

**Trading Costs and Returns for US Equities:
Estimating high-frequency measures of liquidity
from low-frequency data**

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Comments welcome

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The latest version of this paper and a SAS dataset containing the long-run Gibbs sampler estimates are available on my web site at www.stern.nyu.edu/~jhasbrou.

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Abstract

This study examines various measures of trading costs estimated from high-frequency (TAQ) data and the extent to which these measures can be estimated from daily data (CRSP). The high-frequency measures tend to be positively correlated. Posted spreads and effective costs are very highly correlated. Price impact measures and other statistics derived from dynamic models, however, are only modestly correlated. Among the set of proxies constructed from daily data, a Gibbs estimate of the effective cost based on Roll (1984) stands out, achieving a correlation of 0.944 with the corresponding TAQ estimate. A variant of the illiquidity measure suggested by Amihud (2002) is the best proxy for the price impact coefficient (a correlation of 0.721 with the TAQ measure). Both the Gibbs estimate of effective cost and the illiquidity ratio covary positively with risk-adjusted returns, but the relations exhibit marked seasonality and are not robust to the use of alternative measures of correlation.

JEL classification codes: C15, G12, G20

1. Introduction

As liquidity and transaction costs have become more important in empirical asset pricing and corporate finance research, the limitations of the high-frequency data samples conventionally used to estimate these costs have become more apparent. While the CRSP daily file begins in 1962, for example, the corresponding trade and quote databases start in 1983 (at the earliest) and encompass many different trading and reporting regimes. The construction of historical liquidity estimates from return data of daily (or longer) frequency therefore stands as an important goal. This paper broadly advances this line of inquiry. In a comparison sample of US equity data for which we possess both high-frequency and daily data, the paper surveys the joint behavior of transaction cost/liquidity measures estimated from the former and proxies computed from the latter. The analysis establishes guidelines for the subsequent use of the proxies.

As no single measure summarizes all the attributes of “liquidity,” the high-frequency estimates reflect diverse approaches. From a narrow perspective, an individual trader projecting the cost of achieving a particular position may compare the expected trade price to some pre-trade benchmark. This suggests measuring the trading cost as half the posted or effective spread, for orders accomplished in a single trade. Execution strategies that span multiple orders, however, must take into account the impacts of early trades on the prices obtained in later trades. To capture these effects, the present study examines estimates of the trade impact coefficient from a dynamic model of trades and prices.

Liquidity may also be more broadly defined as reflecting the distortions in prices and holdings resulting from the trading process. Grossman and Miller (1987) suggest that dealers smooth the asynchronous demands of customers. The dealers’ accommodation of a one-sided order flow induces a price change that is subsequently reversed. This reversal is usually estimated on the basis of (unsigned) volume data (Campbell, Grossman and Wang (1993); Llorente, Michaely, Saar and Wang (2002); Pastor and Stambaugh (2003)). The present study describes a representative reversal measure based on signed order flows.

Most of the analyses in the paper are based on a sample of 250 firms per year, from 1993 to 2003. Comparisons between high-frequency and daily estimates are possible in this period because we possess both sorts of data. In this comparison sample all measures, whether computed from daily or high-frequency data, exhibit numerous extreme values, with some of the kurtosis coefficients on the order of a thousand or more. Although some of these may be artifacts of sampling or data errors, it is also likely that the extreme values arise from large cross-sectional variation in actual trading costs.

The high-frequency liquidity estimates do not uniformly agree. Within the set of measures consisting of average intraday spread, the closing spread and the effective cost have correlations of about 0.95. Partial correlations, which control for price level, market capitalization and volatility, are only slightly lower (around 0.9). Correlations involving the impact coefficients and reversal measures, however, are much more variable. Thus, there is no overall concordance, and no single measure that captures all dimensions of liquidity. Stoll (2000) arrives at similar conclusions, using a panel of liquidity measures that partially

The literature suggests various approaches to estimating high-frequency measures from returns and unsigned volumes observed at a daily frequency. The effective cost is most conveniently estimated using the Roll (1984) model. The usual estimate is a moment estimate computed as the square root of (minus) the first-order return autocovariance. In the frequently-encountered case where the sample autocovariance is positive, however, this estimate is infeasible. As an alternative, Hasbrouck (2004) suggests a Gibbs estimate. This approach adopts a Bayesian perspective and incorporates a prior restriction of a non-negative effective cost.

Daily proxies for high-frequency impact and reversal coefficients are less direct, however, because total trading volume is quite different from net signed order flow. Proxies for the price impact coefficient include the Amivest liquidity ratio (Cooper, Groth and Avera (1985)) and the Amihud (2002) illiquidity measure, both of which involve ratios of trade volumes to absolute returns. The reversal measure suggested by Pastor and Stambaugh (2003) is based on a

specification in which the daily return is regressed against lagged total volume signed by the lagged excess return. This latter quantity is, in effect, a proxy for signed net volume.

The core of the paper is an analysis of the correlations between the high-frequency liquidity estimates and the proxies constructed from daily data. The simple single-trade measures are relatively easy to proxy. The Roll estimate of the bid-ask spread (with infeasible estimates set to zero) performs well, achieving a correlation of 0.852 with the average effective cost computed from high-frequency data. The Gibbs estimate, however, does even better, attaining a 0.944 correlation. The price impact coefficient is more difficult to proxy. Here, the winner is a square-root variant of the Amihud (2002) illiquidity measure, for which the relevant correlation is 0.721. The signed reversal measure is yet more difficult, being at best weakly correlated with the unsigned reversal coefficient.

Having established the strong performance of the Gibbs estimate of effective cost in the set of comparison firms, the paper then turns to investigation of this measure in other samples. Analysis of estimates based on the full CRSP daily file indicates that smaller firms on both NYSE/Amex and Nasdaq have effective costs that are on average high (one to two percent) and quite variable. Effective costs for medium and large firms are substantially lower and less variable. Despite the strong performance of the Gibbs estimate as a proxy in the cross-section, however, analysis of the Dow stocks suggests that it does not capture variation in effective cost when this cost is substantially smaller than the daily price volatility.

As an application, the study examines the relation between the liquidity proxies calculated for the CRSP daily file and risk-adjusted returns, suggested by Brennan, Chordia and Subrahmanyam (1998). When risk-adjusted returns are regressed against the proxies individually, both the Gibbs estimate of the effective cost and the illiquidity ratio are positively correlated with BCS risk-adjusted returns. These results, however, are not robust. The relations between liquidity measures and risk-adjusted returns are sensitive to extreme values. Moreover, these relations exhibit marked seasonality, with January values being the highest. This is consistent with Eleswarapu and Reinganum (1993).

The paper is organized as follows. The next section summarizes measures of trading cost based on high-frequency trade and quote data. Section 3 describes the proxies constructed from daily data. Reversal measures, however, are sufficiently distinct to warrant a separate discussion in Section 4. Section 5 describes the construction of the high-frequency/daily comparison sample and the estimation details. The properties and interrelations of these measures are discussed in Section 6. The remaining two sections examine the long-term evidence. Section 8 describes the time-series and cross-section properties of the Gibbs estimates of effective cost in the CRSP daily data file. Section 9 presents the asset-pricing specifications. A brief summary concludes the paper in Section 10.

2. Microstructure-based measures of transaction costs and liquidity

This section discusses measures generally motivated by microstructure models and estimated with high-frequency data. The following describes in turn posted and effective spreads, and impact measures based on dynamic models of prices and trades. Reversal measures are discussed separately in section 4.

a. Spreads: posted and effective

The implementation shortfall approach of Perold (1988) provides a framework for imputation of trading costs. This approach focuses on the difference between the actual portfolio return and the return that would have been achieved had all purchases and sales occurred at hypothetical prices that were free of trading costs. The difference is the cost of implementing the strategy.

For a single executed trade this suggests measuring the cost as the difference between the average transaction price and a hypothetical benchmark price taken prior to the initial trade. One common benchmark is the midpoint of the bid and ask prevailing at the time of the order submission. For a trade executed at the bid or ask, the implied cost is one-half the bid-ask spread. For the spread and related measures, the analysis explores both log and level forms, but with emphasis on the former. The log spread prevailing before the k th trade is $s_k = a_k - b_k$, where a_k

and b_k are the log ask and bid prices. The level spread is $S_k = A_k - B_k$, where B_k and A_k are the bid and ask prices in dollars per share.

In many markets and for a variety of reasons, market orders often transact at prices better or worse than the posted quotes. This motivates use of the log effective cost, defined for the k^{th} trade as

$$c_k = \begin{cases} p_k - m_k, & \text{for a buy order} \\ m_k - p_k, & \text{for a sell order} \end{cases} \quad (1)$$

where p_k is the log trade price and m_k is the log quote midpoint prevailing at the time the order was received. The level effective cost, C_k , is defined analogously. The effective cost is most meaningful for small market orders that can be accommodated in a single trade. It figures prominently in US securities regulation. Under SEC rule 11ac1-5, market centers must periodically report summary statistics of this measure.

