0.024	0.013	0.006	0.005	0.017	0.018	0.061	0.041	0.017	0.188	0.140	0.011	0.021	331	15,111	1/96
Philippines	Phillipine	0.024	0.038	0.013	0.011	0.007	0.023	0.032	0.070	0.042	0.036	0.286	0.232	0.017	0.033	218	9,540	1/96
Poland	Warsaw	0.027	0.034	0.007	0.020	0.007	0.019	0.011	0.063	0.047	0.016	0.152	0.110	0.014	0.028	222	6,819	11/00
Portugal	Lisbon	0.009	0.008	0.003	0.006	0.003	0.008	0.009	0.019	0.009	0.008	0.173	0.159	0.007	0.008	44	987	7/05
Singapore	Singapore	0.016	0.025	0.007	0.009	0.007	0.020	0.030	0.051	0.028	0.025	0.250	0.213	0.015	0.024	644	32,313	1/96
South Africa	Johannes.	0.026	0.032	0.011	0.015	0.006	0.019	0.026	0.056	0.030	0.026	0.224	0.177	0.014	0.032	658	28,049	3/96
South Korea	Korea	0.015	0.012	0.005	0.010	0.004	0.016	0.004	0.029	0.008	0.007	0.079	0.073	0.014	0.010	750	76,246	10/97
Spain	Barcelona	0.007	0.007	0.002	0.004	0.004	0.009	0.004	0.018	0.006	0.005	0.092	0.088	0.008	0.007	171	11,043	1/99
Sweden	Stockholm	0.016	0.021	0.010	0.006	0.006	0.017	0.015	0.037	0.017	0.014	0.168	0.134	0.011	0.021	526	30,204	1/96
Switzerland	SWX Swiss	0.015	0.015	0.006	0.009	0.005	0.014	0.004	0.028	0.012	0.010	0.173	0.119	0.010	0.016	311	21,154	8/96
Taiwan	Taiwan	0.007	0.007	0.002	0.004	0.002	0.009	0.007	0.022	0.007	0.007	0.110	0.107	0.002	0.006	752	68,365	1/96
Thailand	Thailand	0.016	0.024	0.009	0.007	0.006	0.019	0.014	0.046	0.025	0.022	0.225	0.183	0.014	0.014	561	33,960	1/96
Turkey	Istanbul	0.009	0.008	0.001	0.007	0.003	0.011	0.011	0.029	0.012	0.011	0.162	0.160	0.011	0.008	313	10,141	1/05
UK	London	0.016	0.024	0.014	0.003	0.001	0.008	0.002	0.036	0.020	0.016	0.192	0.178	0.007	0.029	2,187	77,972	1/96
USA	New York	0.006	0.005	0.007	0.000	0.011	0.000	0.000	0.017	0.004	0.003	0.050	0.050	0.007	0.012	199	13,052	1/96
USA	American	0.034	0.031	0.030	0.004	0.022	0.001	0.005	0.049	0.020	0.017	0.147	0.118	0.018	0.050	74	3,868	1/96
USA	NASDAQ	0.024	0.027	0.025	-0.001	0.027	0.001	0.001	0.045	0.015	0.013	0.100	0.084	0.020	0.026	638	37,015	1/96
Global		0.017	0.022	0.009	0.008	0.006	0.014	0.012	0.038	0.019	0.015	0.161	0.125	0.012	0.021	24,847	1,531,162	

Table 4

Mean of the Monthly Cost-Per-Volume Benchmarks and Proxies

The cost-per-volume benchmark (slope of the price function lambda) is calculated from every trade and corresponding BBO quote in the SIRCA Thomson Reuters Tick History database for a sample stock-month. All cost-per-volume proxies are calculated from daily stock price and volume data for a sample stock-month. The sample spans 43 exchanges around the world from 1996-2007. It consists of all stock-months with at least five positive-volume days and five non-zero return days. This results in 1,531,162 stock-months from 24,847 firms. The means of all price impact benchmarks and proxies are multiplied by 1,000 except for the mean of Amivest which is divided by 1,000,000. All variables are winsorized at 1st and 99th percentile in each exchange-year.

		Cost/Volume Benchmark	Cost Per Volume Proxies													
Country	Exchange	Slope of the Price Function Lambda	Roll Impact	Extend-ed Roll Impact	Effec-tive Tick Impact	LOT Mixed Impact	LOT Y-split Impact	FHT Impact	Zeros Impact	Zeros2 Impact	High -Low Impact	Closing % Quo Sprd Impact	Amihud	Paster and Stam-baugh	Amivest	Stock-Months
Argentina	Buenos Ar.	0.029	0.052	0.229	0.538	0.902	0.593	0.492	5.598	3.016	0.227	0.460	0.840	0.000	0.081	3,965
Australia	Australian	0.044	0.481	1.203	1.697	2.965	1.856	1.660	8.664	5.399	0.908	1.552	4.895	0.000	0.404	84,495
Austria	Vienna	0.016	0.318	0.669	0.522	1.590	1.017	0.815	7.493	3.774	0.497	1.926	1.571	0.000	0.504	4,459
Belgium	Brussels	0.020	0.179	0.447	0.163	0.989	0.549	0.466	5.576	3.377	0.315	0.635	0.903	0.000	0.651	8,721
Brazil	Sao Paulo	0.085	0.116	0.359	0.278	0.887	0.548	0.461	3.291	1.339	0.265	0.800	2.443	0.000	14.348	2,893
Canada	Toronto	0.065	1.328	1.925	1.828	3.518	1.928	1.809	8.296	4.570	1.359	0.641	5.955	0.000	0.584	73,105
Chile	Santiago	0.000	0.000	0.000	0.000	0.001	0.001	0.000	0.006	0.004	0.000	0.000	0.001	0.000	312.645	3,256
China	Hong Kong	0.009	0.055	0.136	0.143	0.328	0.212	0.177	1.088	0.522	0.113	0.228	0.706	0.000	1.539	66,075
China	Shanghai	0.004	0.000	0.001	0.001	0.003	0.001	0.001	0.011	0.009	0.002	0.001	0.005	0.000	2.941	77,271
China	Shenzhen	0.004	0.000	0.001	0.001	0.002	0.001	0.001	0.011	0.009	0.002	0.001	0.005	0.000	2.598	57,488
Denmark	Copenhag.	0.006	0.026	0.053	0.041	0.118	0.070	0.060	0.669	0.328	0.038	0.085	0.133	0.000	2.181	12,158
France	Paris	0.031	0.334	0.763	0.386	1.772	0.949	0.822	8.931	4.846	0.870	1.654	1.869	0.000	1.646	41,098
Finland	Helsinki	0.003	0.333	0.699	0.673	1.438	0.877	0.749	7.235	3.830	0.446	0.858	2.202	0.000	0.745	10,209
Germany	Frankfurt	0.125	2.029	3.780	3.809	8.774	4.964	4.406	26.634	12.792	3.275	7.799	12.888	0.000	0.036	46,246
Greece	Athens	0.067	0.432	1.123	1.158	2.785	1.371	1.215	11.845	9.112	1.093	1.502	3.439	0.000	0.084	23,603
India	Bombay	0.133	2.965	6.206	3.119	13.448	7.942	6.683	21.279	5.056	4.968	11.363	19.722	0.000	0.093	82,624
Indonesia	Jakarta	0.000	0.000	0.001	0.001	0.002	0.001	0.001	0.004	0.002	0.001	0.001	0.008	0.000	418.337	14,278
Ireland	Irish	0.029	0.265	0.452	0.404	1.121	0.864	0.524	2.928	1.434	0.329	0.563	2.478	0.000	0.956	2,708
Israel	Tel Aviv	0.048	0.108	0.327	0.053	0.995	0.685	0.460	3.931	0.836	0.327	0.588	1.414	0.000	0.346	22,686
Italy	Milan	0.011	0.115	0.214	0.114	0.383	0.206	0.184	2.282	1.322	0.143	0.252	0.453	0.000	1.923	23,976
Japan	Tokyo	0.002	0.001	0.003	0.002	0.006	0.003	0.003	0.026	0.017	0.001	0.003	0.004	0.000	56.473	270,518
Japan	Osaka	0.005	0.005	0.012	0.011	0.027	0.016	0.014	0.119	0.064	0.007	0.012	0.019	0.000	1.409	22,212
Malaysia	Kuala Lum.	0.053	0.379	0.801	0.768	1.709	1.068	0.903	7.547	4.365	0.509	1.389	2.713	0.000	0.088	79,565
Mexico	Mexican	0.008	0.011	0.033	0.047	0.089	0.064	0.055	0.393	0.148	0.030	0.092	0.753	0.000	7.065	5,042
Netherlands	AEX	0.033	0.242	0.529	0.591	1.241	0.709	0.606	4.654	2.899	0.404	0.813	1.668	0.000	3.573	11,620
New Zealand	New Zea.	0.024	0.098	0.268	0.562	0.846	0.552	0.484	5.815	4.204	0.214	0.457	0.943	0.000	0.213	5,052
Norway	Oslo	0.005	0.024	0.068	0.069	0.162	0.111	0.078	0.480	0.228	0.039	0.094	0.196	0.000	2.848	15,111
Philippines	Phillipine	0.011	0.023	0.063	0.078	0.164	0.112	0.094	0.511	0.278	0.045	0.103	0.381	0.000	0.967	9,540
Poland	Warsaw	0.091	2.131	3.358	2.499	7.463	5.515	3.560	20.086	9.403	1.976	7.781	15.421	0.000	0.100	6,819
Portugal	Lisbon	0.016	0.289	0.366	0.303	0.701	0.375	0.338	6.397	4.487	0.263	0.533	1.095	0.000	1.245	987
Singapore	Singapore	0.020	0.434	0.807	1.176	1.740	1.135	1.009	6.910	4.254	0.586	1.020	2.877	0.000	0.168	32,313
South Africa	Johannes.	0.021	0.211	0.449	0.553	1.181	0.786	0.675	2.453	1.524	0.339	0.703	4.158	0.000	2.138	28,049
South Korea	Korea	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.000	0.000	0.001	0.000	282.845	76,246
Spain	Barcelona	0.009	0.034	0.063	0.050	0.140	0.068	0.059	1.038	0.941	0.053	0.079	0.124	0.000	3.945	11,043
Sweden	Stockholm	0.006	0.058	0.153	0.129	0.320	0.191	0.167	0.998	0.477	0.091	0.286	0.336	0.000	3.918	30,204
Switzerland	SWX Swiss	0.020	0.096	0.205	0.080	0.408	0.228	0.202	1.990	1.020	0.151	0.273	0.474	0.000	0.917	21,154
Taiwan	Taiwan	0.003	0.001	0.004	0.004	0.012	0.005	0.005	0.064	0.046	0.003	0.012	0.022	0.000	13.400	68,365
Thailand	Thailand	0.022	0.047	0.104	0.061	0.245	0.154	0.135	0.801	0.354	0.088	0.064	0.916	0.000	1.901	33,960
Turkey	Istanbul	0.016	0.011	0.041	0.047	0.104	0.049	0.044	0.648	0.639	0.041	0.035	0.090	0.000	0.279	10,141
UK	London	0.036	0.000	0.001	0.001	0.006	0.004	0.003	0.029	0.024	0.001	0.006	0.005	0.000	146.156	77,972
USA	New York	0.008	0.021	0.001	0.000	0.047	0.018	0.015	0.188	0.182	0.014	0.045	0.053	0.000	6.228	13,052
USA	American	0.194	2.437	0.075	1.138	4.768	2.375	2.125	9.512	6.008	1.978	6.650	9.808	0.047	0.036	3,868
USA	NASDAQ	0.079	1.048	0.018	0.069	1.672	0.705	0.624	3.500	2.096	0.739	1.376	3.186	-0.005	0.992	37,015
Global		0.033	0.389	0.605	0.539	1.513	0.904	0.748	4.650	2.447	0.529	1.226	2.492	0.001	30.222	1,531,162

