International Review of Financial Analysis 29 (2013) 10–23

Contents lists available at ScienceDirect

International Review of Financial Analysis

Liquidity and expected returns—Evidence from 1926–2008

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ARTICLE INFO

Article history:
Received 12 October 2012
Received in revised form 26 February 2013
Accepted 10 March 2013
Available online 27 March 2013

JEL classification:
G0
G1
G12
G120

Keywords:
Liquidity
Asset pricing
Transaction costs
Effective spread

ABSTRACT

This paper re-examines the liquidity effect on stock expected returns in the NYSE over the period 1926–2008, the pre-1963 period, for which there is a lack of research, and the post-1963 period. The results from the entire sample of 1926–2008 show that expected returns increase with the stock *level* illiquidity. However, illiquidity level has explanatory power in the cross-sectional variation of stock expected returns only over the post-1963 period, and is, both economically and statistically, insignificant for the whole sample and the pre-1963 period. These findings are robust after taking into account various characteristics such as size and risk controls. On the other hand, evidence from the entire sample and the pre-1963 sample suggests that the *systematic* liquidity risk plays a significant role in the cross-sectional variation of stock expected returns. The different result for the pre- and post-1963 is explained by the portfolio shifts occurred during the economic downturns.

1. Introduction

Liquidity is important in many financial markets for both investors and policy makers, and a large and growing body of work has considered identifying the liquidity cost and its impact on asset pricing. These studies use different proxies for liquidity, and most of them report a significant positive association between illiquidity *level*, as a stock characteristic, and stock expected returns (e.g., Gottesman & Jacoby, 2005; Korajczyk & Sadka, 2008). A major problem in investigating the role of liquidity in asset prices is that, while it has been suggested to use long time-series in asset pricing studies,[1] the intra-day data that enable the estimation of liquidity from the actual sequences of trades and quotes are not available prior to 1983 (in the US markets). Even the data related to the common low-frequency measures (such as quoted spreads) are not available prior to 1963. Therefore, current literature in liquidity-asset pricing concentrates mostly on the post-1963 period.

This paper adopts a recently developed low-frequency measure for liquidity and investigates a premium for the liquidity level (as a stock characteristic) by extending the sample to include pre-1963 data. More particularly, we investigate the role of liquidity in explaining cross-sectional variation of stock expected returns for stocks listed on the NYSE over the 1926–2008 and pre-1963 periods, for which there is a lack of research, as well as the post-1963 period.

Our liquidity measure is Effective Tick4 (henceforth EFFT), developed by Holden (2009), which is computed from daily data and intended to be a proxy for effective spread computed from intra-day data. It has been shown that this proxy has high correlations with the high-frequency benchmarks, and performs better than the other proxies for the effective spread[2] (Holden, 2009). Liquidity has many facets, and it is important to note that EFFT, as a proxy for intra-day effective spread, captures only the transaction cost dimension of liquidity and does not include the total price impact of a trade. Nevertheless, effective spread is simple to calculate, easy to interpret, and is widely used as an indicator of market quality (Hasbrouck, 2009; Lee, 1993; Stoll, 2006).

Using all common shares on the NYSE over the period 1926–2008 and employing the Fama–Macbeth approach in portfolios, we find that expected returns increase with the stock level illiquidity. However, this positive relationship is not statistically significant at the conventional levels. Nonetheless, we find that a 1% (standard deviation) of liquidity level translates into a monthly expected premium of about 0.12% or 12 basis points.

The point estimate of 0.12 implies a 17-month holding period or 70% annual turnover rate for a round-trip trader. This rate of turnover seems

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[1] In asset pricing studies, realised returns are usually used as the proxy for expected returns. Since the variance of realised returns around the expected returns is high, long time-series data provide a large amount of data that increases the power of asset pricing tests (Amihud, Mendelson, & Pedersen, 2005). Accordingly, many asset pricing tests make use of US equity returns from 1926 onward (Hasbrouck, 2009).

[2] For example, the monthly time-series correlation with high-frequency effective spreads based on equally weighted portfolios is approximately 0.96 (Holden, 2009).

1057-5219/$ – see front matter
http://dx.doi.org/10.1016/j.irfa.2013.03.007

to be reasonable as an average for the NYSE from 1929 to 2008, as the average annual turnover rate for the NYSE has been around one in 2008 and lower than one for most of the last century. Thus, our result for the coefficient of EFFT is consistent with the straightforward trading stories.

Interestingly, the evidence for the liquidity *level* premium is not consistent across the subsamples. Results from the subsamples show that liquidity level has explanatory power in cross-sectional variation of stock expected returns over the post-1963 period, but not, either economically or statistically, over the pre-1963 period. These findings are robust after taking into account various characteristics such as size and risk controls, including the Fama–French three factors and the systematic liquidity factor. Our market liquidity risk factor is calculated as the monthly profits from buying one dollar of equally weighted low-liquid portfolio and selling one dollar of equally weighted high-liquid portfolio after controlling for market risk factor. On the other hand, evidence from the entire sample of 1926–2008 and pre-1963 suggests that *market* liquidity risk is marginally significant in association with cross-sectional differences in stock expected returns. These findings suggest that liquidity statistically affects the cross-sectional variation of expected returns over the entire sample as well as the subsamples, though the channel for this effect seems to be different over the various periods. For the post-1963 sample, the premium with respect to the liquidity level is more prevalent than that of the systematic liquidity risk. The opposite is true over the pre-1963 period and the entire sample. However, the most reliable evidence for the liquidity effect is provided over the entire sample. The analysis over the 1926–2008 period shows that systematic *market* liquidity risk plays a significant role, as the liquidity effect, in stock expected returns.