Accurate computation of the effective cost requires knowledge of order characteristics, most importantly the arrival time and direction (buy or sell). Studies of order data are common (e.g., Keim and Madhavan (1995), Harris and Hasbrouck (1996), Chan and Lakonishok (1993), and Conrad, Johnson and Wahal (2003)), but none of the samples spans a long history. When order data are unavailable, the effective cost is often estimated from transaction and quote data. A trade priced above the midpoint of the bid and ask (prevailing at the time of the trade report or a brief time earlier) is presumed to be a buy order; a trade priced below the midpoint is presumed to be a sale. Effective costs computed in this fashion are often used in academic studies (see Bessembinder and Kaufman (1997) and Bessembinder (2003)).

b. Measures based on dynamic models

Many economic models imply joint dynamics for orders and price changes that involve both permanent and temporary effects. The former reflect the information content of the order, with Kyle (1985) and Glosten and Milgrom (1985) exemplifying the two main approaches. The latter arise from transient liquidity effects, inventory control behavior, price discreteness, etc. In practical trading situations, the principal advantage of the dynamic models over the single-trade

approaches discussed above lies in their ability to project execution costs when trades are distributed over time.

The literature contains a large number of approaches. The following specification is representative. The evolution of the log quote midpoint is:

$$m_t = m_{t-1} + \lambda Q_t + u_t \quad (2)$$

Here, t indexes five-minute intervals, and Q_t is a measure of the cumulative signed order flow over the interval. Defining q_k as the direction of the k th trade (+1 if buyer-initiated, -1 if seller-initiated, 0 if indeterminate), the measure used here is the sum $Q_t = \sum_{k \in N_t} q_k$ where N_t is the number of trades in the interval. Alternative specifications that involved signed dollar volume and signed square-root dollar volume gave similar results and are not reported. The λ coefficient in Eq. (2) measures the impact of orders on prices.

c. Other measures

Reversal measures quantify the transient effects of order imbalances. While the measures discussed in the present section are based on high-frequency trade and quote data, however, reversal measures are usually implemented with daily price and volume data. It will facilitate the exposition, therefore, to defer discussion of reversal measures until section 4.

Even within the class of high-frequency measures, however, the set described above is, although representative, far from exhaustive. Easley, Hvidkjaer and O'Hara (2002) estimate return specifications in which liquidity is measured by the estimated probability of informed trading, *PIN* (Easley, Kiefer and O'Hara (1997)). Sadka (2004) estimates permanent and transitory trade impact coefficients in a dynamic framework similar to, but more comprehensive than the model given in Eq. (2).

3. Transaction cost and liquidity measures based on daily data

Estimation of the measures discussed in the previous section generally requires intraday quote and trade data. I now turn to measures that can be estimated using daily return and volume data.

a. Moment estimates of the Roll model, c^M and c^{MZ}

Roll (1984) suggested a simple model of the spread in an efficient market. Following the notation used earlier, the model may be stated as:

$$\begin{aligned} m_k &= m_{k-1} + u_k \\ p_k &= m_k + c q_k \end{aligned} \quad (3)$$

The time subscript, k , can be thought of as indexing successive trades. m_k is the log quote midpoint prevailing prior to the trade, p_k is the log trade price, q_k is the direction indicator, and c is the effective cost (cf. Eq. (1)), which is presumed constant. The model may also be specified using levels in lieu of logs for the price variables. It has essentially the same form under time aggregation. In particular, although the model is sometimes estimated with transaction data (e.g., Schultz (2000)), it was originally applied to daily data, with q_t being interpreted as the direction variable for the last trade of the day. The estimation approaches described below take this perspective.

The Roll model is usually estimated by method-of-moments. The model implies

$$\Delta p_t = m_t + c q_t - (m_{t-1} + c q_{t-1}) = c \Delta q_t + u_t, \quad (4)$$

from which it follows that $c = \sqrt{-Cov(\Delta p_t, \Delta p_{t-1})}$. The moment estimate, denoted c^M , is the sample analog of this. It possesses all the usual properties of GMM estimators, including consistency and asymptotic normality. Moment estimation for this model is relatively easy to implement and often satisfactory.

c^M only exists, however, if the first-order sample autocovariance is negative. In samples of daily frequency this is often not the case. In annual samples of daily returns, Roll found positive autocovariances in roughly half the cases. Harris (1990) discusses this and other aspects

of this estimator. His results show that positive autocovariances are more likely for low values of the spread. Accordingly, one simple remedy to the problem is to assign an a priori value of zero.

I define the moment/zero estimate as:

$$c^{MZ} = \begin{cases} \sqrt{-Cov(\Delta p_t, \Delta p_{t-1})}, & \text{if } Cov(\Delta p_t, \Delta p_{t-1}) \leq 0 \\ 0, & \text{otherwise} \end{cases}$$

The corresponding estimates based on a price level model are denoted C^M and C^{MZ} .

Gibbs-sampler estimates of the Roll model, c^{Gibbs} and C^{Gibbs}

Hasbrouck (2004) advocates Bayesian estimation using the Gibbs sampler. To complete the Bayesian specification, I assume here that $u_t \stackrel{d}{\sim} i.i.d. N(0, \sigma_u^2)$ and that the data sample is $p \equiv \{p_1, p_2, \dots, p_T\}$. The prior for c is $c \sim N^+(0, \sigma_c^2, \text{prior})$ where the “+” superscript denotes restriction to the positive domain. The prior for σ_u^2 is inverted gamma distribution, $\sigma_u^2 \stackrel{d}{\sim} IG(\alpha, \beta)$. Numerical values for the prior parameters are discussed in section 5. In the Bayesian approach, the unknowns comprise both the model parameters $\{c, \sigma_u^2\}$ and the latent data, i.e., the trade direction indicators $q \equiv \{q_1, \dots, q_T\}$ and the efficient prices $m \equiv \{m_1, \dots, m_T\}$. The parameter posterior density $f(c, \sigma_u^2 | p)$ is not obtained in closed-form, but is instead characterized by a random sample of draws. These draws are constructed by iteratively drawing from the full conditional distributions. The Gibbs estimate of c , denoted c^{Gibbs} , is the sample mean of the posterior draws. The Gibbs estimate of the level effective cost, denoted C^{Gibbs} , is constructed in a similar fashion.

The Gibbs estimate offers some advantages over the moment estimate. First, the prior can restrict the effective cost estimates to be positive. Second, within the framework of the model, the posterior is an exact small sample distribution. A third advantage stems from the CRSP convention of reporting the midpoint of the closing bid and ask (flagged as a negative value) in lieu of the transaction price if there are no trades on a particular day.

The implications of the CRSP convention differ for the moment and Gibbs estimates. The moment estimate is based on the sample return autocovariance, which is proportional to $\sum_t r_t r_{t-1}$.

The summand here is $r_t r_{t-1} = (p_t - p_{t-1})(p_{t-1} - p_{t-2})$. In principle, since the model applies to trade prices, a term should be included only if it encompasses a sequence of three trade prices. For many stocks, however, this would drastically reduce the sample size. To avoid this attenuation, the present study uses all closing prices in the moment estimates irrespective of whether they represent trades or quote midpoints.

The Gibbs estimate, on the other hand, is easily generalized to accommodate quote midpoints. Specifically, if a quote midpoint is reported on day t , the trade direction indicator is set to zero. From Eq. (3), this implies $p_t = m_t$. Intuitively, this prevents the observation from contributing directly to the estimate of c , but allows one or both of the adjacent prices to contribute (assuming that they have valid transaction prices).¹

This treatment of the Roll model is almost certainly misspecified in a number of important respects. Actual samples of stock returns typically contain many more extreme observations than the normal density plausibly admits. Trade directions are unlikely to be independent of the efficient price evolution. Realized prices are discrete. The effective cost is unlikely to be constant within a sample, etc. Hasbrouck (2004) discusses various extensions to deal with some of these features, but for the sake of computational expediency and programming simplicity, the present paper uses the most basic form of the sampler.

Lest misspecification appear to be a major concern, it must be emphasized that the Gibbs estimate (like all daily proxies considered here) is compared against values constructed independently from high-frequency data. There is accordingly no immediate need to assess the appropriateness of the model assumptions or implementation procedures. If the Gibbs estimates are strongly correlated with the corresponding high-frequency values, these concerns are of secondary importance.

¹ Formally, this procedure can be justified by embedding the Roll model in a more general framework in which observation of a quote midpoint or trade price is determined randomly (and independently of the other variables).

The Gibbs sampler generates random draws from the parameter posterior, thus characterizing the entire distribution. By tabulating, say, the 0.05 and 0.95 quantile points of the distribution, one could in principle establish a confidence band for the estimate. Unlike the mean point estimate, however, the estimated confidence limits cannot easily be validated by comparison to estimates constructed independently.

b. The (Amivest) liquidity ratio, L

The effective cost estimates discussed in the prior two section use only daily price data. The remaining measures use volume data as well. This imposes a practical limitation because the interpretation of reported volume may depend on institutional arrangements. Volume in an order-driven market (such as the NYSE) is not, for example, generally comparable to volume in a quote-driven market (such as Nasdaq).