Table 5

Availability of Closing Bid and Ask Prices in Datastream

The percentage of stocks in Datastream that have daily bid and ask prices by exchange-year. To be considered, we require that a stock have more than 10 non-zero return days.

Country	Exchange	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Argentina	Buenos Ar.			90%	89%	91%	89%	95%	99%	94%	97%	99%	99%
Australia	Australian	70%	73%	74%	74%	72%	73%	76%	90%	92%	93%	94%	96%
Austria	Vienna				83%	83%	85%	85%	83%	83%	90%	92%	95%
Belgium	Brussels				93%	93%	92%	92%	94%	93%	93%	89%	96%
Brazil	Sao Paulo			64%	81%	83%	82%	81%	86%	89%	93%	95%	95%
Canada	Toronto	49%	49%	50%	52%	52%	53%	54%	56%	61%	61%	69%	75%
Chile	Santiago							81%	83%	82%	82%	88%	90%
China	Hong Kong	87%	87%	88%	89%	89%	89%	90%	90%	90%	89%	88%	85%
China	Shanghai	100%	100%	100%	100%	96%	95%	96%	97%	97%	98%	96%	96%
China	Shenzhen	95%	95%	94%	94%	95%	96%	96%	99%	99%	99%	99%	100%
Denmark	Copenhag.	77%	79%	78%	79%	83%	83%	83%	92%	94%	96%	96%	97%
France	Paris				75%	73%	74%	74%	74%	76%	91%	93%	96%
Finland	Helsinki				91%	92%	94%	96%	96%	99%	100%	100%	100%
Germany	Frankfurt				67%	69%	72%	75%	77%	81%	84%	85%	90%
Greece	Athens						93%	96%	98%	98%	98%	99%	99%
India	Bombay	82%	81%	79%	82%	82%	74%	81%	83%	88%	91%	92%	94%
Indonesia	Jakarta	98%	99%	99%	99%	99%	99%	99%	99%	98%	98%	99%	99%
Ireland	Irish					76%	80%	81%	82%	82%	83%	83%	88%
Israel	Tel Aviv	10%	14%	74%	77%	79%	80%	82%	83%	85%	92%	95%	99%
Italy	Milan				94%	95%	95%	96%	97%	98%	99%	97%	98%
Japan	Tokyo	79%	79%	80%	81%	88%	89%	91%	92%	94%	96%	97%	98%
Japan	Osaka	95%	96%	98%	98%	97%	98%	98%	98%	99%	100%	100%	100%
Malaysia	Kuala Lum.	84%	85%	85%	85%	96%	97%	98%	99%	99%	99%	99%	99%
Mexico	Mexican	19%	20%	77%	83%	84%	87%	94%	93%	97%	98%	95%	97%
Netherland	AEX				28%	86%	89%	89%	91%	91%	99%	99%	100%
New Zealand	New Zea.	64%	65%	65%	67%	61%	66%	68%	76%	83%	88%	91%	93%
Norway	Oslo	73%	79%	90%	90%	89%	89%	96%	96%	97%	98%	97%	100%
Philippines	Phillipine	87%	89%	90%	92%	94%	92%	95%	94%	95%	93%	97%	97%
Poland	Warsaw					97%	98%	98%	99%	99%	99%	99%	100%
Portugal	Lisbon										79%	80%	92%
Singapore	Singapore	90%	94%	93%	92%	91%	92%	93%	94%	95%	96%	97%	97%
South Africa	Johannes.	80%	83%	83%	87%	89%	89%	93%	93%	93%	95%	96%	97%
South Korea	Korea	1%	81%	85%	86%	87%	89%	92%	96%	98%	98%	99%	99%
Spain	Barcelona				92%	93%	92%	95%	95%	95%	97%	98%	98%
Sweden	Stockholm	88%	77%	75%	78%	81%	82%	84%	85%	86%	87%	89%	91%
Switzerland	SWX Swiss	66%	74%	77%	80%	80%	82%	74%	88%	86%	88%	88%	88%
Taiwan	Taiwan	92%	83%	80%	75%	80%	85%	88%	91%	94%	94%	93%	95%
Thailand	Thailand	93%	92%	92%	93%	94%	95%	96%	95%	95%	94%	95%	95%
Turkey	Istanbul										100%	99%	99%
UK	London	66%	60%	62%	63%	59%	72%	75%	76%	78%	76%	77%	80%
Global Average		72.7%	76.4%	81.6%	82.0%	84.7%	86.0%	87.5%	89.7%	90.9%	92.5%	93.3%	95.1%

Table 6

The Global Performance of Liquidity Proxies Compared to Liquidity Benchmarks

The percent-cost benchmarks (percent effective spread, percent quoted spread, percent realized spread, and percent price impact) and a cost-per-volume benchmark (slope of the price function lambda) are calculated from every trade and corresponding BBO quote in the SIRCA Thomson Reuters Tick History database for a sample stock-month. All percent-cost proxies and cost-per-volume proxies are calculated from daily stock price data for a sample stock-month. The sample spans 43 exchanges around the world from 1996-2007. It consists of all stock-months with at least five positive-volume days and five non-zero return days. This results in 1,782,309 stock-months from 25,582 firms. A solid box means the highest correlation or the lowest average root mean squared error (RMSE) in the row. Dashed boxes mean correlations that are statistically indistinguishable from the highest correlation or average RMSEs that are statistically indistinguishable from the lowest average RMSE in the row at the 5% level. Bold-faced numbers are statistically different from zero or proxies have predictive power that is significant at the 5% level.

