



Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/jfec

Do liquidity measures measure liquidity? ☆

Ruslan Y. Goyenko^a, Craig W. Holden^b, Charles A. Trzcinka^{b,*}^a Desautels Faculty of Management, McGill University, Montreal, Quebec, Canada H3A 1G5^b Kelley School of Business, Indiana University, 1309 East Tenth Street, Bloomington, IN 47405-1701, USA

ARTICLE INFO

Article history:

Received 21 February 2005

Received in revised form

25 February 2008

Accepted 9 June 2008

Available online 3 February 2009

JEL classifications:

C15

G12

G20

Keywords:

Liquidity

Transaction costs

Effective spread

Price impact

Asset pricing

ABSTRACT

Given the key role of liquidity in finance research, identifying high quality proxies based on daily (as opposed to intraday) data would permit liquidity to be studied over relatively long timeframes and across many countries. Using new measures and widely employed measures in the literature, we run horseraces of annual and monthly estimates of each measure against liquidity benchmarks. Our benchmarks are effective spread, realized spread, and price impact based on both Trade and Quote (TAQ) and Rule 605 data. We find that the new effective/realized spread measures win the majority of horseraces, while the Amihud [2002. Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets* 5, 31–56] measure does well measuring price impact.

© 2009 Published by Elsevier B.V.

1. Introduction

The role of liquidity in empirical finance has grown rapidly over the past five years influencing conclusions in asset pricing, market efficiency, and corporate finance. A number of studies have proposed liquidity measures derived from daily return and volume data as proxies for investors' liquidity and transaction costs. These studies usually test whether security returns are related to these liquidity measures but rarely test whether the measures are related to actual transaction costs. The assumption

that the available liquidity proxies capture the transaction costs of market participants is often not tested because of the limited availability of actual trading costs. In the US markets transaction data are only available since 1983 and in many countries transaction data are not available at all. The consequences of not testing liquidity proxies on actual trading data is that there is little consensus on which measures are better and little evidence that any of the proposed measures are related to investor experience.

Further, while a handful of studies, Lesmond, Ogden, and Trzcinka (1999), Lesmond (2005), and Hasbrouck (2009), test whether some of the available liquidity proxies are related to liquidity benchmarks computed from transaction data, they construct the liquidity proxies on an annual or quarterly basis. Yet the vast majority of the literature using liquidity proxies employs them on *monthly* (or finer) data. Given the limited number of liquidity proxies previously tested, the limited set of liquidity benchmarks used in the literature, and the absence of monthly proxies, it is not surprising that there

☆ We thank Utpal Bhattacharya, Andrew Ellul, Jaden Falcone, Joel Hasbrouck, Christian Lundblad, Darius Miller, Marios Panayides, Xiaoyun Yu, and seminar participants at Indiana University and the Frontiers of Finance Conference in Bonaire, Netherlands Antilles. We also thank Charles Jones for making Dow spreads available. We are solely responsible for any errors.

* Corresponding author. Tel.: +1812 855 9908; fax: +1812 855 5875.

E-mail address: ctrzcink@indiana.edu (C.A. Trzcinka).

are conflicting views about which measure is better and that there is little assurance that these measures actually capture the transaction costs of market participants. In short, not much is known about whether transaction cost proxies measure what researchers claim they measure.

The purpose of this paper is to address this gap in the literature by providing a comprehensive study of liquidity measures. We run “horseraces” of all the widely used proxies for liquidity, plus three new proxies for effective and realized spread, and nine new proxies for price impact. We use multiple liquidity benchmarks, two high-frequency data sets (TAQ and Rule 605 data), multiple performance metrics, and a long sample period that includes the decimals regime.

We find a close association between many of the measures and actual transaction costs. Some measures are able to precisely estimate the magnitude of effective and realized spreads and many are highly correlated with both spreads and price impact. We can safely assert that the literature has generally not been mistaken in the assumption that liquidity proxies measure liquidity. The new measures we introduce in this paper consistently win a majority of the effective/realized spread horseraces. A measure commonly used in the literature, Pastor and Stambaugh’s (2003) Gamma, is clearly dominated by other measures while the widely used Amihud (2002) measure is a good proxy for price impact.

The paper is organized as follows. Section 2 discusses the empirical design of the paper. In Section 3 we develop the high-frequency liquidity benchmarks used in the horserace and in Sections 4 and 5 we develop the low-frequency spread proxies and price impact proxies used in the horserace. Section 6 describes the data sets and methodology. Section 7 presents the horserace results. Section 8 concludes the paper.

2. Empirical design

Our basic hypothesis is that useful monthly and annual liquidity measures can be constructed from low-frequency (daily) stock returns and volume data, giving researchers an access to liquidity measures over a long price history and in many markets. The US daily stock returns and volume data are available from the Center for Research in Security Prices (CRSP) covering NYSE/AMEX firms from 1926 to the present and NASDAQ firms from 1983 to the present. A wide variety of vendors provide daily stock returns and volume data for international equity markets. For example, Thomson Financial’s Datastream provides daily stock returns and volumes covering firms in more than 60 countries from 1994 to the present and daily stock returns for several developed markets going back to the early 1970s.

These tests should be of interest to a broad spectrum of empirical research in financial economics. In the asset pricing literature, Chordia, Roll, and Subrahmanyam (2000) show that various spread measures vary systematically. Goyenko (2006) shows that various spread measures are priced. Sadka (2006), Acharya and Pedersen

(2005), Pastor and Stambaugh (2003), and Watanabe and Watanabe (2006) show that various price impact measures are priced. Fujimoto (2003), Korajczyk and Sadka (2008), Hasbrouck (2009), and others test the pricing of both spread and price impact measures in the US while Bekaert, Harvey, and Lundblad (2007) test the measures in emerging markets where liquidity concerns may be more pronounced. All of these studies use monthly liquidity estimates. Reliable monthly spread and price impact measures going back in time and/or across countries are needed to determine if these asset pricing relationships hold up. In the market efficiency literature, De Bondt and Thaler (1985), Jegadeesh and Titman (1993, 2001), Chan, Jegadeesh, and Lakonishok (1996), Rouwenhorst (1998), and many others have found monthly trading strategies that appear to generate significant abnormal returns. Yet, Chordia, Goyal, Sadka, Sadka, and Shivakumar (2008) show that one of the oldest trading strategies in the literature, the post earnings announcement drift, cannot produce returns greater than the Keim and Madhavan (1997) measures. Clearly liquidity measures over time and/or across countries are needed in order to determine if these trading strategies are truly profitable net of a relatively precise measure of cost of trading.

Finally there is a growing need in corporate finance research for useful monthly liquidity measures. Kalev, Pham, and Steen (2003), Dennis and Strickland (2003), Cao, Field, and Hanka (2004), Lipson and Mortal (2004a), Schrand and Verrecchia (2004), Lesmond, O’Connor, and Senbet (2008), and many others examine the impact of corporate finance events on stock liquidity. Helfin and Shaw (2000), Lipson and Mortal (2004b), Lerner and Schoar (2004), and many others examine the influence of liquidity on capital structure, security issuance form, and other corporate finance decisions. Liquidity measures over a longer period of time would expand the potential sample size of this literature. Liquidity measures across many additional countries would greatly extend the potential diversity of international corporate finance environments that this literature could analyze.

To determine which liquidity measures are best, we compare proxies calculated from low-frequency data to sophisticated benchmarks of liquidity calculated from two high-frequency data sets using time-series correlations, cross-sectional correlations, and prediction errors. Specifically, we compare spread proxies to effective and realized spreads and we compare price impact proxies to two price impact benchmarks. All four of these benchmarks are calculated using the NYSE’s Trade and Quote (TAQ) data set from 1993 to 2005. Our monthly benchmarks are computed as monthly averages based on every trade and corresponding BBO¹ quote over the month and our annual benchmarks are computed as annual averages based on every trade and corresponding BBO quote over the year. We also compare spread proxies to the effective

¹ BBO means the best bid and offer. It is the highest bid and lowest ask available for a given stock at a moment in time.

spread for marketable orders² and compare price impact proxies to the price impact across order sizes.³ Both of these benchmarks are calculated using data disclosed under Securities and Exchange Commission (SEC) Rule 605 of Regulation NMS (formerly Regulation 11Ac1-5) from October 2001 to December 2005. Rule 605 requires that all exchanges and other market centers disclose detailed order-based performance statistics by stock, order type, and order size, providing a cross-check to the TAQ based results.

Our tests consist of running monthly and annual horseraces between 12 spread proxies and 12 price impact proxies, gauging their abilities to match the salient features of our high-frequency-based benchmarks. While some contestants are well established in the literature, many are being tested for the first time. The new spread proxies (described in detail below) are: “Effective Tick,” and “Effective Tick2,” developed jointly by this paper and Holden (2009); “Holden” from Holden (2009); and “LOT Y-split” developed by this paper. The other spread proxies from the previous literature are: “Roll” from Roll (1984); “Gibbs” from Hasbrouck (2004); “LOT Mixed,” “Zeros,” and “Zeros2” from Lesmond, Ogden, and Trzcinka (1999); “Amihud” from Amihud (2002); “Pastor and Stambaugh” from Pastor and Stambaugh (2003); and finally “Amivest Liquidity.”⁴ The latter three measures are also tested on price impact dimension. The other nine price impact contestants (also described below) are developed by this paper as extensions of the Amihud measure.

Our first performance metric is the average cross-sectional correlation based on individual firms between the low-frequency liquidity proxy and the high-frequency liquidity benchmark (effective spread, realized spread, or one of the price impact benchmarks). Our second performance metric is the time-series correlation based on an equally weighted portfolio between the liquidity proxy and the liquidity benchmark. Both of these performance metrics are most relevant for asset pricing purposes, where the magnitude of the correlation, not the scale of the low-frequency proxy, matters. Our third and fourth performance metrics are the prediction error between the liquidity proxy and the liquidity benchmark as measured by mean bias and the root mean squared error, respectively. These metrics are most relevant for market efficiency and corporate finance tests, where the scale of the proxy *does* matter as one wishes to subtract a correctly scaled proxy for transaction costs.

Hasbrouck (2009) runs annual tests between four effective cost measures, comparing each to effective

spread and price impact computed from TAQ data for the 1993 to 2005 period. Among the measures he tests, Gibbs dominates as a proxy for annual effective spread and Illiquidity dominates as a proxy for annual price impact.⁵ Using three annual measures, Lesmond, Ogden, and Trzcinka (1999) find that LOT dominates Roll and Zeros. Lesmond (2005) runs quarterly horseraces between five liquidity measures for 23 emerging countries, and finds that LOT dominates Roll, Illiquidity, Liquidity, and Turnover.

We generally conclude that liquidity measures based on daily data provide good measures of high-frequency transaction cost benchmarks (i.e., liquidity measures do measure liquidity). In the monthly and annual effective and realized spread horseraces, we find that Holden, Effective Tick, and LOT Y-split are the best overall. We also find that in more recent years, during the decimals regime, the performance of all measures deteriorates with the exception of Zeros and the Amihud measures. In the price impact horseraces, the new class of price impact measures introduced in this paper either marginally dominate the Amihud measure or is insignificantly different from it, depending on the benchmark. The new class of price impact measures is also able to capture the magnitude of the special Rule 605 version of price impact. Pastor and Stambaugh’s Gamma and Amivest’s Liquidity are never in the winning group of any horserace and have very low association with the six liquidity benchmarks analyzed.

3. High-frequency liquidity benchmarks

3.1. Spread benchmarks

We analyze three spread benchmarks. Our first spread benchmark is the effective spread as calculated from the high-frequency TAQ database. Specifically, for a given stock, the TAQ effective spread on the k th trade is defined as

$$\text{Effective Spread (TAQ)}_k = 2 \cdot |\ln(P_k) - \ln(M_k)|, \quad (1)$$

where P_k is the price of the k th trade and M_k is the midpoint of the consolidated BBO prevailing at the *time of the k th trade*. Aggregating over a time interval i (either a month or a year), a stock’s Effective Spread (TAQ) _{i} is the dollar-volume-weighted average of Effective Spread (TAQ) _{k} computed over all trades in time interval i .

Our second spread benchmark is the realized spread from Huang and Stoll (1996), which is the temporary component of the effective spread. Specifically, for a given

² Marketable orders are a combination of market orders and marketable limit orders.

³ Defined as the difference in the effective spread between large and small orders divided by the difference in the average share size between large and small orders.

⁴ The Amihud, Pastor and Stambaugh, and Amivest measures are perhaps more naturally thought of as price impact measures, but the use of these measures in the literature has been more broadly and loosely justified. Therefore, we test these measures relative to *both* effective spread and price impact benchmarks.

⁵ Hasbrouck extends his basic model to include a latent common liquidity factor for a subsample of stocks. He also estimates his Gibbs measure for all common NYSE/AMEX/NASDAQ stocks from 1927 to 2005 and tests whether liquidity is a priced risk factor.

stock, the TAQ realized spread on the k th trade is defined as

$$\text{Realized Spread (TAQ)}_k = \begin{cases} 2 \cdot (\ln(P_k) - \ln(P_{k+5})) & \text{when the } k\text{th trade is a buy} \\ 2 \cdot (\ln(P_{k+5}) - \ln(P_k)) & \text{when the } k\text{th trade is a sell,} \end{cases} \quad (2)$$

where $P_{(k+5)}$ is the price of trade *five-minutes after the k th trade*. The trades are signed according to the Lee and Ready (1991) algorithm. Aggregating over a time interval i (either a month or a year), a stock's Realized Spread (TAQ) $_k$ is the dollar-volume-weighted average of Realized Spread (TAQ) $_k$ computed over all trades in time interval i .

Our third spread benchmark is the effective spread as aggregated from the Rule 605 database. Specifically, for a given stock, the Rule 605 dollar effective spread based on the trade generated by the k th order is defined as

$$\text{\$Effective Spread (605)}_k = \begin{cases} 2 \cdot (P_k - m_k) & \text{for marketable buys} \\ 2 \cdot (m_k - P_k) & \text{for marketable sells,} \end{cases} \quad (3)$$

where m_k is the midpoint of the consolidated BBO prevailing at the *time of receipt* of the k th order at the exchange.⁶ Aggregating over month i , a stock's Effective Spread (605) $_i$ is the share-volume-weighted average of $\text{\$Effective Spread (605)}_k$ computed over all market centers (spanning all trades) in month i divided by \bar{P}_i , the average price in month i .

In principle, Effective Spread (605) $_i$ should be an improvement over Effective Spread (TAQ) $_i$, as each market center constructs their Rule 605 figures from *order data*, which are more refined than trade and quote data for several reasons. First, the Rule 605 midpoint is based on an order's *time of receipt*, whereas a TAQ midpoint is based on the trade's time of execution—an order's time of receipt is a closer proxy to the trader's information set at the time of order submission. Second, there is no confusion in the Rule 605 data about buys vs. sells or about marketable orders vs. non-marketable orders whereas Lee and Radhakrishna (2000) report that the Lee and Ready (1991) method commonly used with TAQ data incorrectly classifies 24% of inside-the-spread trades that have a clear trade initiator. Third, there is no confusion in the Rule 605 data when a marketable buy is crossed with a marketable sell. Lee and Radhakrishna (2000) find that 40% of the trades in their NYSE Trades, Orders, Reports, and Quotes (TORQ) sample are "nondirectional" trades, where a marketable buy and marketable sell are crossed. The Rule 605 data correctly treats this case as two marketable executions (both a marketable buy execution and a marketable sell execution). By contrast, users of TAQ data cannot distinguish nondirectional trades vs. directional trades and usually treat this case as a single

⁶ Marketable buys are market buy orders and marketable limit buy orders. Marketable sells are market sell orders and marketable limit sell orders. Effective spreads are not reported for non-marketable limit orders in the 605 data.

execution.⁷ Accordingly, the Rule 605 data provide a useful cross-check to the TAQ-based results; however, the Rule 605 data are only available from mid-2001, so the comparison is limited to only 51 months in our sample.

3.2. Price impact benchmarks

Based upon the literature, we analyze three different price impact benchmarks. A static version of price impact is the slope of the price function at a moment in time. Essentially, this is the cost of demanding additional instantaneous liquidity and can be thought of as the first derivative of the effective spread with respect to order size. Our first price impact benchmark uses two (aggregated) points on this curve to measure the slope. Specifically, for a given stock, the static price impact based on Rule 605 data over time interval i is

$$\text{Static Price Impact (605)}_i = \frac{\left[\begin{array}{c} (\text{\$Effective Spread (605)}_{\text{Big Orders},i} / \bar{P}_i) \\ - (\text{\$Effective Spread (605)}_{\text{Small Orders},i} / \bar{P}_i) \end{array} \right]}{\left[\begin{array}{c} (\text{Ave Trade Size (605)}_{\text{Big Orders},i}) \\ - (\text{Ave Trade Size (605)}_{\text{Small Orders},i}) \end{array} \right]}, \quad (4)$$

where Big Orders, i is the set of all orders in the range of 2000–9999 shares that execute in time interval i and small Orders, i is the set of all orders in the range of 100–499 shares that execute in time interval i .