The Amivest liquidity ratio is the average ratio of volume to absolute return:

$$L = \overline{Vol_d / |r_d|} \quad (5)$$

where the average is taken over all days in the sample for which the ratio is defined, i.e., all days with nonzero returns. It is based on the intuition that in a liquid security, a large trading volume may be realized with small change in price. This measure has been used in the studies of Cooper, Groth et al. (1985), Amihud, Mendelson and Lauterbach (1997), and Berkman and Eleswarapu (1998), among others. Sample distributions of L often exhibit extreme values. Cooper et al and Amihud et al use $\log(L)$ in subsequent analysis. The present study employs the square-root transform in lieu of the log. (Zero values of L can in principle exist.) Furthermore, the transform is applied to the daily ratios, i.e., before averaging. This transformed variant is defined as

$$L^{1/2} = \sqrt{\overline{Vol_d / |r_d|}}. \quad (6)$$

c. The illiquidity ratio, I

Amihud (2002) suggests measuring *illiquidity* as:

$$I = \overline{|r_d| / Vol_d} \quad (7)$$

where r_d is the stock return on day d and Vol_d is the reported dollar volume. The average is computed over all days in the samples for which the ratio is defined, i.e. days with nonzero volume. This measure loosely corresponds to λ in Eq. (2), but whereas λ measures the return impact of a cumulative signed order flow, I captures the absolute return impact of a cumulative unsigned volume. This measure is used as a risk factor by Acharya and Pedersen (2002).

Analogously to the liquidity ratio, the square-root variant is defined as

$$I^{1/2} = \sqrt{|r_d|/Vol_d} . \quad (8)$$

d. Other approaches

The set of daily proxies considered above is representative, but not all inclusive. Lesmond, Ogden and Trzcinka (1999) propose a measure based on the frequency of no-trade intervals. Goyenko, Holden, Lundblad and Trzcinka (2005) discuss an estimate derived from clustering of last sale prices, and suggest that it outperforms the Gibbs estimate at monthly (but not annual) frequencies.

4. Reversal measures

Reversal measures of liquidity summarize the association between return and lagged order flow. The intuition is that order flow induces a price adjustment that initially overshoots, then subsequently reverts to, true value. This might arise, for example, due to inventory adjustments by market makers.

Drawing on this intuition, Pastor and Stambaugh (2003) suggest estimating liquidity by γ in the regression (using present notation):

$$r_t^e = \theta + \varphi r_{t-1} + \gamma \text{sign}(r_{t-1}^e) V_{t-1}^{\text{Dollar}} + \varepsilon_t \quad (9)$$

where r_t^e is the stock's excess return (over the CRSP value-weighted market return). γ is expected to be negative, with magnitude increasing with illiquidity. Pastor and Stambaugh estimate this specification using daily return and volume data.

The logic of this specification is most apparent from a specification suggested by Pastor and Stambaugh that is similar to Eq. (9), but involves signed order flow. In present notation:

$$r_t^e = \phi(X_{t-1} - X_t) + u_t \quad (10)$$

Where r_t^e is the excess return over a market-wide common factor, u_t is a firm-specific component, and X_t is the signed dollar order flow on day t . By comparison with Eq. (9), it is apparent that lagged order flow (X_{t-1}) is being proxied by dollar volume, signed by excess return. Pastor and Stambaugh find that when they simulate data using Eq. (10) and estimate via Eq. (9), ϕ and the γ estimated from Eq. (9) are very highly correlated. The present study investigates the correspondence by estimating Eq. (9) from CRSP data, and estimating Eq. (10) using signed order flow constructed from TAQ data.

5. The comparison sample and estimation

a. Construction of the comparison sample

The comparison sample is a random selection of firm-years for which both TAQ (high frequency) and CRSP (daily) data are available. For each of the eleven years 1993-2003, 250 firms are chosen at random from the CRSP database. To be eligible for selection in a given year, a firm has to satisfy the following criteria:

1. The issue is an ordinary common share (CRSP share code 10, 11 or 12).
2. The issue is present in the CRSP database on the last trading day of the year.
3. There is no change of trading venue, ticker symbol or cusip identifier after August of the year.

The first criterion simply limits the sample to those issues usually considered in asset pricing tests. The remaining criteria are imposed to ensure reasonable homogeneity in a firm's trading characteristics over the year. The selection is made based on information in the CRSP events file. Of the 2,750 firms selected, two were subsequently determined to have no valid return or

price observations for the year, and were dropped from the sample. Of the remaining 2,748 firm-years, 719 were NYSE listings, 344 were Amex, and 1,785 were Nasdaq.

Asset pricing studies sometimes exclude low-priced stocks (e.g., below five dollars). This practice is deliberately avoided in the present study. Casual observation suggests that transaction costs are indeed high for low-price stocks. In investigating the effects of transactions costs, therefore, the observations corresponding to these firms might well be the most informative. Some studies also exclude firms where the value of an estimated statistic is determined to be extreme. There is a sensible rationale for this, in that extreme values often reflect errors or other features of the data that render the observation inappropriate for the model. These filters are not used in the present study because considerable anecdotal evidence (as well as the statistics presented below) suggest that actual transaction costs are highly leptokurtotic. Generally in the present study, estimates are only excluded (in practice, set to ‘missing’) when the estimate is based on a small number of observations, and the presumed estimation error would be high. The discussion now turns to estimation details.

b. Estimation of TAQ-based liquidity measures

Estimates are computed for individual firms using up to a year’s worth of data. The TAQ quote record is filtered to remove quotes with zero bid or ask, offers greater than five times the bid and spreads greater than five dollars. Only quotes from a stock’s primary listing exchange are used, and only quotes posted during regular trading hours. Spreads are first averaged within the day, weighted by the time the spread was in force (i.e., the time to the next quote revision or market close). The daily values are then averaged across all days. These average level and log spreads are denoted S and s , respectively.

The other measures involve transaction as well as quote data. The TAQ transaction record is filtered to remove all trades with nonstandard settlement or corrections. Trades from all venues are retained, not just the primary listing exchange. Trades are signed and effective costs computed using quote midpoints prevailing two seconds prior to the reported trade time. When there are at least 100 trades in a month, effective cost outliers (observations above the 95th

percentile) are removed.² The effective cost observations are averaged over each month, weighted by dollar volume of the trade, and these monthly observations are then averaged over the year. The resulting level and log effective cost estimates are denoted C and c , respectively.

Using quote and signed trade data aggregated over five-minute intervals, Eq. (2) is estimated for each month in which there are at least twenty-five intervals over which the price change is non-zero and the cumulative signed-trades are non-zero. The coefficient estimate used in subsequent analysis is the average of the monthly estimates, and is denoted λ^{5min} . A similar specification is estimated where the data are time-aggregated over days. For this estimation the CRSP daily return is used as the dependent variable, and one estimation is computed using all the days in the year. The coefficient estimate from this regression is denoted λ^{Day} . When there are fewer than fifty days with non-zero returns, the estimate is dropped from subsequent analysis. The reversal coefficient ϕ is estimated in a similar fashion using Eq. (10).

c. Estimation of CRSP-based liquidity measures

The remaining measures are based solely on CRSP price, return and volume data. The moment estimates of effective cost, c^M and c^{MZ} , are estimated using the sample first-order autocovariance (section 3). If this autocovariance is positive, c^M is set to “missing”, and c^{MZ} is set to zero. The level effective cost estimates C^M and C^{MZ} are constructed in a similar fashion.

For the Gibbs estimate, the prior for the effective cost is constructed as a normal distribution truncate to the positive region, denoted $N^+(\mu = 0, \sigma_c^{2, Prior})$. (Note that μ and $\sigma_c^{2, Prior}$ are merely the parameters of the density. Due to the truncation, the actual mean and variance of the distribution are different.) For the effective cost and log effective cost estimates, $\sigma_c^{2, Prior}$ and $\sigma_C^{2, Prior}$ are both set to unity. In case of the log effective cost, a value of $c=1$ for a US equity would be extremely, arguably implausibly, high. So the unit interval (0, 1)

² The only results in the paper that are sensitive to this trimming are those that deal with daily estimates of effective cost for the Dow stocks (Section 8.a). Failure to remove extreme values in this case results in elevated variability of the daily effective cost graph in Figure 1.)

would be expected to contain all actual values. Within this region, the normal density does not exhibit extreme variation. These remarks also apply, although to a lesser degree, for the level effective cost, C .

Although this prior is fairly broad, it is not completely uninformative. This is deliberate and necessary. In the Gibbs sampler, simulation of the posterior for c requires estimation via regression of Eq. (4). This estimation is conditional on simulated values of q . In the process, there is a possibility that at a particular draw all of the q_t are either -1 or $+1$. In this case, all of right-hand-side variables in the regression (the Δq_t) are zero. The estimated regression coefficient is therefore undefined, and the new value of c must be drawn from the prior.

The Gibbs sampler is initialized by setting the trade direction indicators to the sign of the most recent price change (except for prices reported as quote midpoints). Next, 1,000 sweeps of the sampler are computed. The first 200 draws are discarded (as a burn-in period, to minimize start-up effects). Parameter estimates are determined as the mean of the final 800 draws. The number of sweeps was chosen to achieve a manageable computation time. One thousand draws would not be considered sufficient in many applications, but experimentation with more draws did not materially change the estimates.

The liquidity coefficient L and its square-root variant $L^{1/2}$ are estimated using Eqs. (5) and (6). The illiquidity coefficients I and $I^{1/2}$ are estimated using Eqs. (7) and (8). The reversal coefficient γ is estimated from Eq. (9).