	Roll	Extended Roll	Effective Tick	LOT Mixed	LOT Y-split	FHT	Zeros	Zeros2	High -Low	Closing % Quo Sprd
Panel A: Average Cross-Sectional Correlation of Monthly Percent-Cost Proxies Compared to Percent-Cost Benchmarks										
Percent Effective Spread	**0.225**	**0.364**	**0.349**	**0.535**	**0.527**	**0.581**	**0.404**	**0.207**	**0.563**	**0.802**
Percent Quoted Spread	**0.234**	**0.385**	**0.363**	**0.575**	**0.577**	**0.638**	**0.455**	**0.204**	**0.595**	**0.920**
Percent Realized Spread	**0.190**	**0.255**	**0.254**	**0.362**	**0.372**	**0.408**	**0.317**	**0.174**	**0.385**	**0.592**
Percent Price Impact	**0.125**	**0.264**	**0.248**	**0.397**	**0.370**	**0.413**	**0.254**	**0.124**	**0.416**	**0.562**
Panel B: Portfolio Time-Series Correlation of Monthly Percent-Cost Proxies Compared to Percent-Cost Benchmarks										
Percent Effective Spread	**0.388**	**0.678**	**0.595**	**0.678**	**0.676**	**0.720**	**0.357**	**0.204**	**0.756**	**0.827**
Percent Quoted Spread	**0.351**	**0.654**	**0.616**	**0.704**	**0.725**	**0.766**	**0.407**	**0.241**	**0.745**	**0.871**
Percent Realized Spread	**0.322**	**0.515**	**0.483**	**0.528**	**0.544**	**0.575**	**0.323**	**0.202**	**0.565**	**0.627**
Percent Price Impact	**0.253**	**0.499**	**0.429**	**0.507**	**0.496**	**0.517**	**0.247**	0.133	**0.572**	**0.634**
Panel C: Average Root Mean Squared Error of Monthly Percent-Cost Proxies Compared to Percent-Cost Benchmarks										
Percent Effective Spread	0.0259	**0.0228**	0.0281	0.0407	**0.0267**	**0.0190**	0.1875	0.1470	**0.0163**	**0.0153**
Percent Quoted Spread	0.0309	**0.0258**	0.0311	0.0374	**0.0264**	**0.0201**	0.1822	0.1447	**0.0216**	**0.0094**
Percent Realized Spread	0.0217	0.0242	0.0274	0.0483	0.0304	**0.0215**	0.1959	0.1532	**0.0157**	**0.0227**
Percent Price Impact	0.0208	0.0208	0.0246	0.0485	0.0295	0.0202	0.1968	0.1536	**0.0132**	0.0229

	Roll Impact	Extended Roll Impact	Effective Tick Impact	LOT Mixed Impact	LOT Y-split Impact	FHT Impact	Zeros Impact	Zeros2 Impact	High -Low Impact	Closing % Quo Sprd Impact	Amihud	Paster & Stam-baugh	Amivest
Panel D: Average Cross-Sectional Correlation of Monthly Cost-Per-Volume Proxies Compared to the Cost-Per-Volume Benchmark													
Lambda	**0.249**	**0.450**	**0.414**	**0.539**	**0.494**	**0.511**	**0.493**	**0.454**	**0.546**	**0.563**	**0.514**	**0.041**	**-0.210**
Panel E: Portfolio Time-Series Correlation of Monthly Cost-Per-Volume Proxies Compared to the Cost-Per-Volume Benchmark													
Lambda	**0.448**	**0.615**	**0.553**	**0.645**	**0.615**	**0.622**	**0.589**	**0.586**	**0.614**	**0.594**	**0.624**	0.098	**-0.460**
Panel F: Average Root Mean Squared Error (ARMSE) of Cost-Per-Volume Proxies Compared to Lambda / Mean of Lambda													
ARMSE / Mean of Lambda	53.4	60.6	63.0	137.4	90.4	73.5	350.5	188.0	51.2	**121.8**	273.1	3.4	2228.1

Table 7

Liquidity Proxy Performance in Developed Countries vs. Emerging Countries

A percent-cost benchmark (percent effective spread) and a cost-per-volume benchmark (slope of the price function lambda) are calculated from every trade and corresponding BBO quote in the SIRCA Thomson Reuters Tick History database for a sample stock-month. All percent-cost proxies and cost-per-volume proxies are calculated from daily stock price data for a sample stock-month. The sample spans 43 exchanges around the world from 1996-2007. It consists of all stock-months with at least five positive-volume days and five non-zero return days. This results in 1,782,309 stock-months from 25,582 firms. A solid box means the highest correlation or the lowest average root mean squared error (RMSE) in the row. Dashed boxes mean correlations that are statistically indistinguishable from the highest correlation or average RMSEs that are statistically indistinguishable from the lowest average RMSE in the row at the 5% level. Bold-faced numbers are statistically different from zero or proxies have predictive power that is significant at the 5% level.

	Roll	Extended Roll	Effective Tick	LOT Mixed	LOT Y-split	FHT	Zeros	Zeros2	High -Low	Closing % Quo Sprd
Panel A: Average Cross-Sectional Correlation of Monthly Percent-Cost Proxies When Compared to Percent Effective Spread										
Developed Countries	**0.260**	**0.402**	**0.411**	**0.574**	**0.562**	**0.624**	**0.431**	**0.261**	**0.600**	**0.824**
Emerging Countries	**0.185**	**0.321**	**0.278**	**0.490**	**0.488**	**0.532**	**0.373**	**0.146**	**0.521**	**0.777**
Panel B: Portfolio Time-Series Correlation of Monthly Percent-Cost Proxies When Compared to Percent Effective Spread										
Developed Countries	**0.518**	**0.749**	**0.575**	**0.719**	**0.706**	**0.739**	**0.422**	**0.272**	**0.804**	**0.876**
Emerging Countries	**0.238**	**0.597**	**0.619**	**0.631**	**0.642**	**0.699**	**0.282**	**0.126**	**0.700**	**0.853**
Panel C: Average Root Mean Squared Error of Monthly Percent-Cost Proxies When Compared to Percent Effective Spread										
Developed Countries	0.0228	**0.0205**	0.0248	0.0378	**0.0246**	**0.0165**	0.1843	0.1465	**0.0139**	0.0131
Emerging Countries	0.0295	**0.0255**	0.0319	0.0439	**0.0291**	**0.0218**	0.1912	0.1476	**0.0192**	0.0177

	Roll Impact	Extended Roll Impact	Effective Tick Impact	LOT Mixed Impact	LOT Y-split Impact	FHT Impact	Zeros Impact	Zeros2 Impact	High -Low Impact	Closing % Quo Sprd Impact	Amihud	Paster & Stam-baugh	Amivest
Panel D: Average Cross-Sectional Correlation of Monthly Cost-Per-Volume Proxies When Compared to Lambda													
Developed Countries	**0.286**	**0.456**	**0.426**	**0.550**	**0.507**	**0.518**	**0.491**	**0.464**	**0.541**	**0.561**	**0.525**	**0.050**	**-0.194**
Emerging Countries	**0.207**	**0.443**	**0.401**	**0.526**	**0.479**	**0.503**	**0.496**	**0.441**	**0.552**	**0.564**	**0.501**	**0.032**	**-0.227**
Panel E: Portfolio Time-Series Correlation of Monthly Cost-Per-Volume Proxies Compared to Lambda													
Developed Countries	**0.525**	**0.622**	**0.574**	**0.658**	**0.630**	**0.639**	**0.620**	**0.636**	**0.617**	**0.628**	**0.664**	**0.149**	**-0.512**
Emerging Countries	**0.360**	**0.606**	**0.528**	**0.631**	**0.598**	**0.602**	**0.553**	**0.529**	**0.610**	**0.555**	**0.578**	**0.039**	**-0.401**
Panel F: Average Root Mean Squared Error (ARMSE) of Cost-Per-Volume Proxies Compared to Lambda / Mean of Lambda													
ARMSE/Mean(Lambda):Dev	46.0	44.3	56.0	115.1	70.3	62.7	328.2	188.4	47.6	**93.7**	210.7	3.9	830.1
ARMSE/Mean(Lambda):Emg	62.7	81.1	71.8	165.4	115.6	87.0	378.5	187.4	55.7	**157.2**	351.7	2.8	3989.6

Table 8

The Performance of Daily Liquidity Proxies Compared to Daily Liquidity Benchmarks on a Global, Developed, and Emerging

The percent-cost benchmarks (percent effective spread, percent quoted spread, percent realized spread, and percent price impact) and a cost-per-volume benchmark (slope of the price function lambda) are calculated from every trade and corresponding BBO quote in the SIRCA Thomson Reuters Tick History database for a sample stock-day. All percent-cost proxies and cost-per-volume proxies are calculated from daily stock data for a sample stock-day. The sample spans 43 exchanges around the world from 1996-2007. This results in 19,543,557 stock-days from 21,361 firms. A solid box means the highest correlation or the lowest average root mean squared error (RMSE) among the compared proxies. Dashed boxes mean correlations that are statistically indistinguishable from the highest correlation or average RMSEs that are statistically indistinguishable from the lowest average RMSE among the compared proxies at the 1% level. Bold-faced numbers are statistically different from zero or have predictive power that is significant at the 1% level.