Our second price impact benchmark introduces a time dimension that is not present in Static Price Impact. Five-minute price impact measures the derivative of the cost of demanding a certain amount of liquidity over five minutes which may be very different from the analogous curve for demanding the same amount of liquidity immediately. In constructing this measure, we follow Hasbrouck (2009) and calculate the price impact as the slope coefficient $\lambda(\text{TAQ})$ of the regression

$$r_n = \lambda(\text{TAQ}) \cdot S_n + u_n, \quad (5)$$

where for the n th five-minute period,⁸ r_n is the stock return, S_n is the signed square-root dollar volume, that is, $S_n = \sum_k \text{sign}(v_{kn}) \sqrt{|v_{kn}|}$, v_{kn} is the signed dollar volume of the k th trade in the n th five-minute period, and u_n is the error term.

Our third price impact benchmark focuses on the change in quote midpoint after a signed trade. Price impact is commonly defined as the increase (decrease) in the midpoint over a five-minute interval beginning at the time of the buyer- (seller-) initiated transaction. This is the permanent price change of a given transaction, or equivalently, the permanent component of the effective

⁷ There are downsides to 605 data as well. An order that is re-routed between market centers is double-counted. Further, the 605 data do not include block trades. The SEC is therefore an imperfect monitor of data quality. For more discussion of these issues, see Boehmer, Jennings, and Wei (2003).

⁸ We also tested a 15-minute interval with similar results, suggesting that our results are independent of the time interval over which we aggregate the data.

spread. Specifically, for a given stock, the TAQ five-minute price impact aggregated over a time interval i is

$$\begin{aligned} \text{5-Minute Price Impact (TAQ)}_k &= \begin{cases} 2 \cdot (\ln(M_{k+5}) - \ln(M_k)) & \text{when the } k\text{th trade is a buy} \\ 2 \cdot (\ln(M_k) - \ln(M_{k+5})) & \text{when the } k\text{th trade is a sell,} \end{cases} \\ & \quad (6) \end{aligned}$$

where M_{k+5} is the midpoint of the consolidated BBO prevailing five minutes after the k th trade, and M_k is the midpoint prevailing at the time of the k th trade. We follow the Lee and Ready (1991) algorithm to identify buy and sell transactions. For a given stock aggregated over a time interval i (either a month or a year), the 5-Minute Price Impact (TAQ) $_k$ is the dollar-volume-weighted average of 5-Minute Price Impact (TAQ) $_k$ computed over all trades in time interval i .

4. Low-frequency spread proxies

Nine low-frequency spread proxies are explained below. For each measure, we require that the measure always produce a numerical result.⁹

4.1. Roll

Roll (1984) develops an estimator of the effective spread based on the serial covariance of the change in price as follows. Let V_t be the unobservable fundamental value of the stock on day t . Assume that it evolves as

$$V_t = V_{t-1} + e_t, \quad (7)$$

where e_t is the mean-zero, serially uncorrelated public information shock on day t .

Next, let P_t be the last observed trade price on day t . Assume it is determined by

$$P_t = V_t + \frac{1}{2}SQ_t, \quad (8)$$

where S is the effective spread and Q_t is a buy/sell indicator for the last trade that equals +1 for a buy and -1 for a sell. Assume that Q_t is equally likely to be +1 or -1, is serially uncorrelated, and is independent of e_t . Taking the first difference of Eq. (8) and combining it with Eq. (7) yields

$$\Delta P_t = \frac{1}{2}S\Delta Q_t + e_t, \quad (9)$$

where Δ is the change operator. Given this setup, Roll shows that the serial covariance is

$$\text{Cov}(\Delta P_t, \Delta P_{t-1}) = \frac{1}{4}S^2, \quad (10)$$

or equivalently

$$S = 2\sqrt{-\text{Cov}(\Delta P_t, \Delta P_{t-1})}. \quad (11)$$

When the sample serial covariance is positive, the formula above is undefined and so we substitute a default numerical value of zero. We therefore use a modified

version of the Roll estimator:

$$\text{Roll} = \begin{cases} 2\sqrt{-\text{Cov}(\Delta P_t, \Delta P_{t-1})} & \text{When } \text{Cov}(\Delta P_t, \Delta P_{t-1}) < 0 \\ 0 & \text{When } \text{Cov}(\Delta P_t, \Delta P_{t-1}) \geq 0 \end{cases} \quad (12)$$

4.2. Effective tick

Holden (2009) and this paper jointly develop a proxy of the effective spread based on observable price clustering.¹⁰ Based on the negotiation cost theory of Harris (1991), we assume that trade prices are clustered in order to minimize negotiation costs between potential traders. Let S_t be the realization of the effective spread at the closing trade of day t . Assume that the realization of the spread on the closing trade of day is randomly drawn from a set of possible spreads s_j , $j = 1, 2, \dots, J$ with corresponding probabilities γ_j , $j = 1, 2, \dots, J$. By convention, the possible effective spreads s_1, s_2, \dots, s_J are ordered from smallest to largest. For example on a $\$ \frac{1}{8}$ price grid, S_t is modeled as having a probability γ_1 of $s_1 = \$ \frac{1}{8}$ spread, γ_2 of $s_2 = \$ \frac{1}{4}$ spread, γ_3 of $s_3 = \$ \frac{1}{2}$ spread, and γ_4 of $s_4 = \$1$ spread.

Following the intuition of Christie and Schultz (1994), we assume that price clustering is completely determined by spread size. For example, if the spread is $\$ \frac{1}{4}$, the model assumes that the bid and ask prices employ only even quarters. The quote could be $\$25 \frac{1}{4}$ bid, $\$25 \frac{1}{2}$ offered, but never $\$25 \frac{3}{8}$ bid, $\$25 \frac{5}{8}$ offered. Thus, if odd-eighth transaction prices are observed, one infers that the spread must be $\$ \frac{1}{8}$. This implies that the simple frequency with which closing prices occur in particular price clusters can be used to estimate the spread probabilities $\hat{\gamma}_j$, $j = 1, 2, \dots, J$. For example on a $\$ \frac{1}{8}$ fractional price grid, the frequency with which trades occur in four, mutually exclusive price sets (odd $\frac{1}{8}$ s, odd $\frac{1}{4}$ s, odd $\frac{1}{2}$ s, and whole dollars) can be used to estimate the probability of a $\$ \frac{1}{8}$ spread, $\$ \frac{1}{4}$ spread, $\$ \frac{1}{2}$ spread, and a $\$1$ spread. Similarly for a decimal price grid, the frequency with which trades occur in five, mutually exclusive sets (off pennies, off nickels, off dimes, off half-dollars, and whole dollars) can be used to estimate the probability of a penny spread, nickel spread, dime spread, quarter spread, and whole dollar spread.

Let N_j be the number of trades on prices corresponding to the j th spread ($j = 1, 2, \dots, J$) using only positive-volume days in the time interval. In the $\$ \frac{1}{8}$ price grid example (where $J = 4$), N_1 through N_4 are the number of trades on odd $\frac{1}{8}$ prices, the number of trades on odd $\frac{1}{4}$ prices, the number of trades on odd $\frac{1}{2}$ prices, and the number of trades on whole dollar prices, respectively.

Let F_j be the probabilities of trades on prices corresponding to the j th spread ($j = 1, 2, \dots, J$). These empirical probabilities are computed as

$$F_j = \frac{N_j}{\sum_{j=1}^J N_j} \quad \text{for } j = 1, 2, \dots, J. \quad (13)$$

⁹ If a measure cannot be computed we substitute a default value. Our results are not sensitive to the default value selected.

¹⁰ Holden (2009) also develops and tests additional versions of the Effective Tick measure.

Let U_j be the unconstrained probability of the j th spread ($j = 1, 2, \dots, J$). The unconstrained probability of the effective spread is

$$U_j = \begin{cases} 2F_j, & j = 1 \\ 2F_j - F_{j-1}, & j = 2, 3, \dots, J - 1 \\ F_j - F_{j-1}, & j = J. \end{cases} \quad (14)$$

The effective tick model directly assumes price clustering (i.e., a higher frequency on rounder increments). However, in small samples it is possible that reverse price clustering may be realized (i.e., a lower frequency on rounder increments). Reverse price clustering unintentionally causes the unconstrained probability of one or more effective spread sizes to go above one or below zero. Thus, constraints are added to generate proper probabilities. Let $\hat{\gamma}_j$ be the constrained probability of the j th spread ($j = 1, 2, \dots, J$). It is computed in order from smallest to largest as follows:

$$\hat{\gamma}_j = \begin{cases} \text{Min}[\text{Max}\{U_j, 0\}, 1], & j = 1 \\ \text{Min}\left[\text{Max}\left[U_j, 0, 1 - \sum_{k=1}^{j-1} \hat{\gamma}_k\right], 1\right], & j = 2, 3, \dots, J. \end{cases} \quad (15)$$

Finally, the effective tick measure is simply a probability-weighted average of each effective spread size divided by \bar{P}_i , the average price in time interval i

$$\text{Effective Tick} = \frac{\sum_{j=1}^J \hat{\gamma}_j S_j}{\bar{P}_i} \quad (16)$$

A second version, called *Effective Tick2*, is otherwise the same except that it uses the daily prices from all days, rather than just positive-volume days only. The difference between the two measures depends on the informativeness of the no trade prices.

4.3. Holden

Holden (2009) develops a model that uses both serial correlation (like the Roll measure) and price clustering

$$\Pr(P_t, P_{t+1}, P_{t+2} | \mu, \gamma_1, \gamma_2, S_H, \bar{e}, \sigma_e, \lambda) = \sum_{(H_t, H_{t+1}, H_{t+2}) \in H} \left\{ \frac{\Pr(C_t) \cdot \Pr(C_{t+1}) \cdot \Pr(C_{t+2}) \cdot \Pr(H_t | C_t) \cdot \Pr(H_{t+1} | C_{t+1}) \cdot \Pr(H_{t+2} | C_{t+2})}{n(P_{t+1} - H_{t+1} - (P_t - (1 - \lambda)H_t)) \cdot n(P_{t+2} - H_{t+2} - (P_{t+1} - (1 - \lambda)H_{t+1}))} \right\} \quad (19)$$

(like *Effective Tick*) to estimate the effective spread. Indeed, the Holden model formally nests both the Roll model and the *Effective Tick* model as special cases. His model is based on modifying the model of Huang and Stoll (1997). Huang and Stoll develop a generalized model of the components of the bid–ask spread. A by-product of the Holden model is a two-way decomposition of the bid–ask spread as estimated from low-frequency data.

Holden begins by modifying the Huang and Stoll model to account for changing spreads linked to price clustering. Just like the *Effective Tick* model above, he specifies a random probability of jumping each period among multiple spreads that are linked price cluster regimes.

Next, he derives a price change process that is a natural extension of Eq. (9) above

$$\Delta P_t = \frac{1}{2} S_t Q_t - (1 - \lambda) \frac{1}{2} S_{t-1} Q_{t-1} + e_t, \quad (17)$$

where the effective spread S_t is allowed to change each day and λ is the percentage of the half-spread attributable to the sum of adverse selection and inventory holding costs. Conversely, $1 - \lambda$ is the percentage of the half-spread attributable to order processing costs.¹¹ The public information shock e_t is assumed to be normally distributed with mean \bar{e} and standard deviation σ_e .

Let μ be the probability of a trading day and $1 - \mu$ be the probability of a non-trading day. Consider a $\frac{1}{8}$ price grid where S_t has a probability γ_1 of $s_1 = \frac{1}{8}$ spread, γ_2 of $s_2 = \frac{1}{4}$ spread, γ_3 of $s_3 = \frac{1}{2}$ spread, and γ_4 of $s_4 = 1$ spread. Of course, the spread probabilities must sum to one: $\sum_{j=1}^J \gamma_j = 1$. The Holden spread proxy is just the weighted-average of the possible spreads:

$$\text{Holden} \equiv S_H = \sum_{j=1}^J \gamma_j s_j. \quad (18)$$

Define the variable C_t as the observable price cluster on day t . Specifically, on a zero-volume day, let $C_t = 0$. On a positive-volume day, let clusters $C_t = 1, 2, 3$, and 4 correspond to when the trade price is on odd $\frac{1}{8}$ s, odd $\frac{1}{4}$ s, odd $\frac{1}{2}$ s, and whole dollars, respectively. Define \hat{Q}_t as a buy/sell/zero volume indicator on day d that equals +1 for a buy, -1 for a sell, and zero for a zero-volume day. Define the *unobserved* signed half-spread on day t as $H_t = \frac{1}{2} S_t \hat{Q}_t$. Considering all spread and indicator combinations, there are nine possible values of the signed half-spread H_t : $\frac{1}{2}, \frac{1}{4}, \frac{1}{8}, \frac{1}{16}, 0, -\frac{1}{16}, -\frac{1}{8}, -\frac{1}{4}, -\frac{1}{2}$.

For three successive trading days we observe a price triplet (P_t, P_{t+1}, P_{t+2}) , which corresponds to a price cluster triplet (C_t, C_{t+1}, C_{t+2}) . Define H as the set of all half-spread triplets (H_t, H_{t+1}, H_{t+2}) that are feasible given the observed price cluster triplet.¹² For a given a set of parameter values $(\mu, \gamma_1, \gamma_2, S_H, \bar{e}, \sigma_e, \lambda)$, Holden calculates the likelihood of the price triplet

where $n(\cdot)$ is the normal density with mean \bar{e} and standard deviation σ_e . Using three prices at a time allows the serial correlation of the price changes to be picked up, but avoids the combinatoric explosion of feasible half-spread

¹¹ This component also includes any liquidity provider rents due to market power or price discreteness.

¹² For example, suppose that the price $P_t = \$25\frac{3}{8}$, which is an odd-eighth that corresponds to price cluster $C_t = 1$. For this price cluster the only feasible spread is $S_t = \frac{1}{8}$. Thus, there are only two feasible values of the signed half-spreads $H_t \in \{\frac{1}{16}, -\frac{1}{16}\}$. Similarly, P_{t+1} and P_{t+2} imply the feasible values of the signed half-spreads H_{t+1} and H_{t+2} . Taking all combinations of the feasible values on each day yields the set of feasible half-spread triplets.

combinations that would result if all observations were used at the same time.

Taking the log of Eq. (19), the likelihood function is the sum of the log likelihoods of all price triplets in the time period of aggregation

$$\sum_{t=1}^{T-2} \ln(\Pr(P_t, P_{t+1}, P_{t+2} | \mu, \gamma_1, \gamma_2, S_H, \bar{e}, \sigma_e, \lambda)), \quad (20)$$

where T is the number of days in the time period of aggregation. The likelihood function is maximized by choice of the parameters $\mu, \gamma_1, \gamma_2, S_H, \bar{e}, \sigma_e, \lambda$ subject to the constraints that $\gamma_1, \gamma_2, \gamma_3, \gamma_4, \mu, S_H, \sigma_e$, and λ are greater than or equal to zero and the constraints that $\gamma_1, \gamma_2, \gamma_3, \gamma_4, \mu$, and λ are less than or equal to one.¹³

4.4. Gibbs

Hasbrouck (2004) introduces a Gibbs sampler estimation of the Roll model using prices from all days. Hasbrouck assumes that the public information shock e_t in the Roll model is normally distributed with mean of zero and variance of σ_e^2 . He denotes the half-spread in the Roll model as $c \equiv \frac{1}{2}S$.

Hasbrouck uses the Gibbs sampler to numerically estimate the model parameters $\{c, \sigma_e^2\}$, the latent buy/sell/no-trade indicators $Q = \{Q_1, Q_2, \dots, Q_T\}$, and the latent “efficient prices” $V = \{V_1, V_2, \dots, V_T\}$, where T is the number of days in the time interval.¹⁴

4.5. LOT

Lesmond, Ogden, and Trzcinka (1999) develop an estimator of the effective spread based on the assumption of informed trading on non-zero-return days and the absence of informed trading on zero-return days. A standard “market model” relationship holds on non-zero-return days, but a flat horizontal segment applies on zero-return days.

The LOT model assumes that the unobserved “true return” R_{jt}^* of a stock j on day t is given by

$$R_{jt}^* = \beta_j R_{mt} + \varepsilon_{jt}, \quad (21)$$

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

$$\begin{aligned} R_{jt} &= R_{jt}^* - \alpha_{1j} && \text{when } R_{jt}^* < \alpha_{1j} \\ R_{jt} &= R_{jt}^* && \text{when } \alpha_{1j} < R_{jt}^* < \alpha_{2j} \\ R_{jt} &= R_{jt}^* - \alpha_{2j} && \text{when } \alpha_{2j} < R_{jt}^*. \end{aligned} \quad (22)$$

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

$$LOT = \alpha_{j2} - \alpha_{j1}. \quad (23)$$

Lesmond, Ogden, and Trzcinka develop the following maximum likelihood estimator of the model’s parameters:

$$\begin{aligned} L(\alpha_{1j}, \alpha_{2j}, \beta_j, \sigma_j | R_{jt}, R_{mt}) &= \prod_1 \frac{1}{\sigma_j} n \left[\frac{R_{jt} + \alpha_{1j} - \beta_j R_{mt}}{\sigma_j} \right] \\ &\times \prod_0 \left[N \left(\frac{\alpha_{2j} - \beta_j R_{mt}}{\sigma_j} \right) - N \left(\frac{\alpha_{1j} - \beta_j R_{mt}}{\sigma_j} \right) \right] \\ &\times \prod_2 \frac{1}{\sigma_j} n \left[\frac{R_{jt} + \alpha_{2j} - \beta_j R_{mt}}{\sigma_j} \right] \\ S.T. \quad &\alpha_{j1} \leq 0, \alpha_{j2} \geq 0, \beta_j \geq 0, \sigma_j \geq 0, \end{aligned} \quad (24)$$

where $N(\cdot)$ is the cumulative normal distribution.