As noted above, although censoring of extreme values per se is not consistent with the aims of the paper, estimates are dropped when they are based on few observations. Specifically, moment estimates of the effective cost and log effective cost require at least fifty price observations. In the development of the λ_i^{5min} estimate, each monthly estimate going into the overall average is computed subject to a minimum of twenty-five five-minute intervals over which the price change is non-zero and the cumulative signed-trades are non-zero. L and $L^{1/2}$ estimates require at least fifty days where the return (the denominator in (5) or (6)) is nonzero. Similarly, I and $I^{1/2}$ estimates require at least fifty days where the volume (the denominator in

(7) or (8)) is nonzero. The γ estimate requires at least fifty observations. For the Gibbs estimates, there must be at least fifty days on which there was a trade.

6. Analysis of the comparison sample.

a. The TAQ measures

Table 1 reports summary statistics for the total comparison sample. It will be useful to first discuss the mean estimates for all variables, and then turn to estimates of the higher-order moments.

The mean posted log spread is 0.0381 (approximately 4%), or in levels, \$0.277 per share. The corresponding log and level effective costs are 0.0141 and \$0.101. These are somewhat smaller than one-half the corresponding spread, the value that would result if all trades occurred at posted quotes. The magnitude of the mean price impact coefficient, λ^{5min} , implies that a buy order causes an increase of 0.0017 in the log quote midpoint (approximately 17 basis points). The corresponding estimate based on data aggregated over one day, λ^{Day} , is somewhat higher, 0.0024. The daily reversal coefficient ϕ is negative.

The sample distributions of all the TAQ measures exhibit many extreme values. Excess kurtosis (relative to the normal distribution) are notably high. Skewness coefficients generally indicate distributions skewed to the right.

Can these extreme values be considered spurious? While it is not practical to verify each observation, casual evidence and the sentiments of practitioners suggest that for some stocks, trading costs are indeed high. By way of example, the highest average posted spread in this sample is associated with First State Corp. (ticker FSBT) in November, 1996. In the CQ file for that month, there are numerous days when the stock is 22 bid/offered at 26 for the entire day, a spread of four dollars. Effective costs, while lower than half this value, are nevertheless still quite high. As an example, late in the day on November 13, 1996, the market was 23.50 bid/offered at 26, and a trade occurred at a price of 24.75 (an effective cost of one dollar per share).

b. CRSP measures

The remaining variables are based on daily CRSP data. The moment estimate of the log effective cost, c^M , is feasible for only 1,938 of the 2,748 firms (roughly two-thirds). The mean value of 0.0193 is substantially higher than the mean TAQ estimate (c , 0.0141). This suggests that most of the infeasible observations correspond to relatively low values. Consistent with this, the variant of the moment estimate in which infeasible values are set to zero, c^{MZ} , has a mean of 0.0137, which is quite close to the TAQ estimate. Moment estimates for the level effective cost, C^M and C^{MZ} , are similar. The Gibbs estimates of level and log effective cost (C^{Gibbs} and c^{Gibbs}) also have means and medians close to the corresponding estimates based on TAQ data.

The liquidity and illiquidity measures, L and I , exhibit remarkably high skewness and kurtosis. These in turn are likely to arise from extreme values in the underlying return and volume data. Gabaix, Gopikrishnan, Plerou and Stanley (2003) find that distribution tails for volumes and returns follow power laws with exponents $3/2$ and 3 respectively, implying that volume moments of order greater than $3/2$ and return moments of order greater than 3 are not finite. This does not imply that expected values for I and L are infinite, but it does suggest that estimates are likely to be dominated by extreme values. The liquidity ratio implicitly uses volume in the numerator, and might therefore be expected to be particularly ill-behaved. The variants $I^{1/2}$ and $L^{1/2}$ have lower, though still elevated, kurtosis.

The average γ estimate is not negative in this sample, contrary to expectation, but the kurtosis is extreme. A least-squares estimate, γ is essentially a ratio involving products and cross-products of returns and volume. For the same reasons discussed in connection with I and L , the estimate is likely to be dominated by extreme values.

The table also summarizes estimates of the standard deviation of price changes $\sigma_{\Delta P}$ and that of log price changes $\sigma_{\Delta p}$. The latter approximates the standard deviation of returns, but does not reflect dividends. The $\sigma_{\Delta p}$ estimates are generally higher than the Gibbs estimates of the random-walk variance $\sigma_{u,Log}^{Gibbs}$. The former impound bid-ask bounce, while the latter in principle do not.

7. Correlations

Within the set of liquidity measures, there are two important groups of correlations. The TAQ-based liquidity measures reflect the spread, price impact and reversal attributes of the market. The correlations within this set indicate the overlap, the extent to which one measure might (ideally) capture variation in the others. The other important correlations are those between the TAQ-based measures and their CRSP-based counterparts. These will indicate the validity of the latter as proxies for the former.

In all cases, four sorts of correlations are considered. In addition to the usual Pearson correlations, Spearman (rank-order) correlations are reported. These assess nonlinear monotonic associations. They are more robust to outliers than Pearson correlations, an important consideration given the high kurtosis of the measures. In addition, however, there are situations in which an economic model might suggest the direction, but not the linearity, of a liquidity effect.

The study also considers (for both Pearson and Spearman) correlations, the partial correlations, where the set of conditioning variables consists of log market capitalization, the standard deviation of price changes, the standard deviation of log price changes, and the average price. These variables are certainly associated with trading costs, yet in many situations will have alternative roles or proxy for other effects. The partial correlations measure a relation when the explanatory power of these variables has been removed.

a. Correlations involving the TAQ-based measures

Table 2 reports the correlations for a representative set of TAQ-based measures. The correlations between the log spread and the log effective cost are all over 0.9. This strong association is consistent with the results of most other studies. Correlations involving the level

spread and level effective cost (not reported) are very similar.³ The correlation between effective cost and log effective cost is only 0.158. The principal difference between these measures is the price level, but the partial Pearson correlation is also low (0.199). The Spearman correlations are somewhat higher.

The model used to define the price impact coefficients, Eq. (2), is in principle invariant to time aggregation: $\lambda^{5\ min}$ and λ^{day} should be equal (in the population, but not necessarily in sample estimates). Since daily estimations are somewhat easier to program, it is useful to consider whether the day estimate can reliably proxy for the five-minute estimate. The correlations are indeed positive, but weaker than one might hope, ranging from 0.477 (Spearman partial) to 0.771 (Spearman).

The reversal coefficient ϕ estimated from signed data is negatively correlated with the daily price impact coefficient λ^{day} . This is in principle reasonable, since ϕ is positively and λ^{day} negatively related to liquidity. It might further suggest that reversal and impact attributes of liquidity are essentially similar. The relation can more directly be explained, however, by noting that if the dominant effect is contemporaneous, then $(X_{t-1} - X_t)$ in (10) might be serving in part as a noisy proxy for $-X_t$. Alternative specifications suggest that this is likely. In regressions of the form $r_t^e = \lambda X_t + \phi(X_{t-1} - X_t) + u_t$, the λ coefficients tend to dominate the ϕ s.

The study also considers correlations involving the probability of informed trading (PIN, Easley, Hvidkjaer, and O'Hara (2002)) and permanent/transitory impact coefficients (Sadka (2004)). The samples considered in these studies are smaller than the present sample. Both studies examine only NYSE/Amex stocks, and they impose somewhat more demanding data

³ Numerous asset pricing studies, rely on closing (end-of-day) NYSE spreads (Stoll and Whalley (1983), Amihud and Mendelson (1986), Amihud and Mendelson (1989), Eleswarapu and Reinganum (1993), Kadlec and McConnell (1994), and Eleswarapu (1997), among others). The correlation between end-of-day spread and time-weighted spread for the NYSE firms in the comparison sample is 0.925.

requirements on the individual firms. The correlations between these alternative measures (kindly supplied by the authors) and the present set may be summarized as follows. Sadka's transitory impact measure is strongly positively correlated with the effective cost; the permanent impact measure is modestly positively correlated with the present impact estimate. *PIN* is modestly correlated with both the effective cost and impact coefficient. The correlations are large enough to suggest a measure of commonality, but not so large as to establish that any measure is redundant.

b. Proxy relationships for effective cost and log effective cost

The next sets of results are the crux of the analysis, addressing the question of how well high-frequency measures can be proxied using daily data. The daily proxies for log and level effective costs are the moment and Gibbs estimates. Since the basic moment estimates c^M and C^M are infeasible for about a third of the sample, the estimates used in assessing the correlations are those for which infeasible values are set to zero (c^{MZ} and C^{MZ}). The correlations are reported in Table 3.

In comparing the proxy validity of the moment and Gibbs estimates, there is a clear winner. While both are at least moderately positively correlated with the corresponding TAQ measures, the correlations for the Gibbs estimates are uniformly higher. The CRSP estimate c^{Gibbs} has a Pearson correlation of 0.944 with the TAQ measure c ; the moment estimate c^{MZ} achieves a correlation of 0.852. The difference between them is even larger for Spearman and partial correlations. The correlations involving the level effective cost are slightly lower, but the Gibbs estimate is still clearly dominant.