	Average Cross-Sectional Corr.		Portfolio Time-Series Correlation		Average Root Mean Squared Error	
	High -Low	Closing % Quo Sprd	High -Low	Closing % Quo Sprd	High -Low	Closing % Quo Sprd
Panel A: Daily Percent-Cost Proxies Compared to Four Daily Percent-Cost Benchmarks on a Global Basis						
Percent Effective Spread	**0.312**	**0.691**	**0.512**	**0.809**	**0.0182**	**0.0162**
Percent Quoted Spread	**0.344**	**0.739**	**0.534**	**0.850**	**0.0264**	**0.0180**
Percent Realized Spread	**0.241**	**0.503**	**0.403**	**0.628**	**0.0180**	**0.0213**
Percent Price Impact	**0.132**	**0.339**	**0.391**	**0.572**	**0.0165**	0.0242
Panel B: Daily Percent-Cost Proxies Compared to Daily Percent Effective Spread for Developed vs. Emerging Countries						
Developed Countries	**0.339**	**0.715**	**0.588**	**0.824**	**0.0155**	**0.0138**
Emerging Countries	**0.280**	**0.664**	**0.425**	**0.790**	**0.0213**	**0.0189**

	Average Cross-Sectional Corr.				Portfolio Time-Series Correlation				Average Root Mean Squared Error			
	High -Low Impact	Daily % Quo Sprd Impact	Amihud	Amivest	High -Low Impact	Daily % Quo Sprd Impact	Amihud	Amivest	High -Low Impact	Daily % Quo Sprd Impact	Amihud	Amivest
Panel C: Daily Cost-Per-Volume Proxies Compared to Daily Lambda on a Global Basis												
Lambda	**0.369**	**0.453**	**0.469**	**-0.281**	**0.253**	**0.292**	**0.350**	**-0.269**	2.08	**2.07**	10.3	5738.3
Panel D: Daily Cost-Per-Volume Proxies Compared to Daily Lambda for Developed vs. Emerging Countries												
Developed Countries	**0.381**	**0.464**	**0.486**	**-0.291**	**0.293**	**0.331**	**0.370**	**-0.269**	2.26	**2.25**	9.1	2487.5
Emerging Countries	**0.354**	**0.440**	**0.449**	**-0.269**	**0.207**	**0.247**	**0.327**	**-0.270**	1.812	**1.809**	12.0	10490.5

Table 9

Average Cross-Sectional Correlation of Monthly Percent-Cost Proxies with Percent Effective Spread by Exchange and for U.S. Average

Percent effective spread is calculated from every trade and corresponding BBO quote in the SIRCA Thomson Reuters Tick History database for a sample stock-month. All percent-cost proxies are calculated from daily stock price data for a sample stock-month. The sample spans 43 exchanges around the world from 1996-2007. It consists of all stock-months with at least five positive-volume days and five non-zero return days. This results in 1,782,309 stock-months from 25,582 firms. A solid box means the highest correlation in the row. Dashed boxes mean correlations that are statistically indistinguishable from the highest correlation in the row at the 5% level. Bold-faced numbers are statistically different from zero at the 5% level.

Country	Exchange	Roll	Extended Roll	Effective Tick	LOT Mixed	LOT Y-split	FHT	Zeros	Zeros2	High -Low	Closing % Quo Sprd	Months
Panel A: By Exchange												
Argentina	Buenos Ar.	0.070	0.159	**0.277**	**0.574**	**0.583**	**0.595**	**0.533**	**0.268**	**0.524**	**0.801**	114
Australia	Australian	**0.276**	**0.579**	**0.460**	**0.751**	**0.731**	**0.775**	**0.491**	**0.220**	**0.665**	**0.904**	144
Austria	Vienna	**0.219**	**0.414**	**0.359**	**0.627**	**0.644**	**0.658**	**0.472**	**0.234**	**0.517**	**0.853**	108
Belgium	Brussels	**0.176**	**0.359**	**0.343**	**0.584**	**0.581**	**0.586**	**0.443**	**0.305**	**0.527**	**0.746**	108
Brazil	Sao Paulo	0.131	**0.347**	**0.346**	**0.629**	**0.637**	**0.645**	**0.588**	**0.305**	**0.514**	**0.806**	115
Canada	Toronto	**0.400**	**0.617**	**0.473**	**0.719**	**0.682**	**0.702**	**0.455**	**0.255**	**0.740**	**0.885**	144
Chile	Santiago	0.080	**0.195**	0.162	**0.521**	**0.532**	**0.550**	**0.457**	**0.316**	**0.318**	**0.663**	67
China	Hong Kong	**0.215**	**0.399**	**0.308**	**0.537**	**0.520**	**0.541**	**0.356**	0.014	**0.567**	**0.773**	144
China	Shanghai	0.022	0.027	0.058	0.013	0.009	**0.097**	**0.082**	**0.082**	**0.261**	**0.689**	141
China	Shenzhen	0.014	0.035	0.041	**0.157**	**0.096**	**0.083**	0.061	0.055	**0.271**	**0.610**	141
Denmark	Copenhag.	**0.225**	**0.442**	**0.257**	**0.635**	**0.608**	**0.624**	**0.342**	0.046	**0.604**	**0.786**	133
France	Paris	**0.213**	**0.341**	**0.283**	**0.560**	**0.549**	**0.562**	**0.433**	**0.230**	**0.497**	**0.753**	108
Finland	Helsinki	**0.342**	**0.524**	**0.417**	**0.724**	**0.743**	**0.767**	**0.576**	**0.329**	**0.703**	**0.885**	108
Germany	Frankfurt	**0.291**	**0.444**	**0.460**	**0.598**	**0.546**	**0.609**	**0.396**	**0.249**	**0.615**	**0.861**	108
Greece	Athens	**0.178**	**0.325**	**0.314**	**0.492**	**0.481**	**0.508**	**0.318**	**0.196**	**0.538**	**0.711**	84
India	Bombay	**0.279**	**0.484**	**0.466**	**0.683**	**0.622**	**0.658**	**0.479**	**0.097**	**0.654**	**0.790**	141
Indonesia	Jakarta	**0.369**	**0.540**	**0.510**	**0.646**	**0.648**	**0.693**	**0.406**	**0.163**	**0.760**	**0.842**	144
Ireland	Irish	**0.371**	**0.660**	**0.488**	**0.424**	**0.347**	**0.820**	**0.553**	**0.270**	**0.813**	**0.912**	91
Israel	Tel Aviv	**0.209**	**0.417**	**0.147**	**0.653**	**0.635**	**0.680**	**0.603**	**0.147**	**0.607**	**0.837**	109
Italy	Milan	**0.183**	**0.249**	**0.217**	**0.330**	**0.343**	**0.357**	**0.372**	**0.193**	**0.403**	**0.818**	108
Japan	Tokyo	**0.184**	**0.339**	**0.399**	**0.586**	**0.620**	**0.640**	**0.526**	**0.350**	**0.483**	**0.905**	144
Japan	Osaka	**0.180**	**0.355**	**0.299**	**0.473**	**0.477**	**0.515**	**0.303**	**0.131**	**0.521**	**0.812**	144
Malaysia	Kuala Lum.	**0.254**	**0.405**	**0.247**	**0.523**	**0.528**	**0.545**	**0.309**	-0.031	**0.511**	**0.858**	144
Mexico	Mexican	0.131	**0.334**	**0.401**	**0.651**	**0.668**	**0.684**	**0.593**	**0.355**	**0.570**	**0.727**	116
Netherlands	AEX	**0.311**	**0.472**	**0.558**	**0.692**	**0.689**	**0.711**	**0.566**	**0.457**	**0.645**	**0.862**	108
New Zealand	New Zea.	0.107	**0.357**	**0.304**	**0.615**	**0.579**	**0.614**	**0.310**	0.152	**0.588**	**0.684**	144
Norway	Oslo	**0.165**	**0.359**	**0.329**	**0.190**	**0.132**	**0.518**	**0.339**	**0.121**	**0.491**	**0.631**	144
Philippines	Phillipine	**0.201**	**0.408**	**0.336**	**0.586**	**0.583**	**0.623**	**0.330**	-0.045	**0.639**	**0.759**	144
Poland	Warsaw	**0.154**	**0.273**	**0.130**	**0.139**	**0.110**	**0.452**	**0.271**	-0.040	**0.390**	**0.598**	86
Portugal	Lisbon	**0.402**	**0.581**	**0.357**	**0.639**	**0.608**	**0.627**	**0.446**	**0.308**	**0.748**	**0.856**	30
Singapore	Singapore	**0.381**	**0.562**	**0.403**	**0.658**	**0.667**	**0.720**	**0.444**	**0.182**	**0.740**	**0.913**	144
South Africa	Johannes.	**0.336**	**0.538**	**0.465**	**0.721**	**0.710**	**0.732**	**0.412**	**0.224**	**0.709**	**0.793**	142
South Korea	Korea	**0.197**	**0.237**	**0.122**	**0.305**	**0.298**	**0.314**	**0.237**	**0.127**	**0.389**	**0.829**	123
Spain	Barcelona	**0.174**	**0.304**	**0.417**	**0.441**	**0.481**	**0.533**	**0.522**	**0.508**	**0.562**	**0.891**	108
Sweden	Stockholm	**0.291**	**0.495**	**0.451**	**0.647**	**0.639**	**0.657**	**0.419**	**0.139**	**0.638**	**0.844**	144
Switzerland	SWX Swiss	**0.280**	**0.467**	**0.270**	**0.624**	**0.614**	**0.628**	**0.342**	**0.094**	**0.649**	**0.790**	137
Taiwan	Taiwan	0.059	**0.082**	**0.274**	**0.341**	**0.353**	**0.378**	**0.252**	**0.186**	**0.262**	**0.832**	144
Thailand	Thailand	**0.260**	**0.420**	**0.209**	**0.557**	**0.567**	**0.616**	**0.359**	-0.052	**0.639**	**0.830**	144
Turkey	Istanbul	**0.170**	**0.225**	**0.357**	**0.419**	**0.504**	**0.534**	**0.370**	**0.364**	**0.553**	**0.884**	36
UK	London	0.018	**0.193**	**0.445**	**0.657**	**0.597**	**0.654**	**0.468**	**0.437**	**0.545**	**0.818**	144
US	New York	**0.218**	**0.243**	**0.799**	**0.504**	**0.550**	**0.580**	**0.427**	**0.425**	**0.484**	**0.757**	144
US	American	**0.463**	**0.307**	**0.639**	**0.635**	**0.603**	**0.624**	**0.325**	**0.267**	**0.721**	**0.813**	144
US	NASDAQ	**0.493**	**0.151**	**0.418**	**0.544**	**0.558**	**0.589**	**0.390**	**0.271**	**0.644**	**0.883**	144
Panel B: For U.S. Average												
US Average		**0.431**	**0.184**	**0.519**	**0.543**	**0.560**	**0.590**	**0.393**	**0.304**	**0.616**	**0.850**	144