A very important issue concerning LOT is the definition of the three regions over which the estimation is done. The original LOT (1999) measure, which we call LOT Mixed, distinguishes the three regions based on both the X-variable and the Y-variable. That is, 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 $R_{mt} < 0$. In this paper we develop an alternative measure, LOT Y-split, that breaks out the three regions based on the Y-variable. That is, region 0 is $R_{jt} = 0$, region 1 is $R_{jt} > 0$ and region 2 is $R_{jt} < 0$. Interestingly, LOT Y-split and LOT Mixed sometimes produce very different results, so it is worth tracking both of them.

4.6. Zeros

Lesmond, Ogden, and Trzcinka (1999) introduce the proportion of days with zero returns as a proxy for liquidity. Two key arguments support this measure. First, stocks with lower liquidity are more likely to have zero-volume days and thus are more likely to have zero-return days. Second, stocks with higher transaction costs have less private information acquisition (because it is more difficult to overcome higher transaction costs), and thus, even on positive volume days, they are more likely to have no-information-revelation, zero-return days.

Lesmond, Ogden, and Trzcinka define the proportion of days with zero returns as

$$\text{Zeros} = (\# \text{ of days with zero returns})/T, \quad (25)$$

where T is the number of trading days in a month. An alternative version of this measure, Zeros2, is defined as

$$\text{Zeros2} = (\# \text{ of positive-volume days with zero return})/T. \quad (26)$$

For emerging markets, the Zeros measure has been used by Bekaert, Harvey, and Lundblad (2007).

¹³ The constraints $\gamma_3 \geq 0$ and $\gamma_3 \leq 1$ can be expressed as a function of the parameters to be estimated $(\mu, \gamma_1, \gamma_2, S_H, \bar{e}, \sigma_e, \lambda)$ as: $2[1 - S - \gamma_1(\frac{7}{8}) - \gamma_2(\frac{3}{4})] \geq 0$ and $2[1 - S - \gamma_1(\frac{7}{8}) - \gamma_2(\frac{3}{4})] \leq 1$, respectively. Similarly, the constraints $\gamma_4 \geq 0$ and $\gamma_4 \leq 1$ can be expressed as: $1 - \gamma_1 - \gamma_2 - 2[1 - S - \gamma_1(\frac{7}{8}) - \gamma_2(\frac{3}{4})] \geq 0$ and $1 - \gamma_1 - \gamma_2 - 2[1 - S - \gamma_1(\frac{7}{8}) - \gamma_2(\frac{3}{4})] \leq 1$, respectively.

¹⁴ Hasbrouck generously provides the programming code to compute the Gibbs estimator on his Web site. We directly use his code without modification of the main routines for both monthly and annual computations.

4.7. Other proxies

Three additional proxies are tested in the spread horseraces: (1) “Illiquidity” from Amihud (2002), (2) “Gamma” from Pastor and Stambaugh (2003), and (3) the (Amivest) “Liquidity.” These measures are intended to proxy for price impact. Therefore, they are tested only for correlation with effective and realized spreads. All three are described below.

5. Low-frequency price impact proxies

Next, we explain 12 low-frequency price impact proxies. As before, we require that each measure always produce a numerical result.

5.1. Amihud

Amihud (2002) develops a price impact measure that captures the “daily price response associated with one dollar of trading volume.” Specifically, he uses the ratio

$$\text{Illiquidity} = \text{Average} \left(\frac{|r_t|}{\text{Volume}_t} \right), \quad (27)$$

where r_t is the stock return on day t and Volume_t is the dollar volume on day t . The average is calculated over all positive-volume days, since the ratio is undefined for zero-volume days.

5.2. Extended Amihud proxies

We develop a new class of price impact proxies by extending the Amihud measure. We start with the Amihud base model. We then decompose the total return in the base model numerator into a liquidity component and a non-liquidity component. This is done by dividing both sides of the modified Huang and Stoll model in Eq. (17) by P_{t-1} to obtain

$$r_t = \frac{\frac{1}{2}S_t Q_t - (1 - \lambda)\frac{1}{2}S_{t-1} Q_{t-1}}{P_{t-1}} + \frac{e_t}{P_{t-1}}, \quad (28)$$

where the first term on the right-hand side is the liquidity component and the second term is the non-liquidity component. $\frac{1}{2}S_t Q_t - (1 - \lambda)\frac{1}{2}S_{t-1} Q_{t-1}$ is the signed effective half-spread (which includes three components: adverse selection, order processing, and inventory costs) at time t minus the order processing component of the lagged signed effective half-spread at $t-1$, and e_t is the mean-zero, serially uncorrelated public information shock on day t . This model includes the Glosten (1987) model as a special case when inventory costs are zero. Substituting Eq. (28) into Eq. (27), we get

$$\text{Average} \left(\frac{\frac{\frac{1}{2}S_t Q_t - (1 - \lambda)\frac{1}{2}S_{t-1} Q_{t-1}}{P_{t-1}} + \frac{e_t}{P_{t-1}}}{\text{Volume}_t} \right) \quad (29)$$

By assumption, the random variable e_t is independent of the liquidity component. We therefore drop the non-liquidity component to measure the *liquidity costs asso-*

ciated with one dollar of trading volume as

$$\text{Average} \left(\frac{\frac{\frac{1}{2}S_t Q_t - (1 - \lambda)\frac{1}{2}S_{t-1} Q_{t-1}}{P_{t-1}}}{\text{Volume}_t} \right) \quad (30)$$

Essentially, this eliminates a noise term that is unrelated to the variable of interest. The average numerator value is close (at least in magnitude) to the percent effective half-spread. Since we do not observe the numerator in low-frequency data sets, we construct an extended Amihud proxy for time interval i by using a spread proxy over time interval i and the average daily dollar volume over the same time interval as follows:

$$\begin{aligned} \text{Extended Amihud Proxy}_i \\ = \frac{\text{Spread Proxy}_i}{\text{Average Daily Dollar Volume}_i}, \end{aligned} \quad (31)$$

where the whole spread convention is used instead of the half-spread convention. The original Amihud measure computes the average of daily ratios, where each daily ratio is absolute return/dollar volume. The extended Amihud proxies use an alternative convention by computing the ratio of two averages. If we view the spread proxy as representing the average daily spread over interval i , then the ratio can be interpreted as the average daily spread/average daily dollar volume.¹⁵

The equation above defines a class of price impact proxies depending on which proxy for percent effective spread is used. For example, one member of this class is Roll Impact for time interval i , which uses the Roll measure for time interval i and the average daily dollar volume over time interval i as follows:

$$\begin{aligned} \text{Roll Impact}_i \\ = \frac{\text{Roll}_i}{\text{Average Daily Dollar Volume}_i}, \end{aligned} \quad (32)$$

We test nine versions of this class of price impact measures based on nine proxies for percent effective spread. The nine measures we test are: Roll Impact, Effective Tick Impact, Effective Tick2 Impact, Holden Impact, Gibbs Impact, LOT Mixed Impact, LOT Y-split Impact, Zeros Impact, and Zeros2 Impact.

5.3. Pastor and Stambaugh

Pastor and Stambaugh (2003) develop a measure of price impact called Gamma by running the regression

$$r_{t+1}^e = \theta + \phi r_t + (\text{Gamma}) \text{sign}(r_t^e) (\text{Volume}_t) + \varepsilon_t, \quad (33)$$

where r_t^e is the stock's excess return above the CRSP value-weighted market return on day t and Volume_t is the dollar volume on day t . Intuitively, Gamma measures the reverse of the previous day's order flow shock. Gamma should

¹⁵ Both the original Amihud measure and the extended Amihud proxies aggregate trades up to the level of a day. This is justified if all trades are of identical size, but if trades are of varying size, then this is a somewhat arbitrary normalization.

have a negative sign. The larger the absolute value of Gamma, then the larger the implied price impact.

5.4. Amivest liquidity

The Amivest Liquidity ratio is a measure of price impact

$$\text{Liquidity} = \text{Average} \left(\frac{\text{Volume}_t}{|R_t|} \right). \quad (34)$$

The average is calculated over all non-zero-return days, since the ratio is undefined for zero-return days. A larger value of Liquidity implies a lower price impact. This measure has been used by Cooper, Groth, and Avera (1985), Amihud, Mendelson, and Lauterback (1997), Berkman and Eleswarapu (1998), and others.

6. Data

To compute our effective spread, realized spread, and price impact benchmarks, we use two high-frequency data sets. First, we use NYSE TAQ data from 1993 to 2005. Because of the computational limits associated with some of the measures, we select a random sample. Following the methodology of Hasbrouck (2009), a stock must meet five criteria to be eligible: (1) it is a common stock, (2) it is present on the first and last TAQ master file for the year, (3) it has 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) it is listed in CRSP. We randomly select 400 stocks each year from the universe of eligible stocks in 1993. Rolling forward, if any of the 1993 selections is not eligible in 1994, we randomly draw a replacement from the universe of eligible stocks in 1994. We continue rolling forward in likewise fashion over a 13-year span. Thus, we have 5,200 stock-years. We use the same set of stocks for the monthly measures. We lose a small number of observations in extremely illiquid stocks because of insufficient trades (two or less) on positive-volume days to run the Bayesian regression that is part of the Gibbs measure. This results in 62,100 stock-months from TAQ.

Second, we use data that are required to be disclosed under Rule 605 of Regulation NMS (formerly Regulation 11Ac1-5) from October 2001 to December 2005. The data are collected and manually assembled from the Transaction Auditing Group, Inc. (www.tagaudit.com) from October 2001 to December 2005. We use the same stocks as above. Data on NYSE/AMEX firms are taken from their respective market center statistics. Data on NASDAQ firms are aggregated by volume-weighting the disclosed statistics from the following market centers: Small Order Execution System (SOES), all Electronic Communication Networks (ECNs) (Archipelago (ARCA), Instinet (INET), Island (ISLD), NexTrade (NTRD), Redibook (REDI)), and the top 10 NASDAQ market makers¹⁶ (Schwab (SCHB), Brutt (BRUT), Goldman Sachs (GSCO), Knight (NITE and TRIM),

GVR (GVRG), B-Trade (BTRD), Lehman Brothers (LEHM), Credit Suisse First Boston (FBCO), Merrill Lynch (MLCO), and J.P. Morgan (JPMS)).

To compute our low-frequency liquidity measures, we use the Daily Stock database from CRSP over the same time period. We notice that the analytic-formula proxies (Roll, Effective Tick, Effective Tick2, Zeros, Zeros2, Illiquidity, Gamma, and Liquidity) are fast to compute. By contrast, the single measure, numerically iterated proxies (Gibbs, LOT Mixed, and LOT Y-split) are slower to compute as is the combination measure, Holden, which is the most computationally intensive. In perspective, all low-frequency proxies, with the exception of the Holden measure, are faster to compute than their high-frequency counterparts.

Table 1 provides summary descriptive statistics. Panel A describes monthly spread benchmarks and proxies calculated from 1993–2005 TAQ data. The high-frequency benchmark, Effective Spread (TAQ), has a mean of 0.029 and a median of 0.016. Since the effective costs are logarithmic, the mean corresponds to effective costs of about 3%. Looking across the spreads proxies, we see that Roll, Effective Tick, Effective Tick 2, Holden, Gibbs, and LOT Y-split are approximately the same in magnitude as the benchmark. LOT Mixed is approximately double the benchmark. The rest of the low-frequency measures are completely different in order of magnitude. Panel B describes annual spread benchmarks and proxies, where the picture about order of magnitude is essentially the same.

Realized spread is the temporary component of effective spread. Its mean corresponds to 1.5% which is approximately half of the effective spread for monthly data (Panel A). Effective Tick, Effective Tick 2, Holden, and Gibbs are very close in magnitude to the realized spread. The same pattern persists for annual data (Panel B).

Panel C of Table 1 describes monthly spread benchmarks and proxies calculated from 10/2001–12/2005 Rule 605 data. Effective Spread (605) has a mean of 0.015 and a median of 0.006. Again, the low-frequency proxies have essentially the same magnitude relationships as in Panel A. Compared to monthly TAQ effective spread in Panel A, effective spread (605) is almost twice smaller in magnitude. This difference can be attributed to the following. The TAQ effective spread is the percent *dollar*-volume-weighted average spread for each month while the Rule 605 effective spread is the *dollar share*-weighted average monthly spread reported by market centers normalized by the average monthly price. Further, the TAQ effective spread is obtained as the absolute value of the difference between price and the BBO midpoint, while the Rule 605 effective spread is computed by market center as the signed value, where buy and sell transactions are identified by market makers.

Panel D of Table 1 describes monthly price impact benchmarks and proxies calculated from 1993–2005 TAQ data. The high-frequency benchmark, Lambda (TAQ), has a mean of 130.425 and a median of 15.793, after multiplying by 1,000,000. At its median value, the TAQ-based price impact coefficient Lambda implies that a \$10,000 buy order would move the log price by approximately

¹⁶ The top 10 list is based on NASDAQ composite volume for the month of March 2004 at www.nasdaqtrader.com.

Table 1

Descriptive statistics

The benchmarks Effective spread (TAQ), Realized spread (TAQ), Lambda (TAQ), and 5-Minute Price Impact (TAQ) are calculated from every trade and corresponding BBO quote in the NYSE TAQ database for a sample firm-month or firm-year. Effective spread (TAQ) is the dollar-volume-weighted average of two times the absolute value of log price minus log midpoint. Realized spread (TAQ) is the dollar-volume-weighted average of two times the log price minus log of the five-minutes-later price for buys and the negative of previous for sells. Lambda (TAQ) is the coefficient from regressing the stock return over a five-minute interval on the signed square-root dollar-volume over the same interval with intercept omitted. 5-Minute Price Impact (TAQ) is the dollar-volume-weighted average of two times the log five-minutes-later midpoint minus the log midpoint for buys and negative of previous for sells. Lambda (TAQ) is in (percent return)/(square root of dollars). The other three TAQ benchmarks are unitless. The benchmarks Effective Spread (605) and Static Price Impact (605) are calculated from data required to be disclosed under SEC Rule 605 (formerly 11Ac1-5) for a sample firm-month. Effective spread (605) is the share-weighted average of two times the price minus midpoint for buys and of two times the midpoint minus price for sells, then divided by the average price over the month or year. Static Price Impact (605) is dollar effective spread for big orders divided by average price minus dollar effective spread for small orders divided by average price, then divided by the average trade size of big orders minus the average trade size of small orders. Effective spread (605) is unitless. Static Price Impact (605) is in dollars/share. All spread proxies and price impact proxies are calculated from CRSP daily stock price and volume data for a sample firm-month or firm-year. The spread proxies are: Roll from Roll (1984), Effective Tick and Effective Tick2 developed here and in Holden (2009), Holden from Holden (2009), Gibbs from Hasbrouck (2004), LOT Mixed, Zeros, and Zeros2 from Lesmond, Odgen, and Trzcinka (1999), LOT Y-split developed here, Amihud from Amihud (2002), Pastor and Stambaugh from Pastor and Stambaugh (2003), and the Amivest Liquidity ratio. The price impact proxies are: Roll Impact, Effective Tick Impact, Effective Tick2 Impact, Holden Impact, Gibbs Impact, LOT Mixed Impact, and LOT Y-split Impact developed here, Amihud from Amihud (2002), Pastor and Stambaugh from Pastor and Stambaugh (2003), and the Amivest Liquidity ratio. The TAQ sample spans 1993–2005 inclusive and consists of 400 randomly selected stocks with annual replacement of stocks that do not survive, resulting in 62,100 firm-months or 5,200 firm-years. The Rule 605 sample spans 10/2001 to 12/2005 inclusive and consists of 400 randomly selected stocks with annual replacement of stocks that do not survive, resulting in 19,039 firm-months.