These results suggest that the Gibbs estimates are very attractive proxies for log and level effective cost, retaining substantial validity even when controlling for variation in capitalization, standard deviation and price level.

c. Proxy relations for price impact and reversal measures

Table 4 reports correlations that assess the validity of the daily proxies (L , $L^{1/2}$, I , $I^{1/2}$, and γ) for the TAQ-based five-minute impact coefficient $\lambda^{5\ min}$ and the reversal measure ϕ . For $\lambda^{5\ min}$ the results can be summarized as follows. First, the illiquidity measures dominate the liquidity measures. One would expect $\lambda^{5\ min}$ to be positively correlated with I and $I^{1/2}$, and negatively correlated with L and $L^{1/2}$. This is generally the case, but the Pearson partial correlations for L and $L^{1/2}$ are positive. Furthermore, the correlations involving I and $I^{1/2}$ generally have higher magnitudes. The second important feature of the table is that the square-root variants dominate the original measures. There is not much difference in the Spearman and Spearman partial correlations. These reflect rankings, and the square-root transformation does not greatly affect the orderings. The Pearson correlations, however, are stronger.

The correlation patterns involving the reversal measures, however, are less clear. The CRSP-based estimate γ is weakly and inconsistently correlated with the TAQ-based estimate ϕ . ϕ is, on the other hand, moderately negatively correlated with the illiquidity measures.

d. Summary of the proxy results

This phase of the analysis has established several important results. The Gibbs estimate of effective cost is an excellent proxy for the high-frequency measure. The moment estimate (which may be easier to implement) is less powerful, but still may be adequate in many situations. The correlation between the impact coefficient and the illiquidity measure is moderately positive, but the best performance is achieved when square-root of the return/volume ratio is averaged. The liquidity ratio, on the other hand, is a poor proxy. On a stock-by-stock basis, reversal measures are problematic.

8. The Gibbs estimates: further results and discussion

The analysis in the last section strongly supports the general use of the Gibbs sampler as a proxy for effective cost in the comparison sample, a random cross section of firms, 1993-2003.

The present section explores the properties of this estimate in two other samples: the Dow stocks in 1993-2003, and the full CRSP daily database, 1962 to the present. The Dow application is important because it graphically demonstrates the limitations and shortcomings of the estimate. The long-term sample is interesting for historical purposes, and as background for the return estimations to follow.

a. The Dow stocks, 1993-2003

The period beginning in 1993 is an era of profound change in the trading mechanisms for US stocks. There were important trends, such as increased fragmentation and automation. There were also important discrete events, notably the decrease in the tick size from one-eighth to one-sixteenth, the subsequent decrease to one penny, and (in the case of Nasdaq stocks) the order handling rules. These events induced dramatic and visible changes in effective costs (see Bessembinder (1999), Jones and Lipson (2001), Bessembinder (2003), Werner (2003), Chung, Van Ness and Van Ness (1999), Chakravarty, Wood and Van Ness (2004)). The present section investigates the ability of the Gibbs estimate to track these shifts in the Dow stocks (see in particular Jones and Lipson (2001)). The analysis covers the NYSE stocks continuously included in the Dow-Jones index from 1993 to 2003. Survivorship effects are not important for present purposes.

Figure 1 plots the average daily effective cost over the sample (dollar-volume-weighted for each firm, but equally-weighted across firms) estimated from TAQ data. The salient and familiar features are the sharp drops occurring at the tick-size regime shifts. The figure also depicts the average of the Gibbs estimates of the effective cost based on CRSP data. (Computation of these estimates was essentially similar to the procedure used for the comparison sample, except that I introduced sample breaks at the tick regime shifts.)

The Gibbs estimate performs poorly in this sample. The overall level of the estimate is substantially higher than the TAQ-based effective cost. More disturbingly, it increases substantially after the first tick-size reduction, while the TAQ-based estimate drops. The evidence cannot be explained as an artifact induced by one or two firms. While some firms are

“better behaved” than others, the graph is a fair and reasonable summary of the Gibbs estimate’s dismal performance.

How can this be reconciled with the very encouraging results of the correlation analysis discussed earlier? One conjecture might be that there is something about the Gibbs estimate that critically depends on a relatively large tick size. The strong correlations reported in the last section do not, however, deteriorate subsequent to the tick reductions. Computed separately for each of the years 2000 to 2003, the Pearson correlations $Corr(c, c^{Gibbs})$ are 0.864, 0.914, 0.843 and 0.932. These are only slightly lower than the overall correlation in the comparison sample (0.944).

A more plausible explanation involves the relative size of the effective cost and the standard deviation of the efficient price. Simulations suggest that the Gibbs sampler “allocates” price changes (cf. Eq. (4)) between u_t and $c\Delta q_t$ in a fashion similar to what one might attempt intuitively and visually from a price plot. That is, $c\Delta q_t$ components are identified by excessive reversals or spikes. When c is small relative to σ_u , however, it is difficult to differentiate the contribution of the efficient price change and the contribution of transactions costs. From Table 1, between the fifth and ninety-fifth percentiles, the log effective cost goes from 0.0011 to 0.0467, approximately a forty-fold increase. The standard deviation of log price changes, however, only goes from 0.014 to 0.095, roughly a seven-fold increase. Volatility does not increase commensurately with effective cost. As a result, there are many firms in the sample (high-cost firms, in particular) for which the Gibbs estimate is relatively accurate. This finding is nevertheless sobering because it suggests that the Gibbs estimate measures effective costs only when they are large.

A related issue arises in the analysis of effective costs by listing exchange. For Nasdaq, Amex and the NYSE, the respective Pearson proxy correlations $Corr(c, c^{Gibbs})$ are 0.947, 0.911, and 0.705. Relative to the other exchanges, the NYSE has low average effective costs and lower overall sample variation. Even in the NYSE sample, however, the Gibbs estimate performs

markedly better than that moment estimate, for which the corresponding correlation is only 0.409.

b. Broader sample

In view of the strong performance of the Gibbs effective cost estimates in the comparison sample, it is interesting to consider the properties of these estimates over the full historical sample (beginning in 1963) for which daily CRSP data are available. To this end, annual estimates of the daily-based trading cost estimates and proxies were computed for all firms in the daily CRSP file.

Nasdaq closing prices are not extensively reported on the CRSP database until the middle of 1982 (with Nasdaq's introduction of the National Market System). Due to relatively small numbers of stocks, however, the Nasdaq estimates developed in this paper are only reported beginning in 1985. The CRSP Nasdaq sample also changed markedly in 1992 with the inclusion of the Nasdaq SmallCap market.

Figure 1 plots the annual average c^{Gibbs} values for exchange and market capitalization subsamples. As in Fama and French (1992), NYSE/Amex breakpoints are also used for Nasdaq sample.

The NYSE/Amex estimates provide a more complete picture of the long-run time-series variation. Although the series appears roughly stationary, there is substantial volatility, with the largest peak occurring around 1975. In 1975, commission levels dropped following the SEC's deregulation. It is possible that liquidity suppliers increased posted and effective spreads to compensate for decreased commission revenue. Another possible explanation is short-run stickiness in absolute dollar spreads. Most market indices dropped over 1974. At the new lower price levels, relative spreads would be higher.

For both NYSE/Amex and Nasdaq firms, time variation in effective costs is concentrated in the lowest-capitalization subsample. This is particularly true for the Nasdaq lowest-capitalization firms, for which average effective cost goes from around one percent in the early 1980's to roughly four percent in the early 1990's. This may in part reflect the changes in

composition of the Nasdaq population. Smaller, but still quite noticeable variation in effective cost occurs in the other Nasdaq capitalization quartiles. The NYSE/Amex firms in the lowest capitalization subsample have effective costs that vary approximately between 0.5% and 1.5%. There has been no dramatic change in effective costs for the higher capitalization quartiles, but (recalling the Dow results) the accuracy of the Gibbs estimate is apt to be poorer in these groups.

9. Liquidity and stock returns

This section examines the relation between expected returns and liquidity, viewed as a characteristic and proxied by one or more of the daily-based measures c^{Gibbs} , $I^{1/2}$, and γ . In light of the results of section 7, both c^{Gibbs} and $I^{1/2}$ are the best proxies for effective cost and trade impacts, while γ is the only CRSP-based reversal measure considered. In studies that focus on a single liquidity proxy, asset pricing tests usually follow the Fama and MacBeth (1973) approach. This requires the formation of portfolios based on size (or beta) and the liquidity proxy. Since the present study aims at an impartial evaluation of a set of proxies, however, approaches that require portfolio construction are undesirable. As an alternative, I follow the approach of Brennan, Chordia et al. (1998) (BCS).

The BCS procedure is based on an approximate factor model in which the return on the j th security is given by:

$$R_{jt} = ER_j + \beta_j f_t + e_{jt}, \quad (11)$$

where f_t is a vector of factor realizations at time t , and β_j contains the factor loadings for security j . The APT implies $ER_j - R_F = \beta_j \lambda$, where λ is the vector of factor risk premia, and that realized returns satisfy:

$$R_{jt} - R_{Ft} = \beta_j F_t + e_{jt} \quad (12)$$

where $F_t = \lambda + f_t$. The key question is the extent to which the security characteristics can explain the residual in Eq. (12). To implement the test, estimates of the factor loadings, denoted $\hat{\beta}_j$, are computed using data prior to time t . The implied risk-adjusted returns are then computed as

$$R_{jt}^* = R_{jt} - (R_{Ft} + \hat{\beta}_j F_t) \quad (13)$$

In the original BCS procedure, the risk-adjusted returns are regressed against the characteristics. Denote by Z_{jt} a vector of predetermined characteristics for security j . At each t , the risk-adjusted returns are then regressed against this set:

$$R_{jt}^* = d_t Z_{jt} + \tilde{\epsilon}_{jt} \quad (14)$$

Let \hat{d}_t denote the OLS estimate of d_t . BCS suggest two approaches to summarizing the time series of these estimates. The raw overall estimate, denoted \hat{d}_{raw} , is simply the average.