Table 10

Portfolio Time-Series Correlation of Monthly Percent-Cost Proxies with Percent Effective Spread by Exchange and for U.S. Average

Percent effective spread is calculated from every trade and corresponding BBO quote in the SIRCA Thomson Reuters Tick History database for a sample stock-month. All percent-cost proxies are calculated from daily stock price data for a sample stock-month. The sample spans 43 exchanges around the world from 1996-2007. It consists of all stock-months with at least five positive-volume days and five non-zero return days. This results in 1,782,309 stock-months from 25,582 firms. A solid box means the highest correlation in the row. Dashed boxes mean correlations that are statistically indistinguishable from the highest correlation in the row at the 5% level. Bold-faced numbers are statistically different from zero at the 5% level. The number of portfolio-months for Closing % Quo Sprd may be small than those of other proxies due to Datastream quote data limitation.

Country	Exchange	Roll	Extended Roll	Effective Tick	LOT Mixed	LOT Y-split	FHT	Zeros	Zeros2	High -Low	Closing % Quo Sprd	Portfolio-Months
Panel A: By Exchange												
Argentina	Buenos Ar.	-0.121	**0.390**	**0.708**	**0.754**	**0.767**	**0.810**	-0.068	**-0.271**	**0.786**	**0.890**	114
Australia	Australian	**0.223**	**0.794**	**0.437**	**0.694**	**0.771**	**0.788**	-0.125	**-0.303**	**0.819**	**0.880**	144
Austria	Vienna	0.097	**0.365**	**0.487**	**0.489**	**0.510**	**0.555**	**0.543**	**0.437**	0.148	**0.906**	108
Belgium	Brussels	**0.573**	**0.913**	**0.190**	**0.867**	**0.828**	**0.851**	**0.623**	**0.384**	**0.822**	**0.958**	108
Brazil	Sao Paulo	-0.066	**0.468**	**0.406**	**0.533**	**0.546**	**0.536**	**0.576**	**0.313**	**0.609**	**0.749**	115
Canada	Toronto	**0.916**	**0.920**	**0.941**	**0.877**	**0.838**	**0.868**	**0.521**	**0.551**	**0.945**	**0.993**	144
Chile	Santiago	-0.010	**0.668**	0.063	**0.592**	**0.674**	**0.712**	**0.618**	**0.472**	**0.511**	**0.549**	67
China	Hong Kong	**0.340**	**0.660**	**0.809**	**0.632**	**0.750**	**0.769**	**0.257**	0.021	**0.728**	**0.971**	144
China	Shanghai	**0.210**	**0.261**	**0.767**	0.093	-0.036	**0.309**	**0.173**	**0.331**	**0.259**	**0.930**	141
China	Shenzhen	**0.268**	**0.340**	**0.599**	0.128	**0.178**	**0.200**	0.095	**0.262**	**0.391**	**0.647**	141
Denmark	Copenhag.	**0.578**	**0.847**	0.101	**0.878**	**0.714**	**0.743**	-0.066	**-0.299**	**0.929**	**0.830**	133
France	Paris	**0.624**	**0.922**	**0.311**	**0.887**	**0.919**	**0.916**	**0.573**	**0.259**	**0.920**	**0.980**	108
Finland	Helsinki	**0.512**	**0.876**	**0.550**	**0.869**	**0.869**	**0.885**	**0.473**	0.135	**0.930**	**0.922**	108
Germany	Frankfurt	**0.597**	**0.931**	**0.941**	**0.862**	**0.711**	**0.211**	**0.698**	**0.457**	**0.942**	**0.989**	108
Greece	Athens	-0.110	-0.019	**0.813**	0.144	**0.237**	**0.558**	**0.574**	**0.554**	**0.554**	**0.379**	84
India	Bombay	**0.785**	**0.953**	**0.757**	**0.913**	**0.879**	**0.845**	**0.699**	**0.431**	**0.893**	**0.912**	141
Indonesia	Jakarta	**0.448**	**0.930**	**0.682**	**0.929**	**0.948**	**0.958**	**0.310**	**0.294**	**0.972**	**0.973**	144
Ireland	Irish	**0.505**	**0.738**	**0.634**	**0.265**	0.068	**0.526**	**0.470**	**0.189**	**0.800**	**0.937**	91
Israel	Tel Aviv	**0.246**	**0.689**	**0.461**	**0.715**	**0.700**	**0.778**	**0.502**	**0.435**	**0.883**	**0.850**	109
Italy	Milan	**0.284**	**0.289**	**0.921**	**0.369**	**0.381**	**0.362**	**0.703**	**0.606**	**0.857**	**0.856**	108
Japan	Tokyo	**0.741**	**0.935**	**0.909**	**0.916**	**0.903**	**0.912**	**0.612**	**0.520**	**0.878**	**0.989**	144
Japan	Osaka	**0.662**	**0.810**	**0.782**	**0.686**	**0.782**	**0.798**	**0.664**	**0.614**	**0.910**	**0.923**	144
Malaysia	Kuala Lum.	**0.253**	**0.773**	**0.872**	**0.776**	**0.852**	**0.838**	**0.261**	-0.010	**0.784**	**0.970**	144
Mexico	Mexican	**0.248**	**0.620**	**0.537**	**0.778**	**0.725**	**0.776**	**0.594**	**0.424**	**0.735**	**0.849**	116
Netherlands	AEX	**0.518**	**0.879**	**0.761**	**0.873**	**0.863**	**0.860**	**0.670**	**0.574**	**0.845**	**0.959**	108
New Zealand	New Zea.	0.108	**0.359**	**0.400**	**0.494**	**0.403**	**0.514**	0.101	0.016	**0.589**	**0.602**	144
Norway	Oslo	**0.399**	**0.847**	**0.794**	**0.609**	**0.426**	**0.879**	**0.271**	-0.016	**0.832**	**0.911**	144
Philippines	Phillipine	-0.046	**0.628**	**0.544**	**0.607**	**0.647**	**0.649**	**-0.164**	**-0.524**	**0.738**	**0.829**	144
Poland	Warsaw	**0.840**	**0.873**	**0.739**	**0.709**	**0.619**	**0.885**	**0.816**	**0.430**	**0.858**	**0.947**	86
Portugal	Lisbon	**0.429**	**0.566**	**0.266**	**0.400**	**0.605**	**0.623**	**0.373**	**0.297**	**0.683**	**0.720**	30
Singapore	Singapore	**0.499**	**0.832**	**0.853**	**0.893**	**0.925**	**0.939**	**0.293**	0.117	**0.936**	**0.980**	144
South Africa	Johannes.	**0.526**	**0.856**	**0.919**	**0.932**	**0.913**	**0.907**	**0.279**	0.074	**0.900**	**0.950**	142
South Korea	Korea	0.116	**0.652**	**0.838**	**0.812**	**0.827**	**0.808**	**-0.368**	**-0.454**	**0.836**	**0.922**	123
Spain	Barcelona	**0.579**	**0.814**	**0.659**	**0.772**	**0.707**	**0.756**	**0.394**	**0.394**	**0.838**	**0.975**	108
Sweden	Stockholm	**0.626**	**0.934**	**0.799**	**0.906**	**0.907**	**0.923**	0.100	**-0.338**	**0.915**	**0.990**	144
Switzerland	SWX Swiss	**0.564**	**0.943**	**0.535**	**0.898**	**0.892**	**0.900**	**0.315**	**0.174**	**0.955**	**0.824**	137
Taiwan	Taiwan	-0.099	**-0.143**	**-0.188**	**0.115**	**0.242**	**0.253**	**0.266**	**0.300**	0.018	**0.871**	144
Thailand	Thailand	**0.564**	**0.872**	**0.774**	**0.946**	**0.958**	**0.947**	**0.257**	**-0.302**	**0.968**	**0.933**	144
Turkey	Istanbul	-0.134	**0.634**	**0.429**	**0.612**	**0.493**	**0.501**	**-0.331**	**-0.380**	**0.644**	**0.964**	36
UK	London	0.095	**0.569**	**0.263**	**0.883**	**0.853**	**0.835**	**0.238**	**0.211**	**0.471**	**0.679**	144
US	New York	**0.558**	**0.700**	**0.696**	**0.629**	**0.684**	**0.672**	**0.442**	**0.438**	**0.641**	**0.816**	144
US	American	**0.817**	**0.615**	**0.519**	**0.746**	**0.718**	**0.740**	**0.288**	**0.171**	**0.873**	**0.561**	144
US	NASDAQ	**0.909**	**0.655**	**0.315**	**0.678**	**0.873**	**0.872**	**0.817**	**0.789**	**0.946**	**0.944**	144
Panel B: For U.S. Average												
US Average		**0.825**	**0.661**	**0.415**	**0.673**	**0.819**	**0.818**	**0.692**	**0.663**	**0.873**	**0.885**	144