	Spread benchmarks			Spread proxies								
	Effective spread (TAQ)	Effective spread (605)	Realized spread (TAQ)	Roll	Effective Tick	Effective Tick2	Holden	Gibbs	LOT Mixed	LOT Y-split	Zeros	Zeros2
<i>Panel A: Monthly, 1993–2005, using a TAQ benchmark</i>												
Average	0.029	–	0.015	0.027	0.017	0.016	0.018	0.018	0.056	0.023	0.143	0.127
Std dev	0.040	–	0.032	0.037	0.032	0.030	0.030	0.021	0.089	0.051	0.147	0.130
Min	0.0001	–	–0.370	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.016	–	0.005	0.016	0.008	0.007	0.009	0.012	0.031	0.009	0.095	0.095
Max	0.896	–	1.320	0.906	0.929	0.949	0.917	0.673	1.000	1.000	0.909	0.909
<i>Panel B: Annual, 1993–2005, using a TAQ benchmark</i>												
Average	0.026	–	0.014	0.025	0.013	0.013	0.014	0.014	0.074	0.027	0.145	0.128
Std dev	0.034	–	0.024	0.032	0.019	0.018	0.019	0.018	0.117	0.061	0.126	0.101
Min	0.0003	–	–0.044	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000
Median	0.016	–	0.007	0.016	0.007	0.007	0.008	0.007	0.039	0.011	0.115	0.109
Max	0.672	–	0.808	0.327	0.289	0.340	0.269	0.190	1.787	1.119	0.917	0.653
<i>Panel C: Monthly, 10/2001–12/2005, using a 605 benchmark</i>												
Average	–	0.015	–	0.019	0.006	0.005	0.007	0.013	0.025	0.006	0.049	0.046
Std dev	–	0.033	–	0.028	0.015	0.014	0.014	0.015	0.040	0.018	0.073	0.069
Min	–	0.000	–	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Median	–	0.006	–	0.012	0.002	0.002	0.003	0.009	0.014	0.000	0.000	0.000
Max	–	0.948	–	0.906	0.425	0.447	0.482	0.393	1.000	0.581	0.667	0.667

Price impact benchmarks ^a				Price impact proxies ^a											
Lambda (TAQ)	5 Minute Price Impact (TAQ)	Static Price Impact (605)	Roll Impact	Effective Tick Impact	Effective Tick2 Impact	Holden Impact	Gibbs Impact	LOT Mixed Impact	LOT Y-split Impact	Zeros Impact	Zero2 Impact	Amihud	Pastor and Stambaugh	Amivest Liquidity	
<i>Panel D: Monthly, 1993–2005, using a TAQ benchmark</i>															
Average	130.425	0.031	–	3.816	4.587	4.049	4.068	3.626	12.211	9.295	20.917	7.782	6.314	–0.179	639,355
Std dev	2446.202	0.038	–	57.617	154.809	147.568	93.306	75.851	288.448	284.875	305.990	102.754	91.957	10.129	155,561,102
Min	–41544.120	0.000	–	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	–1508.411	0.000
Median	15.793	0.020	–	0.015	0.020	0.019	0.024	0.029	0.074	0.018	0.202	0.148	0.104	0.000	26.622
Max	398507	1.022	–	6978	32742	32742	16371	11399	42000	42000	38000	21000	14160	798	38,762,898,699
<i>Panel E: Annual, 1993–2005, using a TAQ benchmark</i>															
Average	70.285	0.031	–	2.045	1.569	1.335	1.353	1.486	6.604	4.346	12.879	4.972	6.307	0.018	586,003
Std dev	300.430	0.031	–	17.937	25.274	22.932	13.734	14.257	87.651	70.645	191.552	31.360	46.973	0.292	41,202,127
Min	–10943.480	0.002	–	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	–5.598	0.007
Median	15.535	0.021	–	0.015	0.015	0.015	0.017	0.014	0.089	0.023	0.237	0.236	0.148	0.000	36.563
Max	7655.088	0.414	–	834.616	1644.99	1504.080	581.405	578.151	5381.836	3826.47	11554.83	1424.65	1681.365	8.436	2,970,331,874
<i>Panel F: Monthly, 10/2001–12/2005, using a 605 benchmark</i>															
Average	–	–	1.016	1.600	1.057	0.985	0.875	1.071	2.659	1.213	5.713	2.963	4.046	0.025	2,066,923
Std dev	–	–	31.278	19.639	28.910	39.373	12.177	15.198	40.269	27.799	125.983	20.595	66.740	3.446	280,924,448
Min	–	–	–1491.101	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	–91.366	0.002
Median	–	–	0.326	0.003	0.002	0.002	0.004	0.012	0.013	0.000	0.000	0.000	0.034	0.000	94.631
Max	–	–	2407.128	1525.001	3590.67	5229.895	699.319	1372.41	3773.920	3255.19	15587.53	894.38	7245.073	408.992	38,762,898,699
<i>Panel G: Observations classified by exchange listing</i>															
Data	Total			NYSE			AMEX			NASDAQ					
Monthly TAQ, 1993–2005	62,100			15,536			4,431			42,133					
Annual TAQ, 1993–2005	5,200			1,295			370			3,535					
Monthly 605, 10/2001–12/2005	19,039			5,167			1,633			12,239					

^a All price impact benchmarks and proxies are multiplied by 1,000,000, except for Liquidity which is divided by 1,000,000 and 5-Minute Price Impact which is not scaled.

$\sqrt{10,000} \times 16 \times 10^{-6} = 0.0016$, i.e., 16 basis points. The mean of the 5-Minute Price Impact (TAQ) benchmark corresponds to 3% with a median of 2%. Looking at the means of the price impact proxies, we see that none of the proxies are of the same order of magnitude as Lambda (TAQ) or 5-Minute Price Impact (TAQ). The same holds true in Panel E for annual price impact proxies.

Panel F describes monthly price impact benchmarks and proxies calculated from 10/2001–12/2005 Rule 605 data. Price Impact (605) has a mean of 1.016 and a median of 0.326, after multiplying by 1,000,000.

Panel G breaks the firms down by exchange. Roughly 68% are listed on NASDAQ, 25% on the NYSE, and the rest on AMEX. This breakdown is nearly the same as the eligible universe of TAQ and Rule 605 stock symbols.

7. Results

7.1. Monthly/annual spread results

Table 2 provides monthly spread evidence. It compares spread proxies calculated from daily prices and volumes each month (e.g., using a maximum of 23 daily prices and volumes per month) with monthly effective and realized spread benchmarks calculated from the TAQ data (e.g., a volume-weighted average of the effective/realized spread of every trade and corresponding BBO quote over the month). In the tables we highlight the winner of each race by drawing a box around the best-performing measure (or measures if there is a tie).

Panel A reports the average cross-sectional correlation of each low-frequency spread proxy with the effective and realized spreads calculated from TAQ. This is computed in the spirit of Fama and MacBeth (1973) by: (1) calculating, for each month, the cross-sectional correlation across all 400 firms, and then (2) calculating the average correlation value over all 156 months. We find that six measures, Effective Tick, Effective Tick2, Holden, Gibbs, LOT Mixed, and LOT Y-split, have average cross-sectional correlations greater than 0.6. The Holden measure has the highest average cross-sectional correlation at 0.682. The cross-sectional correlation with the realized spread is lower and fluctuates around 0.4 across the same six measures.

We test whether the average cross-sectional correlations are different from each other in Tables 2–8 by running a *t*-test based on the time-series similar to Fama–MacBeth.¹⁷ Specifically, we calculate the cross-sectional correlation each period (month or year) and then compute the pairwise difference in correlations between two candidate measures. We assume that time series of differences is *i.i.d.* over time, and test whether the average correlation difference is different from zero. Standard errors are adjusted for autocorrelation with a Newey–West correction using four lags for monthly data and three lags for annual data.

Table 2, Panel A reports that the correlations of Gibbs and Holden with effective spread are insignificantly different from each other and the remaining proxies are

statistically significantly lower than Holden. Put differently, considering the measure with the highest correlation, Holden, we find that Gibbs is *inside* of its 95% confidence region and the remaining spread proxies are *outside*. The same result holds for the realized spread.

Next, we form equally weighted portfolios across all 400 stocks in a given month. Specifically, we compute a portfolio spread proxy in month *i* by taking the average of that spread proxy over all 400 stocks in month *i*. Panel B reports the time-series correlation over 156 months of each low-frequency portfolio spread proxy with the effective and realized spreads of an equally weighted portfolio calculated from TAQ. Asset pricing researchers may be especially interested in the time-series correlations since so much of asset pricing research involves forming portfolios and exploring co-movement over time. It is worth noting that Panel B results may differ from those in Panel A, not only because they are computed over the time-series vs. across the cross-section, but also because some measurement error that affects individual stocks may be diversified away in portfolios. Consistent with a diversification effect, we find relatively high time-series correlations. Six measures, Roll, Effective Tick, Effective Tick2, Holden, Gibbs, and LOT Y-split, have time-series correlations greater than 0.9.

We test whether time-series correlations are statistically different from each other in Tables 2–9 using Fisher's *Z*-test. The Holden measure has the highest time-series correlation at 0.951 and Effective Tick, Effective Tick2, and LOT Y are in its 95% confidence interval (see Table 2, Panel B). All of the time-series correlations significantly different from zero are highlighted in boldface.¹⁸

Our spread proxies also do a good job in capturing time-series variation in realized spread. The correlation is as high as 0.972 for LOT Y with Effective Tick, Effective Tick2, and Holden being in its 95% confidence interval. Roll and Gibbs, which can be thought of as proxies for the realized spread since the versions we estimate do not include an asymmetric information component, do not do as well. Pastor and Stambaugh's Gamma and Amivest significantly underperform all other proxies in both Panels A and B.

To look at the consistency of the measures' performance, we break the time-series correlations down by subperiods in Panel C. Specifically, we use the same portfolio liquidity measures as above, but compute time-series correlations for three subperiods that closely correspond to minimum tick-size regimes. The subperiods are 1993–1996, 1997–2000, and 2001–2005, which relate to the minimum tick-size regimes of \$1/8, \$1/16, and \$0.01, respectively. Consistent with Panel B, the same six measures, Roll, Effective Tick, Effective Tick2, Holden, Gibbs, and LOT Y-split, do consistently well in each subperiod in terms of correlation with effective spread. All six measures have time-series correlations greater

¹⁷ We are grateful to an anonymous referee for this suggestion.

¹⁸ We test all correlations in Tables 2–9 to see if they are statistically different from zero at the 5% level of confidence 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.

Table 2

Monthly spread proxies compared to TAQ benchmarks

The benchmarks Effective spread (TAQ) and Realized spread (TAQ) are calculated from every trade and corresponding BBO quote in the NYSE TAQ database for a sample firm-month. All spread proxies are calculated from CRSP daily stock price and volume data for a sample firm-month. The spread proxies are: Roll from Roll (1984), Effective Tick and Effective Tick2 developed here and in Holden (2009), Holden from Holden (2009), Gibbs from Hasbrouck (2004), LOT Mixed, Zeros, and Zeros2 from Lesmond, Odgen, and Trzcinka (1999), LOT Y-split developed here, Amihud from Amihud (2002), Pastor and Stambaugh from Pastor and Stambaugh (2003), and the Amivest Liquidity ratio. The sample spans 1993–2005 inclusive and consists of 400 randomly selected stocks with annual replacement of stocks that do not survive, resulting in 62,100 firm-months. Bold numbers are statistically significant at the 5% level. * means that the correlation is statistically significantly different at the 5% level from all other correlations in the same row.

	Roll	Effective Tick	Effective Tick2	Holden	Gibbs	LOT Mixed	LOT Y-split	Zeros	Zeros2	Amihud	Pastor and Stambaugh	Amivest Liquidity
<i>Panel A: Average cross-sectional correlation based on individual firms (400 firms per cross-sectional correlation; average of 156 months)</i>												
Effective spread (TAQ)	0.560	0.626	0.614	0.682	0.667	0.651	0.644	0.427	0.308	0.571	-0.118	-0.136
Insignificantly different from	Amihud	Gibbs LOT Y	*	Gibbs	Eff Tick Holden LOT Mix LOT Y	Gibbs LOT Y	Eff Tick Gibbs LOT Mix	*	*	Roll	Amivest	Pas/Stam
Realized spread (TAQ)	0.371	0.399	0.396	0.422	0.398	0.383	0.356	0.220	0.192	0.305	-0.031	-0.094
Insignificantly different from	Eff Tick Eff Tick2 LOT Mix LOT Y	Roll Eff Tick2 Gibbs LOT Mix	Roll Eff Tick Gibbs LOT Mix	Gibbs	Eff Tick Eff Tick2 Holden Lot Mix	Roll Eff Tick Eff Tick2 Gibbs	Roll	*	*	*	*	*
<i>Panel B: Time-series correlations based on an equally weighted portfolio (156 months)</i>												
Effective spread (TAQ)	0.925	0.941	0.939	0.951	0.905	0.722	0.931	0.874	0.860	0.608	-0.366	-0.145
Insignificantly different from	Eff Tick Eff Tick2 Gibbs LOT Y	Roll Eff Tick2 Holden LOT Y	Roll Eff Tick Holden LOT Y	Eff Tick Eff Tick2 LOT Y	Roll LOT Y Zeros Zeros2	Amihud	Roll Eff Tick Eff Tick2 Holden	Zeros2	Zeros	LOT Mix	*	*
Realized spread (TAQ)	0.825	0.963	0.963	0.970	0.805	0.755	0.972	0.955	0.945	0.511	-0.351	-0.109
Insignificantly different from	Gibbs LOT Mix	Eff Tick2 Holden LOT Y Zeros Zeros2	Eff Tick Holden Holden Zeros2	Eff Tick Eff Tick2 Zeros	Roll LOT Mix	Roll Gibbs	Eff Tick Eff Tick2 Holden	Eff Tick Eff Tick2 Zeros2	Eff Tick Eff Tick2 Zeros	*	*	*
<i>Panel C: Pure time-series correlations based on equally weighted portfolio by subperiods (48, 48, and 60 months, respectively)</i>												
1993–1996 Effective spread (TAQ)	0.901	0.918	0.930	0.932	0.936	0.407	0.909	0.769	0.706	0.476	-0.364	-0.160
1997–2000 Effective spread (TAQ)	0.703	0.886	0.885	0.882	0.663	0.306	0.812	0.304	0.227	0.539	-0.226	-0.045
2001–2005 Effective spread (TAQ)	0.933	0.887	0.884	0.904	0.913	0.896	0.863	0.730	0.665	0.833	-0.215	-0.183
1993–1996 Realized spread (TAQ)	0.818	0.784	0.820	0.826	0.800	0.516	0.785	0.738	0.676	0.532	-0.263	-0.143
1997–2000 Realized spread (TAQ)	0.229	0.733	0.740	0.767	0.175	0.367	0.777	0.688	0.616	0.681	-0.404	-0.051
2001–2005 Realized spread (TAQ)	0.889	0.941	0.933	0.956	0.906	0.960	0.942	0.870	0.817	0.729	-0.158	-0.155
<i>Panel D: Pure time-series correlations based on equally weighted decile portfolios stratified by firm size (156 months)</i>												
Portfolio 1 Eff. spread (TAQ) (Smallest size)	0.924	0.930	0.916	0.930	0.958	0.842	0.921	0.823	0.747	0.514	-0.292	-0.169
Portfolio 2 Eff. spread (TAQ)	0.920	0.890	0.887	0.909	0.944	0.752	0.891	0.774	0.703	0.822	-0.399	-0.022
Portfolio 3 Eff. spread (TAQ)	0.904	0.912	0.912	0.923	0.930	0.732	0.904	0.837	0.824	0.845	-0.273	-0.116
Portfolio 4 Eff. spread (TAQ)	0.863	0.861	0.857	0.870	0.852	0.505	0.844	0.789	0.750	0.732	-0.251	-0.782
Portfolio 5 Eff. spread (TAQ)	0.806	0.862	0.858	0.889	0.789	0.662	0.848	0.809	0.791	0.775	-0.210	0.068
Portfolio 6 Eff. spread (TAQ)	0.767	0.903	0.899	0.928	0.686	0.590	0.895	0.832	0.819	0.823	-0.182	-0.208
Portfolio 7 Eff. spread (TAQ)	0.367	0.897	0.897	0.920	0.400	0.511	0.867	0.800	0.801	0.806	0.130	-0.148
Portfolio 8 Eff. spread (TAQ)	0.046	0.705	0.706	0.712	0.204	0.435	0.683	0.628	0.625	0.639	-0.276	-0.159
Portfolio 9 Eff. spread (TAQ)	0.126	0.886	0.884	0.908	0.202	0.550	0.866	0.771	0.765	0.492	0.051	-0.138
Portfolio 10 Eff. spread (TAQ) (Largest size)	0.362	0.591	0.590	0.627	0.381	0.415	0.545	0.436	0.433	0.188	-0.113	-0.130
Average	0.608	0.844	0.841	0.862	0.635	0.599	0.826	0.750	0.726	0.664	-0.182	-0.181

than 0.900 in 1993–1996, in the interval [0.663, 0.886] in 1997–2000, and greater than 0.86 in 2001–2005. It is not clear why all six measures did worse during the \$1/16 years. Gibbs has the highest correlation in 1993–1996, Effective Tick is the highest in 1997–2000, and Roll is the highest in 2001–2005. While the measures based on the price clustering do slightly worse in the third subperiod compared to the first subperiod, the performance of the Amihud measure moves in the opposite direction. Thus, Amihud seems to represent the effective spread better in the last subperiod, during the decimalization era, where it achieves a correlation of 0.833. This might be associated with a decrease in price clustering during the decimals regime as a result of the majority of trading being done automatically via computerized systems.

A slightly different picture emerges for correlations with realized spread. Measures based on price clustering, Effective Tick, Effective Tick2, and Holden, achieve the highest correlation during decimalization, ranging between 0.933 and 0.956. LOT Mixed, which does not show up as a winner so far, has the highest correlation with realized spread, 0.96. Similar to effective spread, the correlations are lower for all measures during the second subperiod. The drop in correlations is very severe for Roll and Gibbs.