Alternatively, to eliminate possible biases arising from estimation errors in the factor loadings $\hat{\beta}_j$, BCS propose a purged estimator, denoted \hat{d}_{purged} . An element of this vector $\hat{d}_{purged,k}$ is computed as the intercept in a time series regression of \hat{d}_{kt} on the factor realizations F_t . Both raw and purged estimates are computed in the present analysis. As an additional robustness check, however, I also compute the various types of correlations between risk-adjusted returns and the liquidity proxies.

The full set of characteristics includes the liquidity proxies (c^{Gibbs} , $I^{1/2}$, and γ) and other variables suggested by BCS: the log market capitalization, $logMktCap$; the lagged return for the stock over the second and third prior month, $r23$; the return over lagged months four through six, $r46$; and the return over lagged months seven through twelve, $r712$.

Table 5 reports the raw coefficient estimates based on Eq. (14). The purged coefficient estimates are similar and are not reported. Specifications (1)-(3) incorporate one liquidity proxy at a time. In the estimates for the NYSE/Amex sample, the c^{Gibbs} and $I^{1/2}$ coefficients have the anticipated sign and significance in the specifications where they are included one at a time. In the Nasdaq sample, this is only the case for c^{Gibbs} . These findings suggest that c^{Gibbs} is the best single proxy. In specification (4), however, which includes all proxies, the picture is less clear, as there is no clear winner.

Relative to the others, the c^{Gibbs} measure possesses the virtue of an economically interpretable magnitude. This enables us to address the reasonableness of the coefficient. In the NYSE/Amex sample, the coefficient of c^{Gibbs} is approximately 0.3. This implies that a stock with an average effective cost of one percent would have a monthly expected liquidity premium of 30

basis points (3.6% on an annual basis). This might seem high, but a one percent effective cost is well above average in this sample. suggests that this level is exceeded (on average) only in the lowest market capitalization quartile, and here only a small portion of the time. It should also be noted that the effective cost is generally a fraction of the posted bid-ask spread.

In the Nasdaq sample, the coefficient of c^{Gibbs} is approximately 0.2. Although this point estimate is lower than the NYSE/Amex value, Nasdaq effective costs are much higher. Figure 2 suggests that an effective cost of two percent would not be extreme in the lowest Nasdaq quartile (and this is using NYSE breakpoints). A two percent effective cost would imply a monthly liquidity premium of forty basis points.

Alternative tests, however, cast doubt on the robustness of these findings. For the same reasons discussed in connection with the investigation of the liquidity proxies, it is useful to consider various sorts of correlations (Pearson, Spearman, partial) between risk-adjusted returns and the proxies. Analogously to the raw coefficient estimates, a correlation between risk-adjusted returns and a proxy is estimated across firms for each t . Inference is based on the average of these correlations across time.

Table 6 reports the time-series average correlations and their associated t-statistics. The pattern of Pearson correlations is similar to that suggested by the regression estimates, i.e., generally positive correlations between the risk-adjusted returns and the liquidity proxies. The Spearman correlations, however, are negative. The change of sign suggests that the positive Pearson correlations arise from outliers. The table also reports partial correlations, in which control for the other variables in the regression ($\log MktCap$, $r23$, $r46$, and $r712$). These are of varying sign and significance.

Previous research also suggests an interaction between seasonality and estimated liquidity effects. To assess this, Table 7 reports average correlations separately for January and non-January months. The patterns are striking. For correlations involving c^{Gibbs} , the January correlations are all positive and generally significant, while the non-January correlations are uniformly negative and generally significant. For correlations involving $I^{1/2}$ or γ , the signs are

mixed for both January and non-January correlations. This is similar to the results obtained by Eleswarapu and Reinganum (1993), with a different sample and liquidity measure. The reasons for the seasonality are unclear, and warrant further investigation.

10. Conclusion

Datasets of daily security prices generally begin much earlier than those of intraday frequency. The CRSP database of daily US stock prices, for example, begins in 1962, while the corresponding high-frequency data are only available from 1983 (the start of the ISSM). This motivates the construction of measures of liquidity based on daily observations that are good proxies for liquidity estimates conventionally estimated from more detailed data. Accordingly, this study evaluates high-frequency measures of liquidity and their proxies constructed from daily data. The analysis is performed in a comparison sample, consisting of 250 randomly-chosen firms in each of the years 1993-2003, for which both high-frequency (TAQ) and daily (CRSP) data exist.

There exists no single comprehensive measure of liquidity. The microstructure measures constructed here include posted spreads, effective costs, and measures based on dynamic models of prices and signed trades. All estimates exhibit extreme values. While it is impossible to rule out the possibility that some of these are spurious, it is also likely that trading costs for some companies are truly very high.

Posted spreads (both intraday and closing) and average effective costs are relatively easy to estimate and interpret. They are also highly correlated. The measures derived from dynamic trade and price models, while arguably more comprehensive, are more difficult to estimate and interpret. The correlations within this set suggest modest concordance at best. Reversal measures, which summarize the effect of lagged order flow on future expected returns, appear to be the least correlated with the other measures.

It is quite feasible to estimate effective costs from daily return data. Gibbs estimates of the Roll model, using roughly a year's worth of data, are highly correlated with log effective costs. The usual moment estimates of the Roll model are not as highly correlated, but may

nevertheless be adequate in some situations. High-frequency dynamic price impact measures of liquidity are more difficult to proxy, but a variant of the Amihud (2002) illiquidity measure appears moderately correlated. Reversal measures are still more problematic.

When the daily liquidity proxies are introduced into asset pricing tests modeled on Brennan, Chordia et al. (1998), both the Gibbs estimate of effective cost and the illiquidity ratio are positively correlated with risk-adjusted returns in the NYSE/Amex sample. In the Nasdaq sample, only the Gibbs estimate is positively correlated. Although these results provide modest support for the hypothesis that trading cost is a priced characteristic, they are not robust. With alternative correlation measures, the relation between returns and liquidity varies considerably in significance and direction. Moreover, the relation is markedly seasonal for both NYSE/Amex and Nasdaq firms, with the strongest effect arising in January.

There are a number of promising directions for future research. First, since the Gibbs estimate of the effective cost relies solely on the transaction price record, the technique can readily be applied to historical and international settings where only trade prices are available. The present application is to daily data, but there is in principle no reason why the approach would not be useful in weekly or monthly data. Of course, as the frequency drops, drift and diffusion in the efficient price become more pronounced relative to the effective cost, and hence the signal-to-noise ratio is likely to be lower.

A second line of inquiry is refinement of the Gibbs estimation procedure. It seems particularly worthwhile to consider estimation of c jointly with β . The estimates of c should be improved because the market return is a useful signal in estimating the change in the efficient price, which is here taken as unconditionally normal. The estimate of β should also be improved, however, because the specification essentially purges the price change of bid-ask bounce in the firm's return.

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Table 1. Summary statistics for comparison sample

The comparison sample is a set of firms randomly drawn from the combined CRSP/TAQ population. In each of the years 1993-2003, 250 firms were drawn. For each firm, the variables in the table are estimated based on (approximately) one year's worth of data. Table values are calculated across firms. S and s are the time-weighted average level and log of the posted bid-ask spread. C and c are the dollar-volume-weighted average level and log effective cost; $\lambda^{5\ min}$ is the signed trade impact coefficient estimated over five-minute intervals; λ^{Day} is the signed trade impact coefficient estimated over day intervals; ϕ is the daily signed reversal coefficient; C^M and c^M are the moment estimates of the level and log effective cost, with infeasible values set to 'missing'; C^{MZ} and c^{MZ} are the moment estimates of the level and log effective cost, with infeasible values set to zero; I is the illiquidity ratio; $I^{1/2}$ is the square-root illiquidity ratio; L is the liquidity ratio; $L^{1/2}$ is the square-root liquidity ratio; γ is the Pastor-Stambaugh reversal coefficient; $MktCap$ is the end-of-year equity market capitalization (\$ million); $\log MktCap = \log(MktCap)$; $Price$ is the end-of-year share price; $\sigma_{\Delta p}$ is the standard deviation of daily log price changes; $\sigma_{\Delta P}$ is the standard deviation of daily level price changes.

