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HOW DO YOU CAPTURE LIQUIDITY? A REVIEW OF THE LITERATURE ON LOW-FREQUENCY STOCK LIQUIDITY

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Abstract. Researchers have various ways to measure liquidity but most of them come with both merits and demerits. This study provides a literature review of low-frequency liquidity measures with a primary focus on liquidity measurement as well as its implication on asset pricing. Based on the dimension it captures, a range of existing low-frequency measures are divided into four categories of liquidity proxies including transaction cost, volume, price impact, and multidimension-based measures. We review some well-established liquidity proxies, a new bid–ask spread estimator and price impact ratios proposed recently. Finally, we discuss how good low-frequency liquidity measures are at capturing standard liquidity benchmarks, which are constructed from high-frequency intraday data.

Keywords. Low-frequency liquidity measure; Price impact ratio; Transaction costs

1. Introduction

Liquidity and associated issues are one of the primary streams of the finance literature, which receive considerable attention from researchers. Over the last four decades, there are numerous studies focusing on this area such as Amihud and Mendelson (1986a), Eleswarapu and Reingarnum (1993), Vayanos (1998), and Chordia *et al*. (2001). Several important works are Amihud (2002), Vayanos (2004), Acharya and Pedersen (2005), Amihud *et al*. (2005), and Hasbrouck (2009). In spite of abundant theoretical and empirical literature on liquidity and related issues, there is not an appropriate definition of liquidity as well as a consistent liquidity measure for all markets. This is due to the fact that the liquidity concept contains some dimensions including the quantity of trade, trading time, and price impact. One of the most accepted descriptions of liquidity comes from Liu (2006). In particular, liquid stocks are defined as stocks which are able to trade large volume quickly at low cost with little price impact. Four dimensions of stock liquidity can be seen from this definition, namely, trading quantity (how much a security can be traded at a given cost), trading speed (how quickly can a security be traded at a given cost with given quantity), trading costs (all expenses related to the trade of a given quantity of a security), and price impact (how easy it is to trade a security of a given quantity with minimum impact on price). This definition reflects

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five characteristics of a liquidity asset including tightness, immediacy, depth, breadth, and resiliency (see Black, 1971; Sarr and Lybek, 2002). Similar definitions can be seen in Harris (2003) and Amihud and Mendelson (2012).

In addition, several measures are introduced and employed to calculate the liquidity of a security. Each measure captures one or more dimensions of stock liquidity. For example, the effective bid–ask spread measure of Roll (1984) implicit captures the transaction cost aspect of liquidity. On the other hand, the Amihud (2002) illiquidity ratio and Florackis *et al*. (2011) return to turnover ratio are based on the price impact dimension. Furthermore, Liu (2006) presents a multiple dimension-based measure, namely, turnover-adjusted number of zero daily trading volume. Although they are focusing on different aspects of liquidity, these measures are highly related to each other (see, e.g., Goyenko *et al*., 2009; Fong *et al*., 2017).

Based on data frequency, liquidity proxies can be grouped into two strands, namely, high-frequency (intraday) and low-frequency (daily) measures. High-frequency liquidity measures are constructed from intraday data whereas low-frequency liquidity proxies are derived mainly from daily stock returns and volume data. High-frequency liquidity proxies consist of intraday transactions, the data samples are usually very large and thus it requires advanced computer programming and power to analysis them. As a result, high-frequency measures are mostly employed for U.S. markets (see, e.g., Huang and Stoll, 1997; Hasbrouck, 2009). Overcoming these drawbacks, low-frequency liquidity measures are widely used in application due to the following advantages. First, it is easy to access and available for not only large markets like the U.S. and U.K. equity markets, but also for many other less established stock exchanges such as emerging markets. As a result, researchers can obtain the data across countries over long time periods, which enhance the research in the liquidity subject area. Moreover, these measures are very good at capturing the liquidity benchmarks based on intraday data. Indeed, Goyenko *et al*. (2009) compare a wide range of low-frequency liquidity measures with high-frequency benchmarks and find a strong correlation between *Zeros* by Lesmond *et al*. (1999), return to volume ratio of Amihud (2002), and intraday benchmarks.[1] Together with some well-known measures such as the bid–ask spread, turnover, and the Amihud (2002) ratio, new measures are being constructed such as the Florackis *et al*. (2011) price impact ratio, and the Karim *et al*. (2016) free-float–adjusted price impact ratio.

Despite these potential benefits, liquidity measures constructed from low-frequency data exhibit some limitations. For instance, the Illiquidity ratio of Amihud (2002) is considered superior at capturing liquidity than most other measures (Goyenko *et al*., 2009) but it does not incorporate days without trading, which can contain important information about illiquidity. Furthermore, High–Low spread which captures the transaction costs dimension of Corwin and Schultz (2012) is built under the assumption that the stock trades continuously while the market opens. This assumption is violated in practice, decreasing the accuracy of the High–Low spread. As a consequence, a more comprehensive understanding of existing liquidity measures is required for a better application.