We form decile portfolios stratified by firm size (market capitalization) and by effective spread to check the robustness of the measures. For firm size, we sort the 400 stocks *each month* by market capitalization, assigning the first 40 stocks with the smallest size to Portfolio 1, and so on. Each decile portfolio is equally weighted. Panel D reports the time-series correlation of size decile portfolios for both effective and realized spreads. Four measures do quite well across the decile portfolios. Effective Tick, Effective Tick2, Holden, and LOT Y-split have high and statistically significant time-series correlations overall with mildly lower correlations for larger size portfolios. By contrast, Roll and Gibbs do very poorly with the larger firms in Portfolios 7–10. Specifically, they obtain time-series correlations of 0.4 or lower for effective spread and negative but insignificant correlations for realized spread, which appears to be a serious robustness problem. They do much better with the small and medium-size firms in Portfolios 1–6. All measures do much worse than their own average with the largest firms in Portfolio 10.

Next, we form decile portfolios stratified by effective spread in the same manner as above, assigning the 40 stocks with the lowest effective spread to Portfolio 1, and so on. Each decile portfolio is equally weighted. Panel E reports the time-series correlations of these decile portfolios for both effective and realized spreads. Consistent with Panel D, the same four measures, Effective Tick, Effective Tick2, Holden, and LOT Y-split, do quite well with high and statistically significant time-series correlations overall and mildly lower correlations in lower effective spread portfolios. By contrast, Roll and Gibbs do very poorly in Portfolios 1–4. Specifically, they obtain time-series correlations lower than 0.322 for effective spread and lower than 0.161 for realized spread, which continues to represent a serious robustness problem. Undoubtedly, there is a great deal of overlap between

these low effective spread portfolios and the large size portfolios. Roll and Gibbs do far better in Portfolios 6–10. Nearly all measures do worse than their own average with the lowest effective spread firms in Portfolio 1. It therefore appears that large firms and firms with small effective spreads are the most challenging firms for all low-frequency spread proxies.

Finally, we calculate the prediction error between the low-frequency spread proxies and effective spread as calculated from TAQ. Panel F reports two performance metrics: (1) mean bias (e.g., the difference between the low-frequency mean and the high-frequency mean) and (2) root mean squared error. The mean bias corresponds to all 62,100 firm-months. The root mean squared error is calculated every month and then averaged over 156 months. We exclude Zeros, Zeros2, Amihud, Pastor and Stambaugh, and Amivest from these tests because they are measured in different units than the effective spread. We find that Roll, Effective Tick, Effective Tick2, Holden, Gibbs, and LOT Y-split have relatively small biases compared to the effective spread benchmark, ranging from -0.002 to -0.013 . However, all of these biases are significantly different from zero based on a *t*-test. Roll has the smallest bias. This is consistent with Schultz (2000) who shows that Roll well captures the magnitude of the effective spread for intraday data. Roll, Effective Tick, Effective Tick2, Gibbs, and Holden have relatively low root mean squared errors ranging from 0.029 to 0.032.¹⁹ Holden and Gibbs have the lowest root mean squared errors, which are not significantly different from each other based on a paired *t*-test.

For the realized spread, Panel G, Effective Tick2 has the smallest mean bias of 0.001, and Gibbs has the lowest root mean squared error. Interestingly, Roll, which can be thought of as a proxy for realized spread, is outperformed by the new measures on this dimension.

Summarizing the monthly spread evidence in Table 2, we generally conclude that low-frequency measures designed to estimate spread do, in fact, provide accurate measures of both effective and realized spreads computed from TAQ data. These measures are highly correlated at the firm and the portfolio levels, and provide low bias and small mean squared error. Not surprisingly, we find that measures intended to capture other features of transaction costs, Amihud, Pastor and Stambaugh, and Amivest, do a poor job estimating effective and realized spreads, and zero returns is inferior to all other measures designed to capture effective spread. Note that we think of “winning” as providing high and consistent correlations together with low bias and low root mean squared error. Clearly, Effective Tick, Effective Tick2, Holden, and LOT Y-split fit this definition. Roll and Gibbs do well in many

¹⁹ We test all root mean squared errors generated by the liquidity proxies in Tables 2, 3, 6, and 8 to see if they are statistically significant using the U-statistic developed by Theil (1966). Here, if $U^2 = 1$ then the low-frequency liquidity proxy has no predictive power beyond just assuming no deviation from the sample mean. If $U^2 = 0$, then the low-frequency liquidity proxy predicts perfectly. U^2 has an F distribution where the number of degrees of freedom for both the numerator and denominator is the sample size.

Table 3

Annual spread proxies compared to TAQ benchmarks

The benchmarks Effective spread (TAQ) and Realized spread (TAQ) are calculated from every trade and corresponding BBO quote in the NYSE TAQ database for a sample firm-year. All spread proxies are calculated from CRSP daily stock price and volume data for a sample firm-year. The Spread Proxies are: Roll from Roll (1984), Effective Tick and Effective Tick2 developed here and in Holden (2009), Holden from Holden (2009), Gibbs from Hasbrouck (2004), LOT Mixed, Zeros, and Zeros2 from Lesmond, Odgen, and Trzcinka (1999), LOT Y-split developed here, Amihud from Amihud (2002), Pastor and Stambaugh from Pastor and Stambaugh (2003), and the Amivest Liquidity ratio. The sample spans 1993–2005 inclusive and consists of 400 randomly selected stocks with annual replacement of stocks that do not survive, resulting in 5,200 firm-years. Bold numbers are statistically significant at the 5% level. * means that the correlation is statistically significantly different at the 5% level from all other correlations in the same row.

	Roll	Effective Tick	Effective Tick2	Holden	Gibbs	LOT Mixed	LOT Y-split	Zeros	Zeros2	Amihud	Pastor and Stambaugh	Amivest Liquidity
<i>Panel A: Average cross-sectional correlation based on individual firms (400 firms per cross-sectional correlation; average of 13 years)</i>												
Effective spread (TAQ)	0.623	0.707	0.650	0.745	0.779	0.545	0.535	0.590	0.481	0.594	0.152	−0.120
Insignificantly different from	Eff Tick2	*										
	LOT Mix		Roll	Gibbs	Holden	Roll	LOT Mix	Roll	Roll	Roll	*	*
	Zeros					LOT Y	Zeros	LOT Mix	LOT Mix	LOT Mix		
	Zeros2					Zeros	Zeros2	LOT Y	LOT Y	LOT Y		
	Amihud					Zeros2	Amihud	Amihud	Amihud	Zeros		
						Amihud				Zeros2		
Realized spread (TAQ)	0.587	0.605	0.594	0.626	0.628	0.511	0.411	0.428	0.438	0.403	0.172	−0.113
Insignificantly different from	Eff Tick	Roll	Roll	Roll	Roll	Roll	Zeros	LOT Mix	LOT Mix	LOT Y	*	*
	Eff Tick2	Eff Tick2	Eff Tick	Gibbs	Eff Tick	Zeros	Zeros2	LOT Y	LOT Y	Zeros		
	Holden	Gibbs			Holden	Zeros2	Amihud	Zeros2	Zeros	Zeros2		
	Zeros2											
	Gibbs							Amihud	Amihud			
	LOT Mix											
<i>Panel B: Pure time-series correlations based on an equally weighted portfolio (13 years)</i>												
Effective spread (TAQ)	0.982	0.945	0.954	0.966	0.991	0.821	0.934	0.919	0.909	0.797	0.193	−0.490
Insignificantly different from	All except	All except	All except	All except	Roll	All except	All except	All except	All except	All except	Liquidity	Past/Stam
	LOT Mix	Gibbs	Past/Stam	Amihud	Eff Tick2	Roll	Gibbs	Gibbs	Gibbs	Roll		
	Amihud	Past/Stam	Liquidity	Past/Stam	Holden	Gibbs	Past/Stam	Past/Stam	Past/Stam	Holden		
	Past/Stam	Liquidity	Liquidity	Liquidity		Past/Stam	Liquidity	Liquidity	Liquidity	Gibbs	Liquidity	Past/Stam
	Liquidity					Liquidity				Past/Stam	Liquidity	
										Liquidity		
Realized spread (TAQ)	0.925	0.975	0.972	0.989	0.980	0.881	0.982	0.968	0.958	0.720	0.058	−0.371
Insignificantly different from	All except	All except	All except	All except	All except	All except	All except	All except	All except	Roll	Amihud	Past/Stam
	Holden	Amihud	Amihud	Roll	LOT Mix	Holden	LOT Mix	Amihud	Amihud	LOT Mix	Liquidity	
	Past/Stam	Past/Stam	Past/Stam	LOT Mix	Amihud	Gibbs	Amihud	Past/Stam	Past/Stam	Past/Stam		
	Liquidity	Liquidity	Liquidity	Amihud	Past/Stam	LOT Y	Amihud	Liquidity	Liquidity	Past/Stam		
				Past/Stam	Liquidity	Amihud	Past/Stam					
				Liquidity		Past/Stam	Liquidity					
						Liquidity						

	Roll	Effective Tick	Effective Tick2	Holden	Gibbs	LOT Mixed	LOT Y-split	Zeros	Zeros2	Amihud	Pastor and Stambaugh	Amivest Liquidity
<i>Panel C: Prediction error of effective spread (TAQ)</i>												
Mean bias	-0.002	-0.013	-0.014	-0.013	-0.013	0.047	0.000	na	na	na	na	na
Insignificantly different from	LOT Y	Eff Tick2 Holden Gibbs	Eff Tick Holden Gibbs	Eff Tick Eff Tick2 Gibbs	Eff Tick Eff Tick2 Gibbs	Eff Tick Eff Tick2 Gibbs	Roll					
Root mean square error	0.024	0.018	0.020	0.017	0.016	0.092	0.045	na	na	na	na	na
Insignificantly different from	*	*	*	*	*	*	*					
<i>Panel D: Prediction error of realized spread (TAQ)</i>												
Mean bias	0.0105	-0.0008	-0.0013	-0.0004	-0.0004	0.0589	0.0121	na	na	na	na	na
Insignificantly different from	LOT Y	Eff Tick2 Holden Gibbs	Eff Tick Holden Gibbs	Eff Tick Eff Tick2 Gibbs	Eff Tick Eff Tick2 Holden	Eff Tick Eff Tick2 Holden	Roll					
Root mean square error	0.026	0.015	0.015	0.015	0.015	0.096	0.046	na	na	na	na	na
Insignificantly different from	*	*	*	*	*	*	*					

cases, but they are not consistent: they have periods of much lower correlation (1997–2000) and subsamples that are much lower (large cap stocks and low effective spread stocks) than the other measures.

The annual results in Table 3 are mostly consistent with the monthly evidence. We therefore summarize them briefly.²⁰ We again generally conclude that low-frequency measures designed to estimate spread provide accurate measures of effective/realized spread computed from TAQ data. Overall, six measures dominate, in the sense of having a high and consistent correlation together with low bias and mean squared error: Roll, Effective Tick, Effective Tick2, Holden, Gibbs, and LOT Y-split. The discussion of Table 9 below highlights a failure of Roll and Gibbs over annual data in an out-of-sample test. Therefore, effectively, Effective Tick/Tick2, Holden, and LOT Y-split are the best measures on this dimension.

7.2. Monthly/annual price impact results

Table 4 provides monthly price impact evidence, comparing price impact proxies calculated from daily prices and volumes each month with two monthly price impact benchmarks (Lambda and 5-Minute Price Impact) calculated from TAQ data.

Panel A reports the average cross-sectional correlation of each low-frequency price impact proxy with each price impact benchmark. If we look at the measure with the largest correlation and then consider the measures within its confidence interval, we get a picture of which measures are superior. Amihud has the highest correlation with the Lambda of 0.317 and is insignificantly different from Roll Impact, Effective Tick Impact, Effective Tick2 Impact, Holden Impact, Gibbs Impact, LOT Mixed Impact, LOT Y-split Impact, and Zeros Impact. Therefore, all nine measures are in the top leadership group for this horse-race. For the 5-Minute Price Impact, Amihud has the highest correlation at 0.516 and is statistically significantly higher than any other measure.

Next, we form equally weighted portfolios across all 400 stocks in a given month. Panel B reports the time-series correlation over 156 months of each low-frequency price impact proxy portfolio with each price impact benchmark portfolio calculated from TAQ. As before, most portfolio correlations are higher than the individual stock correlations. Roll Impact has the highest correlation with the Lambda of 0.562 and is insignificantly different from all measures except Gamma and Amivest at the 5% level. Roll Impact, however, is significantly different from Effective Tick/Tick2 Impact and Amihud at the 10% level. Overall, all measures except Pastor and Stambaugh's Gamma and Amivest do a reasonable job on this dimension. Roll Impact has the highest correlation with 5-Minute Price Impact of 0.517 and is insignificantly different from Gibbs Impact, Holden Impact, Lot Mixed Impact, LOT Y Impact, Zeros Impact, Zeros2 Impact, and

²⁰ A detailed discussion of the results is available from the authors upon request.

Table 4

Monthly price impact proxies compared to TAQ benchmarks

The benchmarks Lambda (TAQ) and 5-Minute Price Impact (TAQ) are calculated from every trade and corresponding BBO quote in the NYSE TAQ database for a sample firm-month. All price impact proxies are calculated from CRSP daily stock price and volume data for a sample firm-month. The price impact proxies are: Roll Impact, Effective Tick Impact, Effective Tick2 Impact, Holden Impact, Gibbs Impact, LOT Mixed Impact, and LOT Y-split Impact developed here, Amihud from Amihud (2002), Pastor and Stambaugh from Pastor and Stambaugh (2003), and the Amivest Liquidity ratio. The sample spans 1993–2005 inclusive and consists of 400 randomly selected stocks with annual replacement of stocks that do not survive, resulting in 62,100 firm-months. Bold numbers are statistically significant at the 5% level. * means that the correlation is statistically significantly different at the 5% level from all other correlations in the same row.

	Roll Impact	Effective Tick Impact	Effective Tick2 Impact	Holden Impact	Gibbs Impact	LOT Mixed Impact	LOT Y-split Impact	Zeros Impact	Zeros2 Impact	Amihud	Pastor and Stambaugh	Amivest Liquidity
<i>Panel A: Average cross-sectional correlation based on individual firms (400 firms per cross-sectional correlation; average of 156 months)</i>												
Lambda (TAQ)	0.288	0.296	0.305	0.305	0.296	0.309	0.294	0.278	0.259	0.317	−0.064	−0.030
Insignificantly different from.	All except Pas/Stam Amivest	All except Pas/Stam Amivest	All except Pas/Stam Amivest	All except Pas/Stam Amivest	All except Pas/Stam Amivest	All except Pas/Stam Amivest	All except Pas/Stam Amivest	All except Pas/Stam Amivest	All except Amihud Pas/Stam Amivest	All except Zeros2 Imp Pas/Stam Amivest	Amivest	Pas/Stam
5-Minute Price Impact (TAQ)	0.469	0.439	0.464	0.463	0.452	0.467	0.436	0.384	0.413	0.516	0.035	−0.139
Insignificantly different from.	Eff Tick2 Imp Holden Imp LOT Mix	Gibbs Imp LOT Y Imp	Roll Imp Holden Imp Gibbs Imp LOT Mix Imp	Roll Imp Eff Tick2 Imp Gibbs Imp LOT Mix Imp	Eff Tick Imp Eff Tick2 Imp Holden Imp LOT Y Imp	Roll Imp Eff Tick2 Imp Holden Imp	Eff Tick Imp Gibbs Imp	*	*	*	*	*
<i>Panel B: Pure time-series correlations based on an equally-weighted portfolio (156 months)</i>												
Lambda (TAQ)	0.562	0.404	0.406	0.505	0.519	0.482	0.433	0.485	0.434	0.400	−0.192	−0.062
Insignificantly different from.	All except Pas/Stam Amivest	All except Pas/Stam Amivest	All except Pas/Stam Amivest	All except Pas/Stam Amivest	All except Pas/Stam Amivest	All except Pas/Stam Amivest	All except Pas/Stam Amivest	All except Pas/Stam Amivest	All except Pas/Stam Amivest	All except Pas/Stam Amivest	Amivest	Pas/Stam
5-Minute Price Impact (TAQ)	0.517	0.293	0.302	0.397	0.434	0.394	0.337	0.491	0.462	0.511	−0.230	−0.170
Insignificantly different from.	All except Eff Tick Imp Eff Tick2 Imp Pas/Stam Amivest	All except Roll Imp Zeros Imp Amihud Pas/Stam Amivest	All except Roll Imp Zeros Imp Amihud Pas/Stam Amivest	All except Pas/Stam Amivest	All except Pas/Stam Amivest	All except Pas/Stam Amivest	All except Pas/Stam Amivest	All except Eff Tick Imp Eff Tick2 Imp Pas/Stam Amivest	All except Pas/Stam Amivest	All except Eff Tick Imp Eff Tick2 Imp Pas/Stam Amivest	Amivest	Pas/Stam

Table 5

Annual price impact proxies compared to TAQ benchmarks

The benchmarks Lambda (TAQ) and 5-Minute Price Impact (TAQ) are calculated from every trade and corresponding BBO quote in the NYSE TAQ database for a sample firm-year. All price impact proxies are calculated from CRSP daily stock price and volume data for a sample firm-year. The price impact proxies are: Roll Impact, Effective Tick Impact, Effective Tick2 Impact, Holden Impact, Gibbs Impact, LOT Mixed Impact, and LOT Y-split Impact developed here, Amihud from Amihud (2002), Pastor and Stambaugh from Pastor and Stambaugh (2003), and the Amivest Liquidity ratio. The sample spans 1993–2005 inclusive and consists of 400 randomly selected stocks with annual replacement of stocks that do not survive, resulting in 5,200 firm-years. Bold numbers are statistically significant at the 5% level. * means that the correlation is statistically significantly different at the 5% level from all other correlations in the same row. * means that the correlation is statistically significantly different at the 5% level from all other correlations in the same row.