		N	Mean	Median	5 th %'ile	95 th %'ile	Skewness	Kurtosis
TAQ-based measures	s	2,718	0.0381	0.0228	0.0025	0.1231	5.1	59.4
	c	2,703	0.0141	0.0088	0.0011	0.0467	3.4	23.3
	S	2,718	\$0.277	\$0.187	\$0.044	\$0.740	4.3	28.1
	C	2,703	\$0.101	\$0.073	\$0.022	\$0.242	6.5	72.2
	$\lambda^{5\ min}$	2,388	0.001664	0.000893	0.000091	0.005813	5.6	56.7
	λ^{Day}	2,677	0.002388	0.000896	0.000018	0.009126	6.2	58.9
	$\phi \times 10^6$	2,677	-0.235951	-0.012369	-1.090235	-0.000013	-10.0	138.1
CRSP-based measures	c^M	1,938	0.0193	0.0144	0.0028	0.0521	3.3	21.7
	c^{MZ}	2,742	0.0137	0.0086	0.0000	0.0448	3.2	20.8
	C^M	1,886	\$0.145	\$0.108	\$0.022	\$0.373	5.0	47.7
	C^{MZ}	2,742	\$0.100	\$0.063	\$0.000	\$0.319	4.7	46.5
	c^{Gibbs}	2,724	0.015	0.009	0.002	0.048	3.6	24.6
	$\sigma_{u,Log}^{Gibbs}$	2,724	0.038	0.032	0.012	0.084	1.9	7.4
	C^{Gibbs}	2,724	\$0.119	\$0.089	\$0.024	\$0.293	3.9	25.7
	$\sigma_{u,Level}^{Gibbs}$	2,724	\$0.464	\$0.317	\$0.073	\$1.290	5.5	53.2
	I	2,727	7.3645	0.1864	0.0008	31.0932	33.0	1,389.5
	$I^{1/2}$	2,727	0.8405	0.3107	0.0255	3.5113	5.2	52.0
	L	2,736	4,412.1	26.3	0.3	3,964.9	49.2	2,507.7
	$L^{1/2}$	2,736	11.6	4.1	0.3	49.3	4.0	22.0
	$\gamma \times 10^6$	2,742	15.256	0.202	-30.748	155.111	-24.5	1,012.3
	$MktCap$	2,748	\$1,193	\$117	\$5	\$4,779	11.9	199.7
	$\log MktCap$	2,748	4.8882	4.7594	1.6861	8.4719	0.2	-0.3
	$Price$	2,748	\$16.61	\$11.26	\$0.78	\$49.88	3.8	33.3
$\sigma_{\Delta p}$	2,747	0.0434	0.0365	0.0141	0.0946	2.1	9.0	
$\sigma_{\Delta P}$	2,747	\$0.497	\$0.362	\$0.091	\$1.314	5.4	52.3	

Table 2. Correlations between TAQ estimates in the comparison sample

The comparison sample is a set of firms randomly drawn from the combined CRSP/TAQ population. In each of the years 1993-2003, 250 firms were drawn. For each firm, the variables in the table are estimated based on (approximately) one year's worth of data. s is the log spread; c , the log effective cost; C , the level effective cost; $\lambda^{5\ min}$ is the signed trade impact coefficient estimated over five-minute intervals; λ^{Day} is the signed trade impact coefficient estimated over day intervals; ϕ is the daily signed reversal coefficient. Partial correlations control for share price, log market capitalization, the standard deviation of price changes and the standard deviation of log price changes.

		s	c	C	$\lambda^{5\ Min}$	λ^{Day}	ϕ
Pearson	s	1.000	0.981	0.184	0.556	0.762	-0.632
	c	0.981	1.000	0.158	0.580	0.753	-0.639
	C	0.184	0.158	1.000	0.030	0.179	0.021
	$\lambda^{5\ Min}$	0.556	0.580	0.030	1.000	0.740	-0.675
	λ^{Day}	0.762	0.753	0.179	0.740	1.000	-0.744
	ϕ	-0.632	-0.639	0.021	-0.675	-0.744	1.000
	s	1.000	0.987	0.367	0.636	0.823	-0.733
Spearman	c	0.987	1.000	0.322	0.656	0.821	-0.753
	C	0.367	0.322	1.000	0.178	0.384	-0.088
	$\lambda^{5\ Min}$	0.636	0.656	0.178	1.000	0.771	-0.623
	λ^{Day}	0.823	0.821	0.384	0.771	1.000	-0.751
	ϕ	-0.733	-0.753	-0.088	-0.623	-0.751	1.000
	s	1.000	0.927	0.204	0.196	0.459	-0.298
Pearson partial	c	0.927	1.000	0.199	0.246	0.465	-0.294
	C	0.204	0.199	1.000	-0.020	0.096	0.040
	$\lambda^{5\ Min}$	0.196	0.246	-0.020	1.000	0.596	-0.570
	λ^{Day}	0.459	0.465	0.096	0.596	1.000	-0.609
	ϕ	-0.298	-0.294	0.040	-0.570	-0.609	1.000
	s	1.000	0.936	0.657	0.063	0.350	-0.045
Spearman partial	c	0.936	1.000	0.677	0.121	0.371	-0.066
	C	0.657	0.677	1.000	0.112	0.330	-0.010
	$\lambda^{5\ Min}$	0.063	0.121	0.112	1.000	0.477	-0.212
	λ^{Day}	0.350	0.371	0.330	0.477	1.000	-0.325
	ϕ	-0.045	-0.066	-0.010	-0.212	-0.325	1.000

Table 3. Proxies for log and level effective cost in the comparison sample

The comparison sample is a set of firms randomly drawn from the combined CRSP/TAQ population. In each of the years 1993-2003, 250 firms were drawn. For each firm, the variables in the table are estimated based on (approximately) one year's worth of data. C and c are the level and log effective costs (estimated from TAQ data). C^{MZ} and c^{MZ} are the moment estimates where infeasible values are set to zero (estimated from CRSP data). C^{Gibbs} and c^{Gibbs} are the Gibbs estimates (based on CRSP data). Partial correlations control for share price, log market capitalization, the standard deviation of price changes and the standard deviation of log price changes.

		c^{MZ}	c^{Gibbs}	C^{MZ}	C^{Gibbs}
Pearson	c	0.852	0.944	0.037	0.029
	C	0.085	0.122	0.578	0.748
Spearman	c	0.724	0.883	0.192	-0.048
	C	0.162	0.227	0.383	0.660
Pearson partial	c	0.602	0.848	0.210	0.353
	C	0.232	0.261	0.484	0.683
Spearman partial	c	0.357	0.579	0.312	0.461
	C	0.196	0.426	0.242	0.521

Table 4. Proxy correlations for price impact and reversal measures

The comparison sample is a set of firms randomly drawn from the combined CRSP/TAQ population. In each of the years 1993-2003, 250 firms were drawn. For each firm, the variables in the table are estimated based on (approximately) one year's worth of data. λ^{5min} is the signed trade impact coefficient estimated over five-minute intervals (based on TAQ data); ϕ is the signed reversal coefficient (based on TAQ data); I is the illiquidity ratio; $I^{1/2}$ is the square-root illiquidity ratio; L is the liquidity ratio; $L^{1/2}$ is the square-root liquidity ratio; γ is the Pastor-Stambaugh reversal coefficient. Partial correlations control for share price, log market capitalization, the standard deviation of price changes and the standard deviation of log price changes.

		I	$I^{1/2}$	L	$L^{1/2}$	γ
Pearson	λ^{5Min}	0.537	0.721	-0.038	-0.296	0.181
	ϕ	-0.615	-0.764	0.017	0.138	-0.225
Spearman	λ^{5Min}	0.762	0.771	-0.765	-0.774	0.186
	ϕ	-0.786	-0.800	0.814	0.811	-0.278
Pearson partial	λ^{5Min}	0.396	0.557	0.002	0.097	0.070
	ϕ	-0.510	-0.628	-0.007	-0.109	-0.091
Spearman partial	λ^{5Min}	0.416	0.455	-0.441	-0.475	-0.074
	ϕ	-0.203	-0.262	0.341	0.334	-0.018

Table 5. Risk-adjusted return regressions

The sample consists of stocks present in the CRSP monthly and daily files, restricted to ordinary shares. Monthly risk-adjusted returns are computed in accordance with the Brennan, Chordia et al. (1998) procedure using updated Fama and French (1992) factors. In each month, in cross-section, the risk-adjusted returns are regressed against the indicated variables. The table reports the raw averages of the coefficients (across time), and the associated t-statistics. c^{Gibbs} is the Gibbs estimate of the log effective cost, $I^{1/2}$ is the square-root illiquidity ratio, and γ is the Pastor and Stambaugh (2003) reversal measure, all of which are based on CRSP daily data from the prior calendar year. $\log MktCap$ is the log of the equity market capitalization (end of prior year); $r23$ is the return over lagged months one and two; $r46$ is the return over lagged months four through six; $r7to12$ is the return over lagged months seven through twelve.