Table 11

Average Root Mean Squared Error of Monthly Percent-Cost Proxies with Percent Effective Spread by Exchange and for U.S. Average

Percent effective spread is calculated from every trade and corresponding BBO quote in the SIRCA Thomson Reuters Tick History database for a sample stock-month. All percent-cost proxies are calculated from daily stock price data for a sample stock-month. The sample spans 43 exchanges around the world from 1996-2007. It consists of all stock-months with at least five positive-volume days and five non-zero return days. This results in 1,782,309 stock-months from 25,582 firms. A solid box means the lowest average root mean squared error (RMSE) in the row. Dashed boxes mean average RMSEs that are statistically indistinguishable from the lowest average RMSE in the row at the 5% level. Bold-faced proxies have predictive power that is significant at the 5% level.

Country	Exchange	Roll	Extended Roll	Effective Tick	LOT Mixed	LOT Y-split	FHT	Zeros	Zeros2	High -Low	Closing % Quo Sprd	Months
Panel A: By Exchange												
Argentina	Buenos Ar.	0.0227	**0.0191**	0.0306	0.0299	**0.0180**	**0.0148**	0.2273	0.1610	**0.0145**	**0.0088**	114
Australia	Australian	**0.0332**	**0.0256**	0.0526	0.0615	**0.0315**	**0.0239**	0.2560	0.2063	**0.0197**	**0.0139**	144
Austria	Vienna	**0.0296**	**0.0252**	**0.0287**	**0.0283**	**0.0242**	**0.0228**	0.1579	0.1153	**0.0181**	**0.0157**	108
Belgium	Brussels	0.0156	0.0124	0.0147	0.0203	**0.0120**	**0.0113**	0.1673	0.1315	**0.0092**	**0.0073**	108
Brazil	Sao Paulo	**0.0377**	**0.0307**	**0.0355**	**0.0362**	**0.0274**	**0.0260**	0.1759	0.1106	**0.0271**	**0.0202**	115
Canada	Toronto	**0.0357**	**0.0266**	0.0414	0.0473	**0.0268**	**0.0239**	0.1848	0.1451	**0.0214**	**0.0080**	144
Chile	Santiago	**0.0269**	**0.0240**	**0.0274**	**0.0284**	**0.0230**	**0.0205**	0.2324	0.1809	**0.0233**	**0.0298**	67
China	Hong Kong	**0.0303**	**0.0264**	0.0345	0.0531	**0.0305**	**0.0242**	0.2271	0.1746	**0.0186**	**0.0160**	144
China	Shanghai	0.0071	0.0102	0.0041	0.0215	0.0140	0.0048	0.0640	0.0467	0.0066	0.0021	144
China	Shenzhen	0.0071	0.0103	0.0045	0.0150	0.0059	0.0053	0.0624	0.0444	0.0069	0.0037	144
Denmark	Copenhag.	0.0207	**0.0163**	0.0245	0.0289	**0.0165**	**0.0138**	0.2432	0.1777	**0.0125**	**0.0137**	133
France	Paris	**0.0235**	**0.0196**	**0.0229**	**0.0232**	**0.0178**	**0.0176**	0.1522	0.1170	**0.0182**	**0.0133**	108
Finland	Helsinki	**0.0189**	**0.0160**	**0.0231**	0.0310	**0.0149**	**0.0117**	0.2054	0.1484	**0.0096**	**0.0089**	108
Germany	Frankfurt	0.0301	**0.0244**	**0.0267**	0.0421	**0.0281**	**0.0242**	0.1722	0.1140	**0.0184**	**0.0188**	108
Greece	Athens	0.0281	**0.0237**	0.0239	0.0327	**0.0210**	**0.0186**	0.1529	0.1413	**0.0167**	**0.0137**	84
India	Bombay	0.0734	**0.0547**	0.0645	**0.0695**	**0.0521**	**0.0486**	0.1600	0.0837	**0.0469**	**0.0406**	141
Indonesia	Jakarta	**0.0352**	**0.0286**	**0.0444**	0.0768	**0.0434**	**0.0319**	0.2859	0.2400	**0.0152**	**0.0212**	144
Ireland	Irish	**0.0248**	**0.0180**	**0.0301**	0.0894	0.0846	**0.0165**	0.2080	0.1532	**0.0134**	**0.0115**	91
Israel	Tel Aviv	**0.0443**	**0.0367**	**0.0446**	**0.0348**	**0.0318**	**0.0304**	0.1835	0.0686	**0.0328**	**0.0154**	133
Italy	Milan	0.0228	0.0305	0.0111	0.0408	0.0225	0.0187	0.1246	0.1080	**0.0067**	**0.0049**	108
Japan	Tokyo	0.0146	0.0147	0.0147	0.0256	**0.0107**	**0.0088**	0.1499	0.1230	**0.0073**	**0.0049**	144
Japan	Osaka	0.0215	0.0221	0.0288	0.0517	0.0270	0.0202	0.2587	0.1734	**0.0087**	0.0115	144
Malaysia	Kuala Lum.	0.0235	**0.0197**	0.0267	0.0380	**0.0199**	**0.0160**	0.2349	0.1944	**0.0127**	**0.0133**	144
Mexico	Mexican	**0.0256**	**0.0221**	**0.0251**	**0.0295**	**0.0213**	**0.0180**	0.1670	0.1049	**0.0193**	**0.0256**	144
Netherlands	AEX	0.0185	**0.0162**	**0.0172**	0.0244	**0.0141**	**0.0129**	0.1463	0.1202	**0.0119**	**0.0086**	108
New Zealand	New Zea.	0.0215	**0.0170**	0.0314	0.0236	**0.0161**	**0.0135**	0.2801	0.2451	**0.0156**	**0.0114**	144
Norway	Oslo	**0.0298**	**0.0251**	**0.0327**	0.0934	0.0847	**0.0219**	0.2161	0.1600	**0.0207**	**0.0186**	144
Philippines	Phillipine	**0.0321**	**0.0275**	**0.0463**	0.0666	**0.0398**	**0.0287**	0.2918	0.2411	**0.0172**	**0.0217**	144
Poland	Warsaw	0.0683	**0.0617**	**0.0672**	0.1220	0.1208	**0.0569**	0.1985	0.1481	**0.0551**	**0.0644**	86
Portugal	Lisbon	0.0110	**0.0081**	0.0146	0.0164	**0.0090**	**0.0077**	0.2002	0.1838	**0.0064**	**0.0058**	30
Singapore	Singapore	**0.0224**	**0.0183**	0.0470	0.0482	**0.0256**	**0.0185**	0.2652	0.2263	**0.0092**	**0.0134**	144
South Africa	Johannes.	**0.0384**	**0.0311**	**0.0432**	**0.0558**	**0.0325**	**0.0259**	0.2402	0.1897	**0.0258**	**0.0230**	142
South Korea	Korea	0.0201	0.0200	0.0172	0.0263	0.0147	0.0146	0.0979	0.0891	**0.0116**	**0.0083**	144
Spain	Barcelona	0.0128	0.0102	0.0084	0.0248	0.0106	0.0078	0.1317	0.1261	**0.0051**	**0.0027**	108
Sweden	Stockholm	0.0229	**0.0184**	**0.0226**	0.0333	**0.0165**	**0.0141**	0.1918	0.1543	**0.0137**	**0.0126**	144
Switzerland	SWX Swiss	0.0191	**0.0153**	0.0186	0.0239	**0.0138**	**0.0128**	0.2049	0.1420	**0.0116**	**0.0099**	137
Taiwan	Taiwan	0.0098	0.0116	0.0103	0.0208	0.0074	0.0068	0.1332	0.1285	0.0073	**0.0028**	144
Thailand	Thailand	**0.0258**	**0.0227**	**0.0288**	0.0463	**0.0240**	**0.0182**	0.2415	0.1984	**0.0125**	**0.0090**	144
Turkey	Istanbul	0.0109	0.0115	0.0129	0.0269	0.0097	0.0074	0.1820	0.1797	0.0048	**0.0019**	36
UK	London	**0.0245**	**0.0220**	**0.0219**	0.0349	**0.0251**	**0.0176**	0.2337	0.2188	**0.0188**	**0.0189**	144
US	New York	0.0149	0.0097	0.0100	0.0192	**0.0077**	**0.0074**	0.0746	0.0735	**0.0074**	**0.0113**	144
US	American	0.0324	0.0454	0.0413	0.0450	0.0305	0.0291	0.1659	0.1362	**0.0273**	**0.0558**	144
US	NASDAQ	0.0261	0.0327	0.0325	0.0415	**0.0217**	**0.0214**	0.1136	0.0972	**0.0172**	**0.0136**	144
Panel B: For U.S. Average												
US Average		0.0241	0.0287	0.0283	0.0369	**0.0194**	**0.0189**	0.1093	0.0952	**0.0159**	**0.0165**	144

Table 12

Average Cross-Sectional Correlation of Monthly Cost-Per-Volume Proxies with Lambda by Exchange and for U.S. Average

The cost-per-volume benchmark (slope of the price function lambda) is calculated from every trade and corresponding BBO quote in the SIRCA Thomson Reuters Tick History database for a sample stock-month. All cost-per-volume proxies are calculated from daily stock price and volume data for a sample stock-month. The sample spans 43 exchanges around the world from 1996-2007. It consists of all stock-months with at least five positive-volume days and five non-zero return days. This results in 1,782,309 stock-months from 25,582 firms. A solid box means the highest correlation in the row. Dashed boxes mean correlations that are statistically indistinguishable from the highest correlation in the row at the 5% level. Bold-faced numbers are statistically different from zero at the 5% level.