Lower premium for the illiquidity level over the pre-1963 period compared to the post-1963 can be explained by the 'flight to liquidity' hypothesis. During economic recessions investors show a flight to liquidity type of behaviour, where some investors leave the stock market altogether and others shift their stock portfolios into larger and more liquid stocks (e.g. Naes, Skjeltorp, & Odegaard, 2011). The National Bureau of Economic Research (NBER) cycles (NBER, 2013) show that the average contraction (expansion) period per cycle for the period of 1926–1963 is higher (lower) than that of the post-1963. Since during contraction (expansion) period we expect more (less) flight to liquidity phenomenon, the portfolio shifting from illiquid, small stocks into larger and more liquid stocks has been more prevalent in pre-1963 than post-1963. Consequently, as liquidity variation of less liquid firms is higher than the liquidity variation of more liquid firms (Naes et al., 2011), we have less variation in liquidity and less pricing ability for liquidity level over the pre-1963 compared to post-1963. Moreover, systematic liquidity variation is also linked to portfolio shifts during economic downturns. Since illiquidity has the information component about future macro fundamentals (Naes et al., 2011), investors consider *illiquidity risk* when they seek to move away from small, illiquid stocks. This is consistent with our finding that liquidity risk has more pricing ability over pre-1963 period than post-1963.

The paper proceeds as follows. Section 2 reviews the EFFT and its construction. Section 3 presents data and methodology that includes data description, variable and portfolio constructions, and asset pricing tests. Pricing results are provided and discussed in Section 4. Section 5 offers the concluding remarks.

2. The liquidity measure

The liquidity measure that we have used in our study is Effective Tick4 (henceforth EFFT), developed by Holden (2009). It is the daily proxy for the effective spread, and includes two attributes of the daily data: price clustering on trading days, and reported quoted spreads for no-trade days. The proxy has two components corresponding to each of these attributes. The first component, effective tick, based on the observable price clustering, is a proxy for the effective spread. The second component is the average quoted spread from any no-trade days that exist, and enriches effective tick by incorporating the information related to no-trade days. First we review the effective tick and then conclude by reviewing the EFFT estimator. Effective tick is based on the idea that the effective spread on a particular day equals the increment of the price cluster on that particular day. For example, on a \$1/8 fractional price grid, if the spread is \$1/4, the model assumes that prices end on even-eights, or quarters. Thus, if odd-eight transaction prices are observed, one must infer that the spread must be \$1/8. This implies that the simple frequency with which closing prices occur in particular price clusters (in a time interval) can be used to estimate the corresponding spread probabilities and, hence, infer the effective spread for that interval. For example, on a \$1/8 fractional price grid, the frequency with which trades occur in four, mutually exclusive price cluster sets (odd \$1/8 s, odd \$1/4 s, odd \$1/2 s, and whole dollars), can be used to estimate the probability of a \$1/8 spread, \$1/4 spread, \$1/2 spread, and a \$1 spread, respectively. There are similar clusters of special prices on a decimal price grid (off pennies, off nickels, off dimes, off quarters, and whole dollars) that can be used to estimate the probability of a penny spread, nickel spread, dime spread, quarter spread and whole dollar spread, respectively. In order to construct the effective tick proxy for a time interval, the first step is to compute the frequency of each price cluster within that time interval. Take S_t as the realisation of the effective spread at the closing trade of day *t* and assume that S_t is randomly drawn from a set of possible spreads S_j (for example in \$1/8 fractional price grid, $S_1 = \$1/8$ spread, $S_2 = \$1/4$ spread, $S_3 = \$1/2$ spread and $S_4 = \$1$ spread) with corresponding probabilities γ_j, where $j = 1,2,\ldots,J$ and $S_1 < S_2 < \ldots < S_J$. Let N_j be the observed number of trades on prices corresponding to the *j*th spread using only positive-volume days in the time interval. The observed probabilities of trade prices (F_j), corresponding to the *j*th spread is

$$F_j = \frac{N_j}{\sum_{j=1}^{J} N_j} \qquad j = 1, 2, \ldots, J \tag{1}$$

Let U_j be the unconstrained probability of the *j*th spread. The unconstrained probability of the *j*th effective spread is

$$Uj = \begin{cases} 2F_j & j = 1, \\ 2F_j - F_{j-1} & j = 2, 3, \ldots, J-1, \\ F_j - F_{j-1} & j = J. \end{cases} \tag{2}$$

and the constrained probability[3] of the *j*th spread (γ_j) is

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

Then, the effective tick proxy is calculated as the probability-weighted average of each effective spread size divided by the average price ($\overline{p}_i$) in time interval *i*:

$$EffectiveTick_i = \frac{\sum_{j=1}^{J} \hat{\gamma}_j s_j}{\overline{p}_i} \tag{4}$$

Holden (2009) incorporates the average of the quoted spreads in no-trade days into the effective tick estimator and concludes the EFFT. EFFT for the time interval *i* is the probability weighted average

[3] This probability assumes a higher frequency on higher rounded increments which is true in large sample. However, in small samples reverse price clustering may be realised that causes the unconstrained probability of one or more effective spread sizes to go above 1 or below zero. Thus, constraints are added to generate proper probabilities.