	NYSE/Amex				Nasdaq			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Intercept	-0.006 (-1.96)	-0.009 (-2.70)	0.001 (0.21)	-0.010 (-2.78)	-0.005 (-0.88)	-0.005 (-0.68)	0.009 (1.48)	-0.006 (-0.98)
c^{Gibbs}	0.333 (3.89)			0.143 (1.54)	0.291 (3.54)			0.085 (0.73)
$I^{1/2} \times 10^6$		158.788 (5.65)		116.679 (3.86)		142.746 (1.59)		112.944 (1.36)
γ			3.468 (1.52)	-0.909 (-0.41)			18.227 (0.70)	14.497 (0.75)
$\log MktCap$	-0.001 (-2.13)	-0.000 (-0.33)	-0.002 (-3.66)	-0.000 (-0.40)	-0.001 (-0.85)	-0.000 (-0.55)	-0.003 (-3.80)	-0.000 (-0.32)
$r23$	0.007 (2.19)	0.007 (1.94)	0.007 (2.10)	0.007 (2.08)	0.005 (1.09)	0.006 (1.14)	0.006 (1.27)	0.006 (1.13)
$r46$	0.012 (4.16)	0.011 (3.75)	0.011 (3.99)	0.011 (3.90)	0.005 (1.23)	0.004 (1.18)	0.005 (1.48)	0.005 (1.32)
$r7to12$	0.013 (6.54)	0.012 (6.07)	0.012 (6.17)	0.013 (6.40)	0.011 (3.94)	0.010 (3.53)	0.010 (3.83)	0.010 (3.73)
R^2	0.058	0.056	0.053	0.066	0.042	0.042	0.040	0.049

Table 6. Risk-adjusted return correlations

The sample consists of stocks present in the CRSP monthly and daily files, restricted to ordinary shares. Monthly risk-adjusted returns are computed in accordance with the Brennan, Chordia et al. (1998) procedure using updated Fama and French (1992) factors. In each month, in cross-section, the risk-adjusted returns are correlated with the indicated liquidity proxy. The table reports the averages of the correlations (across time), and the associated t-statistics. c^{Gibbs} is the Gibbs estimate of the log effective cost, $I^{1/2}$ is the square-root illiquidity ratio, and γ is the Pastor and Stambaugh (2003) reversal measure, all of which are based on CRSP daily data from the prior calendar year. Partial correlations control for $\log MktCap$ (the log of the equity market capitalization, end of prior year), $r23$ (the return over lagged months one and two), $r46$ (the return over lagged months four through six), and $r7to12$ (the return over lagged months seven through twelve).

	NYSE/Amex			Nasdaq		
	c^{Gibbs}	$I^{1/2}$	γ	c^{Gibbs}	$I^{1/2}$	γ
Pearson	0.019 (2.84)	0.028 (4.56)	0.010 (3.33)	0.025 (3.55)	0.031 (4.73)	0.006 (1.40)
Spearman	-0.036 (-5.80)	-0.026 (-3.90)	-0.006 (-3.24)	-0.035 (-5.16)	-0.019 (-2.51)	-0.018 (-5.33)
Pearson partial	-0.006 (-3.38)	0.007 (4.23)	0.000 (0.02)	-0.005 (-1.07)	0.000 (0.03)	-0.002 (-0.40)
Spearman partial	-0.015 (-9.84)	0.009 (5.72)	-0.000 (-0.20)	-0.015 (-3.15)	0.009 (1.83)	0.001 (0.14)

Table 7. Monthly seasonality in the risk-adjusted return correlations

The sample consists of stocks present in the CRSP monthly and daily files, restricted to ordinary shares. Monthly risk-adjusted returns are computed in accordance with the Brennan, Chordia et al. (1998) procedure using updated Fama and French (1992) factors. In each month, in cross-section, the risk-adjusted returns are correlated with the indicated liquidity proxy. The table reports the averages of the correlations (across time), and the associated t-statistics. c^{Gibbs} is the Gibbs estimate of the log effective cost, $I^{1/2}$ is the square-root illiquidity ratio, and γ is the Pastor and Stambaugh (2003) reversal measure, all of which are based on CRSP daily data from the prior calendar year. Partial correlations control for $\log MktCap$ (the log of the equity market capitalization, end of prior year), $r23$ (the return over lagged months one and two), $r46$ (the return over lagged months four through six), and $r7to12$ (the return over lagged months seven through twelve).

		NYSE/Amex			Nasdaq		
		c^{Gibbs}	$I^{1/2}$	γ	c^{Gibbs}	$I^{1/2}$	γ
January	Pearson	0.262 (13.49)	0.245 (13.17)	0.059 (5.25)	0.180 (8.97)	0.150 (7.22)	0.051 (2.82)
	Spearman	0.187 (8.03)	0.182 (6.82)	0.027 (4.36)	0.106 (6.28)	0.103 (5.11)	0.040 (5.17)
	Pearson partial	0.077 (13.43)	-0.008 (-1.42)	0.006 (1.21)	0.032 (1.92)	-0.041 (-2.53)	-0.002 (-0.12)
	Spearman partial	0.053 (10.28)	-0.027 (-4.62)	0.004 (0.86)	0.004 (0.25)	-0.054 (-3.24)	-0.004 (-0.27)
Non-January	Pearson	-0.003 (-0.40)	0.008 (1.47)	0.005 (1.78)	0.011 (1.62)	0.020 (3.14)	0.002 (0.42)
	Spearman	-0.056 (-10.22)	-0.045 (-7.29)	-0.009 (-4.91)	-0.047 (-7.28)	-0.030 (-3.91)	-0.023 (-6.88)
	Pearson partial	-0.013 (-7.64)	0.008 (4.92)	-0.000 (-0.32)	-0.009 (-1.71)	0.004 (0.79)	-0.002 (-0.38)
	Spearman partial	-0.021 (-13.43)	0.013 (7.51)	-0.001 (-0.46)	-0.017 (-3.35)	0.015 (2.82)	0.001 (0.22)

Figure 1. TAQ and CRSP/Gibbs estimates of log effective costs for the Dow Stocks

Log effective cost estimates from TAQ and CRSP (Gibbs). Averages for all NYSE stocks in the Dow index from 1993 to 2003. Vertical lines mark the dates when the NYSE fully implemented sixteenth pricing (July 1, 1997), and decimal pricing (January 29, 2001).

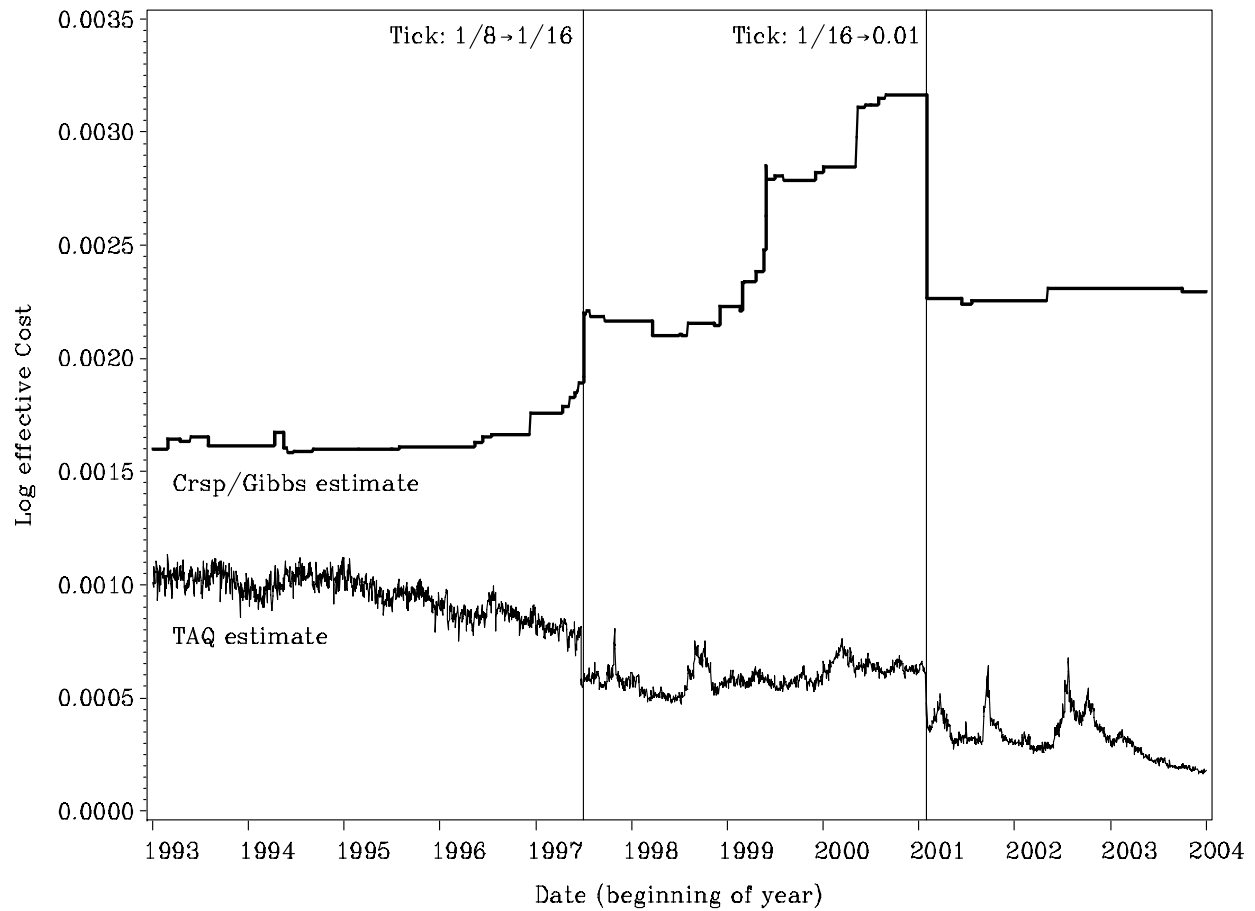


Figure 2. Average log effective cost, Gibbs estimates, 1962-2003

Annual averages of Gibbs estimates of log effective cost for all ordinary shares on the CRSP daily file. For both NYSE/Amex and Nasdaq, market capitalization subsamples are defined using NYSE breakpoints.