Country	Exchange	Roll Impact	Extended Roll Impact	Effective Tick Impact	LOT Mixed Impact	LOT Y-split Impact	FHT Impact	Zeros Impact	Zeros2 Impact	High -Low Impact	Closing % Quo Sprd Impact	Amihud	Paster & Stam-baugh	Amivest	Months
Panel A: By Exchange															
Argentina	Buenos Ar.	0.132	**0.439**	**0.458**	**0.646**	**0.603**	**0.619**	**0.576**	**0.556**	**0.603**	**0.703**	**0.563**	0.046	**-0.376**	114
Australia	Australian	**0.196**	**0.382**	**0.344**	**0.466**	**0.452**	**0.461**	**0.453**	**0.404**	**0.397**	**0.450**	**0.307**	0.034	**-0.127**	144
Austria	Vienna	**0.189**	**0.463**	**0.464**	**0.600**	**0.526**	**0.526**	**0.420**	**0.404**	**0.565**	**0.616**	**0.592**	0.048	**-0.318**	108
Belgium	Brussels	**0.240**	**0.476**	**0.363**	**0.548**	**0.477**	**0.485**	**0.449**	**0.440**	**0.539**	**0.557**	**0.535**	0.074	**-0.253**	108
Brazil	Sao Paulo	**0.166**	**0.381**	**0.454**	**0.469**	**0.476**	**0.471**	**0.441**	**0.381**	**0.480**	**0.449**	**0.439**	-0.003	**-0.184**	115
Canada	Toronto	**0.394**	**0.570**	**0.514**	**0.615**	**0.567**	**0.552**	**0.566**	**0.556**	**0.559**	**0.696**	**0.559**	0.000	**-0.149**	144
Chile	Santiago	0.028	0.113	0.057	**0.220**	**0.218**	**0.222**	**0.237**	**0.213**	**0.199**	0.126	**0.225**	0.017	-0.082	67
China	Hong Kong	**0.226**	**0.392**	**0.312**	**0.473**	**0.459**	**0.459**	**0.419**	**0.311**	**0.435**	**0.455**	**0.353**	0.034	**-0.110**	144
China	Shanghai	**0.104**	**0.476**	**0.438**	**0.387**	**0.207**	**0.440**	**0.418**	**0.385**	**0.812**	**0.738**	**0.785**	**-0.135**	**-0.494**	141
China	Shenzhen	**0.079**	**0.457**	**0.428**	**0.541**	**0.399**	**0.399**	**0.383**	**0.346**	**0.795**	**0.649**	**0.756**	**-0.118**	**-0.530**	141
Denmark	Copenhag.	**0.167**	**0.323**	**0.237**	**0.375**	**0.365**	**0.368**	**0.339**	**0.264**	**0.345**	**0.404**	**0.353**	0.093	**-0.148**	133
France	Paris	**0.286**	**0.517**	**0.378**	**0.574**	**0.492**	**0.500**	**0.480**	**0.440**	**0.611**	**0.569**	**0.543**	**0.088**	**-0.196**	108
Finland	Helsinki	**0.134**	**0.206**	**0.159**	**0.230**	**0.232**	**0.229**	**0.217**	**0.157**	**0.203**	**0.238**	**0.217**	0.040	-0.048	108
Germany	Frankfurt	**0.254**	**0.401**	**0.343**	**0.441**	**0.383**	**0.379**	**0.363**	**0.379**	**0.370**	**0.425**	**0.426**	0.030	**-0.181**	108
Greece	Athens	**0.259**	**0.514**	**0.560**	**0.632**	**0.571**	**0.587**	**0.610**	**0.618**	**0.652**	**0.702**	**0.620**	0.054	**-0.205**	84
India	Bombay	**0.296**	**0.480**	**0.439**	**0.543**	**0.487**	**0.502**	**0.517**	**0.421**	**0.534**	**0.582**	**0.529**	-0.019	**-0.174**	141
Indonesia	Jakarta	**0.178**	**0.311**	**0.271**	**0.368**	**0.356**	**0.365**	**0.386**	**0.311**	**0.354**	**0.384**	**0.258**	**0.092**	**-0.121**	144
Ireland	Irish	**0.257**	**0.520**	**0.516**	**0.512**	**0.466**	**0.580**	**0.575**	**0.560**	**0.575**	**0.609**	**0.570**	0.120	**-0.250**	91
Israel	Tel Aviv	**0.171**	**0.452**	**0.302**	**0.630**	**0.597**	**0.616**	**0.617**	**0.413**	**0.611**	**0.611**	**0.581**	**0.094**	**-0.228**	109
Italy	Milan	**0.239**	**0.358**	**0.293**	**0.390**	**0.349**	**0.355**	**0.383**	**0.357**	**0.431**	**0.438**	**0.418**	0.020	**-0.188**	108
Japan	Tokyo	**0.308**	**0.598**	**0.534**	**0.663**	**0.586**	**0.596**	**0.605**	**0.608**	**0.654**	**0.688**	**0.695**	**0.054**	**-0.257**	144
Japan	Osaka	**0.234**	**0.497**	**0.387**	**0.564**	**0.527**	**0.538**	**0.500**	**0.444**	**0.559**	**0.540**	**0.557**	0.028	**-0.321**	144
Malaysia	Kuala Lum.	**0.352**	**0.622**	**0.549**	**0.685**	**0.647**	**0.654**	**0.667**	**0.598**	**0.652**	**0.685**	**0.587**	**0.099**	**-0.238**	144
Mexico	Mexican	0.139	**0.497**	**0.573**	**0.684**	**0.663**	**0.664**	**0.656**	**0.599**	**0.663**	**0.682**	**0.556**	0.064	**-0.238**	116
Netherlands	AEX	**0.333**	**0.610**	**0.543**	**0.683**	**0.626**	**0.629**	**0.584**	**0.570**	**0.641**	**0.646**	**0.618**	**0.166**	**-0.183**	108
New Zealand	New Zea.	0.122	**0.421**	**0.481**	**0.619**	**0.604**	**0.606**	**0.575**	**0.568**	**0.581**	**0.604**	**0.533**	0.049	**-0.199**	144
Norway	Oslo	**0.146**	**0.280**	**0.270**	**0.306**	**0.279**	**0.338**	**0.328**	**0.286**	**0.351**	**0.368**	**0.349**	0.039	**-0.108**	144
Philippines	Phillipine	0.086	**0.185**	**0.193**	**0.252**	**0.252**	**0.254**	**0.225**	**0.170**	**0.244**	**0.230**	**0.204**	-0.026	**-0.114**	144
Poland	Warsaw	**0.194**	**0.350**	**0.208**	**0.317**	**0.260**	**0.378**	**0.374**	**0.304**	**0.446**	**0.479**	**0.378**	**0.152**	**-0.193**	86
Portugal	Lisbon	**0.440**	**0.737**	**0.643**	**0.809**	**0.782**	**0.777**	**0.734**	**0.692**	**0.791**	**0.798**	**0.753**	-0.001	**-0.260**	30
Singapore	Singapore	**0.337**	**0.498**	**0.379**	**0.549**	**0.532**	**0.537**	**0.525**	**0.446**	**0.531**	**0.569**	**0.465**	0.046	**-0.162**	144
South Africa	Johannes.	**0.297**	**0.471**	**0.479**	**0.570**	**0.551**	**0.556**	**0.573**	**0.533**	**0.548**	**0.590**	**0.398**	0.046	**-0.149**	142
South Korea	Korea	**0.355**	**0.654**	**0.443**	**0.733**	**0.635**	**0.632**	**0.584**	**0.581**	**0.770**	**0.732**	**0.670**	0.055	**-0.258**	123
Spain	Barcelona	**0.321**	**0.634**	**0.509**	**0.667**	**0.600**	**0.612**	**0.584**	**0.584**	**0.703**	**0.692**	**0.704**	0.073	**-0.221**	108
Sweden	Stockholm	**0.186**	**0.319**	**0.288**	**0.354**	**0.329**	**0.332**	**0.336**	**0.300**	**0.351**	**0.372**	**0.357**	0.044	**-0.104**	144
Switzerland	SWX Swiss	**0.362**	**0.601**	**0.410**	**0.664**	**0.609**	**0.608**	**0.559**	**0.496**	**0.640**	**0.659**	**0.633**	0.087	**-0.212**	137
Taiwan	Taiwan	**0.217**	**0.586**	**0.630**	**0.723**	**0.641**	**0.646**	**0.628**	**0.647**	**0.572**	**0.798**	**0.664**	**-0.064**	**-0.279**	144
Thailand	Thailand	**0.207**	**0.300**	**0.214**	**0.330**	**0.318**	**0.327**	**0.319**	**0.233**	**0.324**	**0.328**	**0.231**	0.065	**-0.104**	144
Turkey	Istanbul	**0.310**	**0.681**	**0.637**	**0.765**	**0.714**	**0.730**	**0.766**	**0.765**	**0.807**	**0.790**	**0.763**	**0.135**	**-0.309**	36
UK	London	**0.111**	**0.435**	**0.437**	**0.675**	**0.623**	**0.646**	**0.641**	**0.649**	**0.625**	**0.673**	**0.584**	0.015	**-0.216**	144
US	New York	**0.583**	**0.463**	**0.685**	**0.706**	**0.653**	**0.654**	**0.590**	**0.591**	**0.737**	**0.681**	**0.698**	0.024	**-0.198**	144
US	American	**0.502**	**0.346**	**0.541**	**0.597**	**0.572**	**0.577**	**0.494**	**0.474**	**0.611**	**0.588**	**0.552**	0.052	**-0.216**	144
US	NASDAQ	**0.571**	**0.336**	**0.456**	**0.590**	**0.553**	**0.557**	**0.510**	**0.448**	**0.600**	**0.600**	**0.511**	-0.030	**-0.114**	144
Panel B: For U.S. Average															
US Average		**0.568**	**0.364**	**0.513**	**0.616**	**0.576**	**0.580**	**0.526**	**0.481**	**0.631**	**0.617**	**0.555**	-0.012	**-0.140**	144