	Roll Impact	Effective Tick Impact	Effective Tick2 Impact	Holden Impact	Gibbs Impact	LOT Mixed Impact	LOT Y-split Impact	Zeros Impact	Zeros2 Impact	Amihud	Pastor and Stambaugh	Amivest Liquidity
<i>Panel A: Average cross-sectional correlation based on individual firms (400 firms per cross-sectional correlation; average of 13 years)</i>												
Lambda (TAQ)	0.644	0.655	0.687	0.666	0.634	0.679	0.634	0.538	0.647	0.653	0.186	−0.058
Insignificantly different from.	All except LOT Mix Imp Zeros Imp Past/Stam Amivest	All except LOT Y Imp Zeros Imp Past/Stam Amivest	All except LOT Y Imp Zeros Imp Zeros2 Imp Past/Stam Amivest	All except LOT Mix Imp Zeros Imp Past/Stam Amivest	All except Zeros Imp Past/Stam Amivest	All except LOT Mix Imp Zeros Imp Past/Stam Amivest	Roll Imp Gibbs Imp Zeros2 Imp Amihud	*	All except Eff Tick2 Imp Zeros Imp Past/Stam Amivest	All except Zeros Imp Past/Stam Amivest	*	*
5-Minute Price Impact (TAQ)	0.547	0.537	0.582	0.548	0.516	0.571	0.513	0.450	0.592	0.625	0.224	−0.135
Insignificantly different from.	Eff Tick Imp Holden Imp LOT Mix Imp LOT Y Imp	Roll Imp Holden Imp Gibbs Imp LOT Mix Imp LOT Y Imp	LOT Mix Imp Zeros2 Imp Amihud	Roll Imp Eff Tick Imp LOT Mix Imp Zeros2 Imp	Eff Tick Imp LOT Y Imp	Roll Imp Eff Tick Imp Eff Tick2 Imp Holden Imp Zeros2 Imp Amihud	Roll Imp Eff Tick Imp Gibbs Imp	*	Eff Tick2 Imp Holden Imp LOT Mix Imp Amihud	Eff Tick2 Imp LOT Mix Imp Zeros2 Imp	*	*
<i>Panel B: Pure time-series correlations based on an equally-weighted portfolio (13 years)</i>												
Lambda (TAQ)	0.963	0.876	0.888	0.928	0.949	0.875	0.891	0.881	0.933	0.914	0.264	−0.345
Insignificantly different from.	All except Pas/Stam Amivest	All except Pas/Stam Amivest	All except Pas/Stam Amivest	All except Pas/Stam Amivest	All except Pas/Stam Amivest	All except Pas/Stam Amivest	All except Pas/Stam Amivest	All except Pas/Stam Amivest	All except Pas/Stam Amivest	All except Pas/Stam Amivest	Amivest	Pas/Stam
5-Minute Price Impact (TAQ)	0.764	0.703	0.708	0.740	0.750	0.692	0.709	0.716	0.787	0.726	0.337	−0.643
Insignificantly different from.	All except Amivest	All except Amivest	All except Amivest	All except Amivest	All except Amivest	All except Amivest	All except Amivest	All except Amivest	All except Amivest	All except Amivest	All except Amivest	*

Amihud. These eight measures are in the top leadership group for this horserace.

The prediction error and mean squared error comparisons do not provide any meaningful information if the two variables are on completely different scales. Therefore, we omit the mean bias and root mean squared error calculation for price impact measures.

The annual results of Table 5 are generally consistent with the monthly evidence. For brevity, we skip the discussion of Table 5 and summarize monthly and annual results together.

Summarizing the Lambda (TAQ) horseraces of Tables 4 and 5, Roll Impact seems to have a slight edge because it has the highest correlation in two of the four horseraces. However, in most horseraces, it is statistically insignificantly different from the rest of the new class of price impact proxies developed in this paper and the Amihud measure. Gamma and Amivest are consistently dominated.

Summarizing the 5-Minute Price Impact horseraces of Tables 4 and 5, Amihud is the best single proxy of the five-minute price impact, being in the leadership group in all four correlation tests and standing by itself in one of them. In three of the four horseraces, the new class of price impact proxies is insignificantly different from Amihud. Roll Impact yields the highest correlations of the new class, so it is a close second behind Amihud.

7.3. Rule 605 results

As discussed above, the new Rule 605 data allow us to test the robustness of our previous results by using a completely different high-frequency database. Accordingly, Table 6 presents evidence based on Rule 605 data from October 2001 to December 2005. Panels A, B, and C compare spread proxies with effective spread calculated from the Rule 605 data. Panels D, E, and F compare price impact proxies with static price impact calculated from Rule 605 data.

The Rule 605 results presented in Panel A are relatively similar to the corresponding TAQ results. The same six measures have relatively high average cross-sectional correlations in nearly the same range as the TAQ data and are statistically significant. Amihud has the highest correlation at 0.533 and Effective Tick and Holden are in its 95% confidence interval.

The time-series correlations are presented in Panel B for the Rule 605 data. Like the TAQ results, the time-series correlations of the portfolios are much higher than the cross-sectional correlations of individual stocks. The top measure for the time-series, Effective Tick, has the highest correlation and all measures except Gamma and Amivest are in their 95% confidence interval. Unlike the TAQ results, the highest time-series correlation with Rule 605 effective spreads is 0.528 vs. a time-series correlation of 0.951 with the TAQ effective spread. It is not clear why the correlations are so different, but two benchmarks are fundamentally different. Effective Spread (TAQ) is the average cost of all trades, whereas Effective Spread (605) is the average cost of all marketable orders executed.

A market buy and market sell that cross at the midpoint (with a zero effective spread) counts as one TAQ trade, but counts as two Rule 605 marketable order executions. In addition, there are differences in: (1) trade type uncertainty in TAQ vs. certainty in Rule 605, (2) effective spread computation (absolute value in TAQ vs. signed value in Rule 605), (3) aggregation (dollar-volume-weighted with TAQ vs. share-volume-weighted with Rule 605), and (4) midpoint timing (midpoint at time of trade in TAQ vs. midpoint at time of order submission in Rule 605). However, the leading low-frequency proxies remain in the leadership group no matter which benchmark (TAQ or Rule 605 effective spread) we select.

Next, Rule 605 results presented in Panel C on the prediction error are roughly similar to those in Table 2. Effective Tick2 has the smallest bias and is statistically significantly smaller than any other measure. Gibbs has the smallest root mean squared error and is insignificantly different from Holden. Summarizing Panels A to C, the monthly Rule 605 spreads results show that low-frequency measures computed from daily returns are able to capture effective spreads reported by the market centers. Overall, in terms of correlations and prediction errors, Holden, Effective Tick, and Effective Tick2 are the best proxies of Rule 605 effective spread.

In Panel D, we present evidence on price impact for the Rule 605 data. Recall that Lambda (TAQ) is calculated from a regression, whereas Static Price Impact (605) is calculated as the difference between the effective spreads associated with large and small orders, divided by the difference between large and small order shares. Thus, it is not especially surprising to see very different results for Static Price Impact (605) presented in Panel D and for Lambda (TAQ). Essentially, all of the average cross-sectional correlations between the price impact proxies and Static Price Impact (605) are insignificantly different from zero. All of the proxies fail to pick up Static Price Impact (605). In Panel E, we get similar results. Finally, Panel F reports the prediction errors of the price impact proxies with respect to Static Price Impact (605). We report mean prediction bias and root mean squared error only for the measures that are on the same scale as Static Price Impact (605). While Panels D and E show that the measures fail to capture most of the variation of Static Price Impact (605), they do reasonably well in estimating the level in Panel F. The mean bias is the smallest in absolute value for Effective Tick2 Impact, -0.031 , with Holden and Gibbs Impact falling in its 95% confidence interval. Root mean squared error is the smallest for Gibbs Impact with Effective Tick/Tick2 and Holden Impact being in its 95% confidence interval. Summarizing Panels D to F, while all of the price impact proxies fail to capture time-series or cross-sectional variations in Static Price Impact (605), the new class of price impact does a good job of predicting the level.

Overall, Table 6 shows that actual effective spread data reported by the market centers can be accurately estimated using measures computed from daily returns. The table also shows that the new price impact measures developed in this paper can be used to estimate the level of Static Price Impact (605).

Table 6

Monthly spread and price impact proxies compared to 605 benchmarks

The benchmarks Effective Spread (605) and Static Price Impact (605) are calculated from data required to be disclosed under SEC Rule 605 (formerly 11Ac1-5) for a sample firm-month. All spread proxies and price impact proxies are calculated from CRSP daily stock price and volume data for a sample firm-month. The spread proxies are: Roll from Roll (1984), Effective Tick and Effective Tick2 developed here and in Holden (2009), Holden from Holden (2009), Gibbs from Hasbrouck (2004), LOT Mixed, Zeros, and Zeros2 from Lesmond, Odgen, and Trzcinka (1999), LOT Y-split developed here, Amihud from Amihud (2002), Pastor and Stambaugh from Pastor and Stambaugh (2003), and the Amivest Liquidity ratio. The price impact proxies are: Roll Impact, Effective Tick Impact, Effective Tick2 Impact, Holden Impact, Gibbs Impact, LOT Mixed Impact, and LOT Y-split Impact developed here, Amihud from Amihud (2002), Pastor and Stambaugh from Pastor and Stambaugh (2003), and the Amivest Liquidity ratio. The sample spans 10/2001 to 12/2005 inclusive and consists of 400 randomly selected stocks with annual replacement of stocks that do not survive, resulting in 19,039 firm-months. Bold numbers are statistically significant at the 5% level. * means that the correlation is statistically significantly different at the 5% level from all other correlations in the same row.

	Roll	Effective Tick	Effective Tick2	Holden	Gibbs	LOT Mixed	LOT Y-split	Zeros	Zeros2	Amihud	Pastor and Stambaugh	Amivest Liquidity
<i>Panel A: Average cross-sectional correlation based on individual firms (400 firms per cross-sectional correlation; average of 51 months)</i>												
Effective spread (605)	0.387	0.483	0.457	0.513	0.445	0.464	0.449	0.371	0.340	0.533	0.013	−0.075
Insignificantly different from.	Zeros	Gibbs LOT Mix Amihud	Gibbs LOT Mix LOT Y	Amihud	Eff Tick Eff Tick2 LOT Mix LOT Y	Eff Tick Eff Tick2 Gibbs LOT Y	Eff Tick2 Gibbs LOT Mix	Roll	*	Eff Tick Holden	*	*
<i>Panel B: Time-series correlations based on an equally-weighted portfolio (51 months)</i>												
Effective spread (605)	0.408	0.528	0.522	0.430	0.435	0.419	0.449	0.429	0.383	0.412	0.166	−0.136
Insignificantly different from.	All except Amivest	All except Pas/Stam Amivest	All except Pas/Stam Amivest	All except Amivest	All except Amivest	All except Amivest	All except Amivest	All except Amivest	All except Amivest	All except Amivest	All except Eff Tick Eff Tick2	Pas/Stam
<i>Panel C: Prediction error of effective spread (605) based on individual firms (19,039 firm-months)</i>												
Mean bias	−0.012	0.022	−0.005	−0.006	−0.012	−0.009	0.007	na	na	na	na	na
Insignificantly different from.	*	*	*	*	*	*	*					
Root mean squared error	0.026	0.024	0.025	0.023	0.022	0.030	0.024	na	na	na	na	na
Insignificantly different from.	Eff Tick Eff Tick2	Roll LOT Y	Roll LOT Y	Gibbs	Holden	*	Eff Tick Eff Tick2					

Table 6. (continued)

	Roll Impact	Effective Tick Impact	Effective Tick2 Impact	Holden Impact	Gibbs Impact	LOT Mixed Impact	LOT Y-split Impact	Zeros Impact	Zeros2 Impact	Amihud	Pastor and Stambaugh	Amivest Liquidity
<i>Panel D: Average cross-sectional correlation of price impact based on individual firms (400 firms per cross-sectional correlation; average of 51 months)</i>												
Static Price Impact (605)	0.020	0.024	0.030	0.026	0.031	0.041	0.039	0.069	0.054	0.033	-0.001	-0.022
Insignificantly different from .	All except Zeros Imp	All except Zeros Imp	All except Zeros Imp Amivest	All except Zeros Imp	All	All except Amivest	All except Zeros Imp Amivest	Gibbs Imp LOT Mix Imp Zeros2 Imp Amihud	All except Amivest	All except Amivest	All except Zeros Imp	Roll Imp Eff Tick Imp Holden Imp Gibbs Imp Past/Stam
<i>Panel E: Pure time-series correlations based on an equally-weighted portfolio (51 months)</i>												
Static Price Impact (605)	0.083	0.057	0.057	0.076	0.083	0.087	0.083	0.060	0.033	0.086	0.016	-0.029
Insignificantly different from.	All	All	All	All	All	All	All	All	All	All	All	All
<i>Panel F: Prediction error of Static Price Impact (605) based on individual firms (19,039 firm-months)^a</i>												
Mean bias Insignificantly different from.	0.584 *	0.041 Gibbs Imp LOT Y Imp	-0.031 Holden Imp Gibbs Imp	-0.141 Eff Tick2 Imp Gibbs Imp LOT Y Imp	0.055 Eff Tick Imp Eff Tick2 Imp Holden Imp LOT Y Imp	1.643 *	0.197 Eff Tick Imp Holden Imp Gibbs Imp	na	na	na	na	na
Root mean squared error Insignificantly different from .	4.735 *	3.593 Gibbs Imp LOT Y Imp	3.326 Holden Imp Gibbs Imp LOT Y Imp	3.036 Eff Tick2 Imp Gibbs Imp	2.595 Eff Tick Imp Eff Tick2 Imp Holden Imp	7.664 *	3.775 Eff Tick Imp Eff Tick2 Imp	na	na	na	na	na

^aAll price impact measures are multiplied by 1,000,000, except for Liquidity which is divided by 1,000,000.

Table 7

NYSE/AMEX Vs. NASDAQ breakdown for monthly proxies compared to TAQ benchmarks

The benchmarks Effective spread (TAQ), Realized spread (TAQ), Lambda (TAQ), and 5-Minute Price Impact (TAQ) are calculated from every trade and corresponding BBO quote in the NYSE TAQ database for a sample firm-month. All spread proxies and price impact proxies are calculated from CRSP daily stock price and volume data for a sample firm-month. The spread proxies are: Roll from Roll (1984), Effective Tick and Effective Tick2 developed here and in Holden (2009), Holden from Holden (2009), Gibbs from Hasbrouck (2004), LOT Mixed, Zeros, and Zeros2 from Lesmond, Odgen, and Trzcinka (1999), LOT Y-split developed here, Amihud from Amihud (2002), Pastor and Stambaugh from Pastor and Stambaugh (2003), and the Amivest Liquidity ratio. The price impact proxies are: Roll Impact, Effective Tick Impact, Effective Tick2 Impact, Holden Impact, Gibbs Impact, LOT Mixed Impact, and LOT Y-split Impact developed here, Amihud from Amihud (2002), Pastor and Stambaugh from Pastor and Stambaugh (2003), and the Amivest Liquidity ratio. The sample spans 1993–2005 inclusive and consists of 400 randomly selected stocks with annual replacement of stocks that do not survive, resulting in 62,100 firm-months. Bold numbers are statistically significant at the 5% level.