Table 13

The Performance of Daily Liquidity Proxies Compared to Daily Liquidity Benchmarks by Exchange and for U.S. Average

The percent-cost benchmarks (percent effective spread, percent quoted spread, percent realized spread, and percent price impact) and a cost-per-volume benchmark (slope of the price function lambda) are calculated from every trade and corresponding BBO quote in the SIRCA Thomson Reuters Tick History database for a sample stock-day. All percent-cost proxies and cost-per-volume proxies are calculated from daily stock data for a sample stock-day. The sample spans 43 exchanges around the world from 1996-2007. This results in 19,543,557 stock-days from 21,361 firms. A solid box means the highest correlation or the lowest average root mean squared error (RMSE) among the compared proxies. Dashed boxes mean correlations that are statistically indistinguishable from the highest correlation or average RMSEs that are statistically indistinguishable from the lowest average RMSE among the compared proxies at the 1% level. Bold-faced numbers are statistically different from zero or have predictive power that is significant at the 1% level.

		Percent-Cost Proxies Compared with Percent Effective Spread						Cost-Per-Volume Proxies w.r.t. Lambda			
		Ave. C.S. Corr.		Port. T.S. Corr.		Ave. RMSE		Average Cross-Sectional Correlation			
Country	Exchange	High -Low	Closing % Quo Sprd	High -Low	Closing % Quo Sprd	High -Low	Closing % Quo Sprd	High -Low Impact	Closing % Quo Sprd Impact	Amihud	Amivest
Panel A: By Exchange											
Argentina	Buenos Ar.	0.205	0.622	0.170	0.671	0.0124	0.0123	0.417	0.614	0.601	-0.451
Australia	Australian	0.465	0.736	0.656	0.900	0.0264	0.0234	0.304	0.399	0.440	-0.172
Austria	Vienna	0.310	0.714	0.263	0.756	0.0120	0.0097	0.516	0.596	0.654	-0.433
Belgium	Brussels	0.323	0.692	0.525	0.909	0.0105	0.0085	0.419	0.529	0.543	-0.467
Brazil	Sao Paulo	0.227	0.642	0.283	0.505	0.0335	0.0298	0.150	0.181	0.182	-0.163
Canada	Toronto	0.445	0.775	0.161	0.748	0.0176	0.0140	0.483	0.544	0.585	-0.189
Chile	Santiago	0.059	0.553	0.344	0.431	0.0178	0.0335	0.079	0.124	0.120	-0.098
China	Hong Kong	0.382	0.729	0.317	0.911	0.0297	0.0220	0.257	0.331	0.415	-0.168
China	Shanghai	0.119	0.435	0.101	0.900	0.0095	0.0018	0.472	0.482	0.540	-0.317
China	Shenzhen	0.108	0.469	0.201	0.839	0.0097	0.0018	0.473	0.491	0.542	-0.326
Denmark	Copenhag.	0.307	0.701	0.815	0.872	0.0183	0.0162	0.260	0.329	0.342	-0.236
France	Paris	0.337	0.742	0.516	0.855	0.0150	0.0121	0.526	0.630	0.632	-0.282
Finland	Helsinki	0.420	0.761	0.783	0.902	0.0150	0.0127	0.092	0.116	0.136	-0.083
Germany	Frankfurt	0.368	0.712	0.869	0.969	0.0226	0.0238	0.363	0.465	0.526	-0.261
Greece	Athens	0.247	0.625	0.218	0.896	0.0148	0.0114	0.499	0.576	0.548	-0.302
India	Bombay	0.269	0.587	0.832	0.941	0.0558	0.0586	0.455	0.525	0.544	-0.314
Indonesia	Jakarta	0.562	0.833	0.853	0.915	0.0230	0.0157	0.219	0.268	0.255	-0.202
Ireland	Irish	0.423	0.793	0.568	0.824	0.0150	0.0125	0.375	0.471	0.438	-0.346
Israel	Tel Aviv	0.224	0.692	0.248	0.583	0.0243	0.0195	0.434	0.605	0.608	-0.278
Italy	Milan	0.173	0.634	0.748	0.843	0.0092	0.0071	0.345	0.393	0.382	-0.205
Japan	Tokyo	0.220	0.680	0.706	0.976	0.0095	0.0083	0.438	0.524	0.551	-0.265
Japan	Osaka	0.279	0.625	0.863	0.924	0.0132	0.0141	0.307	0.446	0.457	-0.364
Malaysia	Kuala Lum.	0.287	0.704	0.432	0.937	0.0194	0.0169	0.443	0.549	0.545	-0.311
Mexico	Mexican	0.218	0.648	0.439	0.749	0.0222	0.0251	0.435	0.566	0.563	-0.344
Netherlands	AEX	0.389	0.757	0.784	0.951	0.0127	0.0100	0.550	0.618	0.643	-0.311
New Zealand	New Zea.	0.340	0.593	0.219	0.447	0.0155	0.0134	0.273	0.425	0.407	-0.335
Norway	Oslo	0.308	0.701	0.806	0.922	0.0205	0.0176	0.233	0.298	0.315	-0.225
Philippines	Phillipine	0.345	0.729	0.490	0.716	0.0235	0.0176	0.154	0.197	0.227	-0.212
Poland	Warsaw	0.234	0.603	0.612	0.650	0.0347	0.0428	0.396	0.500	0.522	-0.392
Portugal	Lisbon	0.471	0.804	0.292	0.519	0.0071	0.0049	0.433	0.514	0.555	-0.481
Singapore	Singapore	0.624	0.793	0.780	0.933	0.0179	0.0167	0.332	0.388	0.383	-0.235
South Africa	Johannes.	0.491	0.732	0.821	0.913	0.0284	0.0272	0.408	0.521	0.510	-0.243
South Korea	Korea	0.190	0.646	0.726	0.848	0.0147	0.0085	0.493	0.508	0.537	-0.271
Spain	Barcelona	0.311	0.720	0.733	0.913	0.0078	0.0050	0.483	0.526	0.541	-0.271
Sweden	Stockholm	0.420	0.761	0.880	0.970	0.0204	0.0170	0.262	0.321	0.346	-0.156
Switzerland	SWX Swiss	0.376	0.723	0.861	0.803	0.0139	0.0122	0.415	0.525	0.537	-0.402
Taiwan	Taiwan	0.291	0.762	-0.049	0.835	0.0093	0.0042	0.253	0.557	0.593	-0.268
Thailand	Thailand	0.234	0.699	0.456	0.767	0.0150	0.0109	0.121	0.138	0.146	-0.156
Turkey	Istanbul	0.282	0.782	0.218	0.869	0.0096	0.0027	0.596	0.676	0.598	-0.332
UK	London	0.303	0.813	0.236	0.668	0.0247	0.0233	0.414	0.490	0.608	-0.261
US	New York	0.175	0.611	0.219	0.808	0.0076	0.0111	0.474	0.538	0.567	-0.298
US	American	0.320	0.586	0.188	0.510	0.0227	0.0290	0.390	0.497	0.472	-0.425
US	NASDAQ	0.322	0.811	0.837	0.973	0.0185	0.0120	0.418	0.482	0.510	-0.233
Panel B: For U.S. Average											
US Average		0.290	0.749	0.649	0.899	0.0164	0.0132	0.428	0.495	0.520	-0.263