	Roll	Effective Tick	Effective Tick2	Holden	Gibbs	LOT Mixed	LOT Y-split	Zeros	Zeros2	Amihud	Pastor and Stambaugh	Amivest Liquidity
<i>Panel A: Average cross-sectional correlation based on individual firms (average of 156 months)</i>												
NYSE/Amex Effective spread (TAQ)	0.503	0.745	0.752	0.782	0.638	0.705	0.690	0.507	0.472	0.633	-0.006	-0.176
Nasdaq Effective spread (TAQ)	0.546	0.594	0.571	0.646	0.659	0.613	0.620	0.389	0.246	0.586	-0.124	-0.126
NYSE/Amex Realized spread (TAQ)	0.319	0.443	0.450	0.460	0.362	0.383	0.375	0.272	0.288	0.254	0.006	-0.097
Nasdaq Realized spread (TAQ)	0.338	0.366	0.362	0.384	0.362	0.345	0.323	0.184	0.158	0.295	-0.026	-0.082
<i>Panel B: Time-series correlations based on an equally-weighted portfolio (156 months)</i>												
NYSE/Amex Effective spread (TAQ)	0.770	0.617	0.616	0.654	0.810	0.428	0.541	0.144	0.121	0.447	-0.047	-0.106
Nasdaq Effective spread (TAQ)	0.930	0.957	0.955	0.967	0.915	0.756	0.956	0.911	0.891	0.664	-0.391	-0.129
NYSE/Amex Realized spread (TAQ)	0.278	0.738	0.730	0.756	0.327	0.550	0.718	0.664	0.656	0.167	-0.067	-0.093
Nasdaq Realized spread (TAQ)	0.885	0.968	0.969	0.977	0.872	0.780	0.977	0.953	0.937	0.633	-0.360	-0.104
	Roll Impact	Effective Tick Impact	Effective Tick2 Impact	Holden Impact	Gibbs Impact	LOT Mixed Impact	LOT Y-split Impact	Zeros Impact	Zeros2 Impact	Amihud	Pastor and Stambaugh	Amivest Liquidity
<i>Panel C: Average Cross-sectional Correlation based on Individual Firms (Average of 156 Months)</i>												
NYSE/Amex Lambda (TAQ)	0.456	0.489	0.504	0.508	0.506	0.504	0.496	0.433	0.468	0.513	0.005	-0.065
Nasdaq Lambda (TAQ)	0.291	0.286	0.298	0.297	0.300	0.302	0.291	0.279	0.224	0.291	-0.066	-0.028
NYSE/Amex 5-Min Price Impact (TAQ)	0.547	0.553	0.571	0.574	0.585	0.599	0.577	0.501	0.532	0.605	0.034	-0.182
Nasdaq 5-Minute Price Impact (TAQ)	0.480	0.446	0.474	0.460	0.460	0.464	0.422	0.361	0.384	0.532	0.032	-0.123
<i>Panel D: Time-series Correlations based on an Equally-weighted Portfolio (156 Months)</i>												
NYSE/Amex Lambda (TAQ)	0.785	0.200	0.354	0.369	0.836	0.628	0.660	0.286	0.074	0.190	-0.462	-0.012
Nasdaq Lambda (TAQ)	0.517	0.500	0.475	0.606	0.513	0.536	0.513	0.582	0.520	0.467	-0.169	-0.069
NYSE/Amex 5-Min Price Impact (TAQ)	0.225	0.219	0.214	0.256	0.182	0.196	0.196	0.177	0.321	0.369	0.029	-0.097
Nasdaq 5-Minute Price Impact (TAQ)	0.644	0.341	0.345	0.493	0.555	0.502	0.448	0.601	0.495	0.570	-0.334	-0.159

7.4. Results by exchange

For robustness, we explore the degree to which our results vary across exchanges. In Table 7, we break out the monthly spread and price impact evidence by exchange, sorting firms into two groups based on NYSE/AMEX and NASDAQ. In Panel A, with respect to average cross-sectional correlations with effective and realized spreads, all spread proxies except Gibbs and Roll²¹ show a lower correlation for NASDAQ stocks than for NYSE stocks. The largest differences are associated with Effective Tick and Holden where the first digit of the correlation coefficient changes. In contrast, the time-series correlations, Panel B, show that the measures do better for NASDAQ stocks than NYSE. Nearly the same pattern holds for correlations with the realized spread. Finally, the price impact measures are mixed across exchanges. The conclusion from this table is that the exchange does not matter very much and should not be a factor in using low-frequency spread or price impact proxies.

7.5. Results by year

Our next robustness check is to explore how our results vary over time. Specifically, Table 8 breaks out the monthly effective spread, realized spread, and price impact evidence by year. Panels A and B report the time variation of cross-sectional correlations and root mean squared error for the effective spread benchmark. In each month there are 400 observations for a correlation and root mean squared error, which are averaged over the year. The two panels tell opposite stories. Panel A shows that the cross-sectional correlations decrease over time for seven measures (Roll, Effective Tick, Effective Tick 2, Holden, Gibbs, LOT Mixed, and LOT Y-split). The decline is strongest during the decimal era (2001–2005). By contrast, the Amihud measure does not decline over time and joins the leadership group in the decimal era only. This result contrasts with the Table 2, Panel C result that the \$1/8 era and decimal era had very high time-series correlations, while the \$1/16 era had somewhat lower time-series correlations. In Panel B, all measures improve in their ability to predict the effective spread. LOT Mixed has a root mean squared error that is 81% more accurate in 2005 than in 1993. The same pattern is observed for the realized spread benchmark in Panels C and D. The mean squared error is the square of the bias plus the variance of the estimator. The fact that the correlation coefficient has fallen but the errors are smaller is the result of the measure having lower bias and smaller variance.

In Panels E and F we present the average correlations between the price impact measures and the two high-frequency measures of price impact used in this paper. Generally, the measures are statistically significant in all tables and demonstrate considerable volatility in Panel E

(Lambda), and deterioration, except Amihud, in Panel F (5-Minute Price Impact).

7.6. Dow Jones data

Our final robustness test is to test the spread measures out-of-sample. We examine the stocks in the Dow Jones Industrial Average from 1962 to 2000.²² The spread benchmark is the percent quoted spread of the Dow portfolio as computed by Jones (2002). For every year we compute each of the low-frequency spread proxies for each of the 30 Dow stocks and then equally weight the measures across stocks for the year since the historical spreads for the Dow stocks are available only on an annual basis.

Table 9 shows the results. The biggest surprise is the large negative and significantly negative correlation coefficients on the Roll and Gibbs measures. Roll's time-series correlation is -0.642 and Gibbs' time-series correlation is -0.395 . Of course, the Dow Jones stocks are large capitalization stocks with low effective spreads. In that respect, the poor *annual* performance of Roll and Gibbs with the Dow Jones stocks is very consistent with the poor *monthly* performance of Roll and Gibbs with large capitalization deciles and low effective spread deciles in Table 2, Panels D and E.

As a double-check on this result, we estimate the average autocovariance of daily price changes for each stock. Whenever we have positive autocovariance we change it to a zero value, consistent with the way we construct the Roll measure. We then correlate the average absolute value of the autocovariance with the spread and find a -55% correlation. Thus, in this sample of large, liquid stocks, the lower the spread the higher the absolute value of the autocovariance. This is the opposite relationship supposed by Roll, who argues that liquid stocks should have lower autocovariance than illiquid stocks.

For the other measures in Table 9, the correlations between the average measure and the average quoted spread are generally smaller than the time-series portfolio correlations of Table 3 Panel B, but they are still large and significant. Effective Tick, Effective Tick2, and Holden all have time-series correlations greater than 0.840 and are statistically insignificantly different from each other. Also, LOT Y and Zeros/Zeros2 fall in their 95% confidence interval. Fig. 1 shows the time series for the quoted spread of the Dow Jones portfolio and the low-frequency measures Holden, LOT Y-split, and Effective Tick. These data generate the correlations of Table 9. The low-frequency measures track the quoted spread very well, especially at the end of the sample. The conclusion of Table 9 and Fig. 1 is that the measures are useful on a different sample of stocks over a different time period.

8. Conclusion

The purpose of this paper is to test the hypothesis that low-frequency measures of transaction costs, measured

²¹ Schultz (2000) estimates the Roll measure using intraday TAQ data. He finds that the intraday Roll measure is a very accurate estimate of effective spread, because various biases in Roll tend to offset each other in his NASDAQ sample.

²² We thank Charles Jones for these data.

Table 8

Year-by-year breakdown for monthly proxies compared to TAQ benchmarks

The benchmarks Effective spread (TAQ), Realized spread (TAQ), Lambda (TAQ), and 5-Minute Price Impact (TAQ) are calculated from every trade and corresponding BBO quote in the NYSE TAQ database for a sample firm-month. All spread proxies and price impact proxies are calculated from CRSP daily stock price and volume data for a sample firm-month. The effective spread proxies are: Roll from Roll (1984), Effective Tick and Effective Tick 2 developed here and in Holden (2009), Holden from Holden (2009), Gibbs from Hasbrouck (2004), LOT Mixed, Zeros, and Zeros2 from Lesmond, Odgen, and Trzcinka (1999), LOT Y-split developed here, Amihud from Amihud (2002), Pastor and Stambaugh from Pastor and Stambaugh (2003), and the Amivest Liquidity ratio. The price impact proxies are: Roll Impact, Effective Tick Impact, Effective Tick2 Impact, Holden Impact, Gibbs Impact, LOT Mixed Impact, and LOT Y-split Impact developed here, Amihud from Amihud (2002), Pastor and Stambaugh from Pastor and Stambaugh (2003), and the Amivest Liquidity ratio. The sample spans 1993–2005 inclusive and consists of 400 randomly selected stocks with annual replacement of stocks that do not survive, resulting in 62,100 firm-months. Bold numbers are statistically significant at the 5% level.

	Roll	Effective Tick	Effective Tick2	Holden	Gibbs	LOT Mixed	LOT Y-split	Zeros	Zeros2	Amihud	Pastor and Stambaugh	Amivest Liquidity
<i>Panel A: Average cross-sectional correlation with effective spread based on individual firms</i>												
1993	0.711	0.689	0.638	0.720	0.838	0.702	0.700	0.438	0.182	0.513	-0.306	-0.173
1994	0.744	0.707	0.700	0.771	0.883	0.781	0.745	0.407	0.142	0.579	-0.262	-0.193
1995	0.714	0.647	0.637	0.741	0.845	0.718	0.718	0.401	0.202	0.614	-0.127	-0.191
1996	0.726	0.691	0.700	0.749	0.880	0.789	0.785	0.422	0.194	0.652	-0.256	-0.153
1997	0.678	0.693	0.649	0.724	0.825	0.711	0.760	0.472	0.287	0.560	-0.182	-0.162
1998	0.554	0.696	0.693	0.757	0.675	0.691	0.708	0.464	0.314	0.650	-0.003	-0.148
1999	0.550	0.663	0.667	0.724	0.681	0.660	0.657	0.452	0.374	0.531	-0.144	-0.161
2000	0.398	0.692	0.699	0.728	0.509	0.619	0.651	0.442	0.404	0.522	0.018	-0.129
2001	0.554	0.618	0.601	0.658	0.614	0.630	0.603	0.380	0.326	0.585	-0.169	-0.106
2002	0.528	0.575	0.553	0.650	0.670	0.658	0.604	0.429	0.387	0.565	-0.070	-0.079
2003	0.421	0.519	0.514	0.530	0.521	0.547	0.529	0.415	0.399	0.448	0.000	-0.106
2004	0.358	0.506	0.495	0.566	0.400	0.479	0.458	0.399	0.391	0.606	0.023	-0.086
2005	0.350	0.449	0.437	0.549	0.324	0.484	0.456	0.425	0.404	0.598	-0.052	-0.076
<i>Panel B: Root mean square prediction error of Effective spread (TAQ) based on individual firms</i>												
1993	0.045	0.050	0.053	0.046	0.046	0.130	0.065	-	-	-	-	-
1994	0.036	0.041	0.041	0.038	0.037	0.075	0.045	-	-	-	-	-
1995	0.035	0.042	0.042	0.035	0.035	0.103	0.048	-	-	-	-	-
1996	0.035	0.040	0.039	0.035	0.033	0.069	0.040	-	-	-	-	-
1997	0.029	0.031	0.033	0.030	0.027	0.149	0.034	-	-	-	-	-
1998	0.032	0.026	0.025	0.024	0.027	0.056	0.028	-	-	-	-	-
1999	0.032	0.025	0.024	0.022	0.022	0.064	0.031	-	-	-	-	-
2000	0.041	0.030	0.030	0.029	0.33	0.057	0.034	-	-	-	-	-
2001	0.035	0.032	0.033	0.031	0.30	0.048	0.032	-	-	-	-	-
2002	0.037	0.036	0.036	0.033	0.30	0.046	0.036	-	-	-	-	-
2003	0.029	0.027	0.028	0.027	0.024	0.028	0.027	-	-	-	-	-
2004	0.020	0.019	0.019	0.018	0.018	0.022	0.019	-	-	-	-	-
2005	0.020	0.018	0.018	0.016	0.020	0.022	0.017	-	-	-	-	-
<i>Panel C: Average cross-sectional correlation with realized spread based on individual firms</i>												
1993	0.547	0.470	0.452	0.500	0.582	0.468	0.426	0.266	0.150	0.308	-0.104	-0.140
1994	0.491	0.488	0.510	0.492	0.480	0.473	0.397	0.213	0.153	0.274	0.011	-0.155
1995	0.574	0.458	0.467	0.509	0.562	0.483	0.420	0.237	0.172	0.289	-0.001	-0.170
1996	0.598	0.564	0.554	0.596	0.647	0.597	0.555	0.264	0.168	0.499	-0.132	-0.124
1997	0.494	0.492	0.454	0.529	0.536	0.511	0.507	0.298	0.270	0.320	0.073	-0.128
1998	0.351	0.459	0.450	0.487	0.436	0.434	0.451	0.276	0.244	0.379	0.053	-0.100
1999	0.360	0.418	0.423	0.441	0.421	0.405	0.366	0.241	0.222	0.302	-0.120	-0.102
2000	0.274	0.416	0.405	0.424	0.328	0.377	0.377	0.243	0.213	0.349	-0.018	-0.073
2001	0.302	0.338	0.354	0.381	0.332	0.306	0.261	0.146	0.164	0.243	-0.113	-0.063
2002	0.279	0.329	0.333	0.334	0.316	0.310	0.241	0.169	0.201	0.208	0.018	-0.043
2003	0.230	0.264	0.248	0.271	0.257	0.256	0.249	0.180	0.179	0.265	-0.019	-0.046
2004	0.201	0.247	0.270	0.265	0.173	0.189	0.179	0.105	0.137	0.323	-0.035	-0.039
2005	0.127	0.238	0.228	0.261	0.099	0.174	0.197	0.228	0.219	0.210	-0.013	-0.035

Table 8. (continued)

	Roll	Effective Tick	Effective Tick2	Holden	Gibbs	LOT Mixed	LOT Y-split	Zeros	Zeros2	Amihud	Pastor and Stambaugh	Amivest Liquidity
<i>Panel D: Root mean square prediction error of Realized spread (TAQ) based on individual firms</i>												
1993	0.0486	0.054	0.054	0.052	0.045	0.134	0.079	-	-	-	-	-
1994	0.046	0.044	0.042	0.046	0.041	0.093	0.062	-	-	-	-	-
1995	0.036	0.041	0.040	0.036	0.031	0.110	0.058	-	-	-	-	-
1996	0.037	0.038	0.037	0.035	0.030	0.084	0.050	-	-	-	-	-
1997	0.034	0.032	0.034	0.031	0.025	0.116	0.040	-	-	-	-	-
1998	0.037	0.025	0.025	0.024	0.025	0.069	0.036	-	-	-	-	-
1999	0.038	0.028	0.025	0.025	0.023	0.075	0.038	-	-	-	-	-
2000	0.043	0.026	0.026	0.024	0.026	0.071	0.037	-	-	-	-	-
2001	0.043	0.029	0.027	0.026	0.029	0.064	0.032	-	-	-	-	-
2002	0.044	0.027	0.026	0.025	0.027	0.062	0.033	-	-	-	-	-
2003	0.029	0.015	0.014	0.015	0.017	0.036	0.015	-	-	-	-	-
2004	0.022	0.011	0.010	0.010	0.015	0.026	0.011	-	-	-	-	-
2005	0.022	0.010	0.010	0.009	0.019	0.028	0.011	-	-	-	-	-
<i>Panel E: Average cross-sectional correlation with Lambda (TAQ) based on individual firms</i>												
1993	0.230	0.171	0.208	0.167	0.206	0.229	0.180	0.228	0.225	0.249	-0.124	-0.031
1994	0.286	0.0336	0.308	0.296	0.273	0.240	0.239	0.258	0.011	0.238	-0.249	-0.033
1995	0.431	0.416	0.495	0.443	0.548	0.529	0.508	0.494	0.239	0.435	-0.066	-0.032
1996	0.553	0.513	0.468	0.473	0.553	0.543	0.506	0.467	0.265	0.478	-0.357	-0.036
1997	0.158	0.203	0.225	0.225	0.175	0.139	0.135	0.185	0.131	0.271	-0.201	-0.031
1998	0.450	0.477	0.510	0.487	0.429	0.443	0.410	0.460	0.423	0.405	0.082	-0.033
1999	0.296	0.257	0.274	0.346	0.339	0.396	0.407	0.371	0.321	0.264	0.015	-0.051
2000	0.294	0.297	0.303	0.305	0.283	0.282	0.259	0.207	0.228	0.278	0.030	-0.039
2001	0.363	0.376	0.392	0.376	0.409	0.484	0.451	0.282	0.354	0.494	0.119	-0.030
2002	0.338	0.385	0.383	0.446	0.357	0.363	0.339	0.413	0.432	0.382	-0.090	-0.023
2003	0.149	0.150	0.213	0.140	0.131	0.214	0.211	0.204	0.309	0.183	-0.083	-0.019
2004	0.093	0.074	0.045	-0.011	0.069	0.029	-0.046	-0.087	0.212	0.272	0.080	-0.016
2005	0.109	0.166	0.167	0.176	0.075	0.130	0.178	0.135	0.222	0.168	0.004	-0.014
<i>Panel F: Average cross-sectional correlation with 5-Minute Price Impact (TAQ) based on individual firms</i>												
1993	0.537	0.499	0.499	0.548	0.514	0.485	0.515	0.455	0.506	0.545	-0.052	-0.181
1994	0.536	0.451	0.467	0.456	0.494	0.479	0.466	0.431	0.388	0.588	0.079	-0.195
1995	0.509	0.500	0.484	0.507	0.483	0.486	0.439	0.432	0.459	0.514	0.120	-0.209
1996	0.523	0.507	0.542	0.550	0.505	0.532	0.544	0.525	0.489	0.547	-0.016	-0.167
1997	0.448	0.444	0.446	0.466	0.387	0.431	0.413	0.366	0.417	0.474	0.127	-0.167
1998	0.485	0.433	0.440	0.427	0.463	0.444	0.392	0.397	0.424	0.578	0.086	-0.153
1999	0.453	0.419	0.452	0.456	0.450	0.496	0.485	0.377	0.434	0.497	0.003	-0.162
2000	0.401	0.463	0.469	0.475	0.411	0.464	0.415	0.333	0.398	0.470	0.055	-0.121
2001	0.526	0.466	0.488	0.490	0.529	0.562	0.542	0.452	0.468	0.560	0.001	-0.100
2002	0.525	0.509	0.575	0.561	0.540	0.511	0.491	0.452	0.471	0.553	0.013	-0.072
2003	0.296	0.333	0.333	0.346	0.297	0.337	0.491	0.285	0.328	0.344	0.014	-0.108
2004	0.421	0.315	0.393	0.330	0.389	0.420	0.306	0.220	0.297	0.521	0.034	-0.093
2005	0.432	0.366	0.449	0.409	0.411	0.425	0.350	0.273	0.288	0.288	-0.007	-0.076

Table 9

Annual spread proxies compared to the quoted spread of the Dow portfolio 1962–2000

For a given year, the benchmark Quoted spread (Dow) is the percentage quoted spread of the Dow Jones Industrial Average portfolio as compiled by Charles Jones. For a given year, all spread proxies are calculated from CRSP daily stock price and volume data for each stock in the Dow 30 and then equally weighted to get the portfolio value. The spread proxies are: Roll from Roll (1984), Effective Tick and Effective Tick2 developed here and in Holden (2009), Holden from Holden (2009), Gibbs from Hasbrouck (2004), LOT Mixed, Zeros, and Zeros2 from Lesmond, Odgen, and Trzcinka (1999), LOT Y-split developed here, Amihud from Amihud (2002), Pastor and Stambaugh from Pastor and Stambaugh (2003), and the Amivest ratio. The sample size is 39 portfolio-years. Bold numbers are statistically significant at the 5% level.

	Roll	Effective Tick	Effective Tick2	Holden	Gibbs	LOT Mixed	LOT Y-split	Zeros	Zeros2	Amihud	Pastor and Stambaugh	Amivest Liquidity
Quoted spread (Dow)	-0.642	0.844	0.844	0.847	-0.395	0.427	0.778	0.741	0.741	0.596	0.120	-0.503
Insignificantly different from:	Gibbs	Eff Tick	Eff Tick	Eff Tick	Roll	Amihud	Eff Tick	Eff Tick	Eff Tick	LOT Mix	LOT Mix	Roll
	Amivest	Holden	Holden	Eff Tick2	Amivest	Past/Stam	Eff Tick2	Eff Tick2	Holden	LOT Y	LOT Mix	Gibbs
	LOT Y	LOT Y	LOT Y	LOT Y			Holden	Holden	Holden	Zeros		
	Zeros	Zeros	Zeros	Zeros			Zeros	LOT Y	LOT Y	Zeros2		
	Zeros2	Zeros2	Zeros2	Zeros2			Zeros2	Zeros2	Zeros			
							Amihud	Amihud	Amihud			

Time-series correlations based on the Dow Jones Industrial Average portfolio 1962–2000 (39 years)

monthly and annually, can usefully estimate high-frequency measures, and if so, to determine which measures are best. Using a sample of 400 randomly selected stocks over the period 1993 to 2005, we compare all prior proxies, three new spread measures, and nine new price impact measures. Specifically, we first compute the effective and realized spreads and several measures of price impact from two high-frequency data sets: TAQ and Rule 605 data disclosed by market centers to the SEC. We then compute the low-frequency measures from daily return and volume data available on CRSP on a monthly and annual basis. We statistically determine how well the low-frequency measures capture high-frequency benchmarks.

The evidence is overwhelming that both monthly and annual low-frequency measures capture high-frequency measures of transaction costs. Indeed, in many applications the correlations are high and the mean squared error low enough that the effort of using high-frequency measures is simply not worth the cost. The only real question then is: which measure should a researcher use? The answer depends on what, exactly, the researcher wants to measure.

For monthly and annual effective and realized spreads, we find that three measures dominate the remaining nine in correlations and mean squared prediction errors. The simplest of the dominant measures is the analytic “Effective Tick.” The most computationally intensive is the “Holden” measure. Intermediate in computational requirements is LOT Y-split. All provide statistically significant and useful measures, high correlations, and low root mean squared errors, regardless of the database we use (TAQ or Rule 605). Without considering computational requirements, Holden delivers the best performance overall. Considering ease of computation, Effective Tick is the best measure to use. Measures widely used in the literature, namely, Amihud’s Illiquidity, Pastor and Stambaugh’s Gamma, and Amivest’s Liquidity, are not appropriate to use as proxies for effective or realized spreads.

We find that price impact is more difficult to capture in our data than effective or realized spread. The measures are not designed to capture the magnitude of high-frequency price impact benchmarks and the correlations with price impact are lower than in the effective/realized spread tests. However, both the new class of price impact measures we introduce in this paper and the Amihud measure do a reasonably good job in the sense that they produce statistically significant positive correlations. Pastor and Stambaugh’s Gamma and Amivest’s Liquidity are ineffective in capturing price impact in our data. We suggest using either the Amihud measure or using one of our effective spread measures divided by volume if a researcher wants to capture price impact.

For specific high-frequency transaction costs benchmarks we suggest different low-frequency measures. To capture Lambda (TAQ), which is the coefficient from regressing return on the square root of signed trading volume over five-minute intervals, we suggest either Amihud’s Illiquidity or one of the new measures. To measure 5-Minute Price Impact, or the five-minute

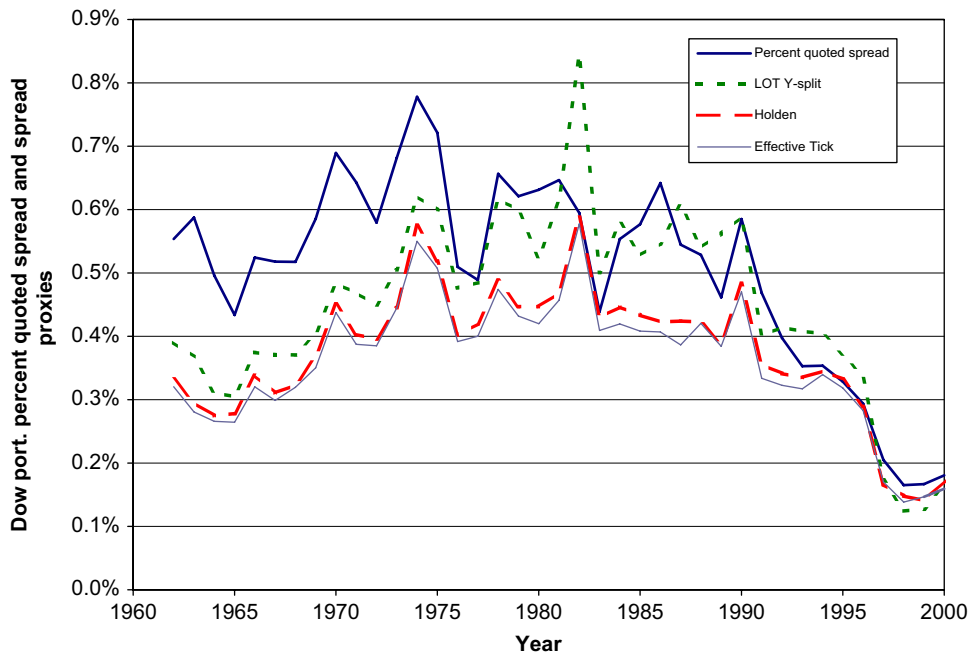


Fig. 1. Dow portfolio percent quoted spread and spread proxies (1962–2000). For a given year, the benchmark is the percent quoted spread of the Dow Jones Industrial Average portfolio as compiled by Charles Jones. For a given year, all spread proxies are calculated from CRSP daily stock price and volume data for each stock in the Dow 30 and then equally weighted to get the portfolio value.

change in midpoint after the trade, we suggest using the Amihud Illiquidity measure.

All price impact measures fail to capture cross-sectional or time-series variation of Static Price Impact (605). It is possible that this difficulty lies primarily in the fact that Rule 605 data exclude block trades, where price impact should be most severe. In other words, much of the variation of Static Price Impact (605) may be noise. However, the new class of price impact measures does a good job in predicting the level of Static Price Impact (605) and has very low mean bias and root mean squared error.

We conduct several robustness checks on these conclusions. First, we examine the pattern of these measures over time. Second, we examine whether listing exchange matters. Finally, we test the ability of these measures to predict the percent quoted spread of the Dow portfolio from 1962 to 2000. The conclusions are essentially the same in these tests. The measures vary over time in their ability to capture high-frequency measures, but the dominant measures are the same group over time. Interestingly, all measures based on price clustering seem to deteriorate in capturing the effective spread during the decimals regime, while the Amihud correlations continue to perform reasonably well during the last years of the sample. Further, exchange listing does not matter and the low-frequency measures do well in predicting the quoted spreads on Dow stocks.

As with any empirical paper several caveats should be mentioned. First, using a random sample in this paper means that caution should be used in applying these measures to other samples or other time periods. Second, we do not know whether the measures are effective on

international data, especially in relation to those stocks with extremely thin trading. Both limitations suggest avenues for future research. With these limitations in mind, we think the results of this paper are strong enough that use of the low-frequency proxies to extend asset pricing, market efficiency, and corporate finance research back in time and around the world is a step that the finance literature needs to take.

References

- Acharya, V., Pedersen, L., 2005. Asset pricing with liquidity risk. *Journal of Financial Economics* 77, 375–410.
- Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets* 5, 31–56.
- Amihud, Y., Mendelson, H., Lauterbach, B., 1997. Market microstructure and securities values: evidence from the Tel Aviv stock exchange. *Journal of Financial Economics* 45, 365–390.
- Bekaert, G., Harvey, C., Lundblad, C., 2007. Liquidity and expected returns: lessons from emerging markets. *Review of Financial Studies* 20, 1783–1831.
- Berkman, H., Eleswarapu, V., 1998. Short-term traders and liquidity: a test using Bombay Stock Exchange data. *Journal of Financial Economics* 47, 339–355.
- Boehmer, E., Jennings, R., Wei, L., 2003. Public disclosure and private decisions: the case of equity market execution quality. Working Paper, Indiana University.
- Cao, C., Field, L., Hanka, G., 2004. Does insider trading impair market liquidity? Evidence from IPO lockup expirations. *Journal of Financial and Quantitative Analysis* 39, 25–46.
- Chan, L., Jegadeesh, N., Lakonishok, J., 1996. Momentum strategies. *Journal of Finance* 51, 1681–1713.
- Chordia, T., Roll, R., Subrahmanyam, A., 2000. Commonality in liquidity. *Journal of Financial Economics* 56, 3–28.
- Chordia, T., Goyal, A., Sadka, G., Sadka, R., Shivakumar, L., 2008. Liquidity and the post-earnings-announcement-drift. Working Paper, University of Washington.

- Christie, W., Schultz, P., 1994. Why do NASDAQ market makers avoid odd-eighth quotes? *Journal of Finance* 49, 1813–1840.
- Cooper, S., Groth, K., Avera, W., 1985. Liquidity, exchange listing and common stock performance. *Journal of Economics and Business* 37, 19–33.
- De Bondt, W., Thaler, R., 1985. Does the stock market overreact? *Journal of Finance* 40, 793–805.
- Dennis, P., Strickland, D., 2003. The effect of stock splits on liquidity and excess returns: evidence from shareholder ownership composition. *Journal of Financial Research* 26, 355–370.
- Fama, E., MacBeth, J., 1973. Risk, return, and equilibrium: empirical tests. *Journal of Political Economy* 81, 607–636.
- Fujimoto, A., 2003. Macroeconomic sources of systematic liquidity. Working Paper, Yale University.
- Glosten, L., 1987. Components of the bid–ask spread and the statistical properties of transaction prices. *Journal of Finance* 42, 1293–1307.
- Goyenko, R., 2006. Stock and bond pricing with liquidity risk. Working Paper, Indiana University.
- Harris, L., 1991. Stock price clustering and discreteness. *Review of Financial Studies* 4, 389–415.
- Hasbrouck, J., 2004. Liquidity in the futures pits: inferring market dynamics from incomplete data. *Journal of Financial and Quantitative Analysis* 39, 305–326.
- Hasbrouck, J., 2009. Trading costs and returns for US equities: estimating effective costs from daily data. *Journal of Finance*, forthcoming.
- Helfin, F., Shaw, K., 2000. Blockholder ownership and market liquidity. *Journal of Financial and Quantitative Analysis* 35, 621–633.
- Holden, C., 2009. New low-frequency liquidity measures. Working Paper, Indiana University.
- Huang, R., Stoll, H., 1996. Dealer versus auction markets: a paired comparison of execution costs on NASDAQ and the NYSE. *Journal of Financial Economics* 41, 313–357.
- Huang, R., Stoll, H., 1997. The components of the bid–ask spread: a general approach. *Review of Financial Studies* 10, 995–1034.
- Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: implications for market efficiency. *Journal of Finance* 48, 65–92.
- Jegadeesh, N., Titman, S., 2001. Profitability of momentum strategies: an evaluation of alternative explanations. *Journal of Finance* 56, 699–720.
- Jones, C., 2002. A century of stock market liquidity and trading costs. Working Paper, Columbia University.
- Kalev, P., Pham, P., Steen, A., 2003. Underpricing, stock allocation, ownership structure and post-listing liquidity of newly listed firms. *Journal of Banking and Finance* 27, 919–947.
- Keim, D., Madhavan, A., 1997. Transactions costs and investment style: an inter-exchange analysis of institutional equity trades. *Journal of Financial Economics* 46, 265–292.
- Korajczyk, R., Sadka, R., 2008. Pricing the commonality across alternative measures of liquidity. *Journal of Financial Economics*, forthcoming.
- Lee, C., Radhakrishna, B., 2000. Inferring investor behavior: evidence from TORQ data. *Journal of Financial Markets* 3, 83–112.
- Lee, C., Ready, M., 1991. Inferring trade direction from intraday data. *Journal of Finance* 46, 733–746.
- Lerner, J., Schoar, A., 2004. The illiquidity puzzle: theory and evidence from private equity. *Journal of Financial Economics* 72, 3–40.
- Lesmond, D., 2005. Liquidity of emerging markets. *Journal of Financial Economics* 77, 411–452.
- Lesmond, D., O'Connor, P., Senbet, L., 2008. Capital structure and equity liquidity. Working Paper, Tulane University.
- Lesmond, D., Ogden, J., Trzcinka, C., 1999. A new estimate of transaction costs. *Review of Financial Studies* 12, 1113–1141.
- Lipson, M., Mortal, S., 2004a. Liquidity and firm characteristics: evidence from mergers and acquisitions. Working Paper, University of Georgia.
- Lipson, M., Mortal, S., 2004b. Capital structure decision and equity market liquidity. Working Paper, University of Georgia.
- Pastor, L., Stambaugh, R., 2003. Liquidity risk and expected stock returns. *Journal of Political Economy* 111, 642–685.
- Roll, R., 1984. A simple implicit measure of the effective bid–ask spread in an efficient market. *Journal of Finance* 39, 1127–1139.
- Rouwenhorst, G., 1998. International momentum strategies. *Journal of Finance* 53, 267–284.
- Sadka, R., 2006. Liquidity risk and asset pricing. *Journal of Financial Economics* 80, 309–349.
- Schrand, C., Verrecchia, R., 2004. Disclosure choice and cost of capital: evidence from underpricing in initial public offerings. Working Paper, University of Pennsylvania.
- Schultz, P., 2000. Regulatory and legal pressures and the costs of NASDAQ trading. *Review of Financial Studies* 13, 917–957.
- Swinscow, T., 1997. *Statistics at Square One*, ninth ed. BMJ Publishing Group, London.
- Theil, H., 1966. *Applied Economic Forecasts*. North-Holland, Amsterdam.
- Watanabe, A., Watanabe, M., 2006. Time-varying liquidity risk and the cross section of stock returns. *Review of Financial Studies*, forthcoming.