Liquidity is considered as a key attribute of capital assets and highly impacts their prices (Amihud and Mendelson, 1991). Previous studies examine the relation between liquidity and stock returns under two avenues. The first stream of research investigates if the level of liquidity as a characteristic has influence on expected returns of the security. When investing in illiquid stocks, investors are compensated by higher stocks' return. Meanwhile, the other stream studies whether stock returns are affected by systematic liquidity risk. Liquidity is considered as a risk factor in asset pricing. The stock whose return is more sensitive to shocks in market liquidity has higher expected return. Numerous studies provide evidence on the former relation to expected stock returns. For example, Amihud and Mendelson (1986a) show that liquidity cost (illiquidity) is positively correlated with expected asset returns when using the bid–ask spread as a liquidity proxy. Focusing on U.S. equities, Brennan *et al*. (1998) also provide evidence that liquidity is negatively correlated with required asset returns when employing turnover ratio and trading volume, respectively, to measure liquidity. This relationship is also confirmed in emerging markets by Bekaert *et al*. (2007). On the other hand, some empirical studies report conflicting evidence.

Bekaert *et al*. (2007) suggest that turnover does not significantly predict future return. Eleswarapu and Reinganum (1993) find evidence of seasonality by demonstrating that bid–ask spread and average returns are positively correlated to each other merely in January. Meanwhile, Hasbrouck (2009) proposes a new estimation of the trading effective cost from daily closing prices, and find mixed evidence when examining the relationship between their cost measure and stock returns. In particular, they demonstrate that the effective cost has a positive association with stock returns with the strongest relationship occurring in January.

The latter relation to stock returns is also widely examined in prior studies. For instance, Pástor and Stambaugh (2003) introduce a marketwide liquidity and show that expected returns of stock are correlated with the sensitivities of returns to fluctuations in aggregate liquidity. They find that the difference in average return of stock with high sensitivities to liquidity and that of low sensitive stock is 7.5% annually. Acharya and Pedersen (2005) show that liquidity is a priced factor in cross section of stock returns. They introduce liquidity-adjusted Capital Asset Pricing Model (CAPM) and argue that it is better than the standard CAPM. Other papers in this line of research are Korajczyk and Sadka (2008), Hasbrouck (2009), and Ben-Rephael *et al*. (2015).

Due to the crucial role of liquidity for both economists and practitioners, it requires a better understanding about liquidity measurement as well as the advantages and disadvantages of existing liquidity measures. Therefore, we aim to provide an extensive review of the literature to reevaluate the existing liquidity measures with primary focus on low-frequency measures, merits, demerits, and its implications on asset pricing.

In particular, the study focuses on a range of well-known low-frequency liquidity proxies in different dimensions. Following Sarr and Lybek (2002) and Liu (2006), we separate liquidity measures into four categories based on the dimension it captures, including transaction cost, volume based, price impact, and multidimension-based measures. Existing measures typically focus on one particular dimension of liquidity. For instance, the bid–ask spread captures the trading cost dimension whereas the illiquidity ratio of Amihud (2002) relates to the price impact dimension. Together with some widely used liquidity measures, recently proposed measures such as the new spread estimate of Florackis *et al*. (2011), Abdi and Ranaldo (2017) return to turnover ratio, and Karim *et al*. (2016) free-float–adjusted price impact ratio, are also considered in this study. In particular, we review prior research in both the United States and other international financial markets. Due to a wide range of liquidity proxies, we are not able to review all of them. Therefore, we focus our attention on some widely used measures of each liquidity dimension. Our paper contributes to the literature concerning liquidity measures by providing a comprehensive and up-to-date review on low-frequency liquidity proxies. We consider not only well-known liquidity proxies but also some recently proposed measures of liquidity. Moreover, we also discuss about any potential issues in using low-frequency liquidity measures.

In summary, we find that each low-frequency liquidity measure usually comes with both advantages and disadvantages. For instance, some proxies such as High–Low spread of Corwin and Schultz (2012) and the Closing Percent Quoted Spread of Chung and Zhang (2014) are good at estimating bid–ask spread but they are not able to encapsulate long-run financial stability. As a result of this, subsequent proposed approximations of liquidity attempt to improve the shortcomings of previous measures. Unlike Corwin and Schultz (2012), the AR spread of Abdi and Ranaldo (2017) provides an adjustment for nontrading periods and it does not rely on bid–ask bounces to capture the effective spread like Roll (1984). In addition, the free-float–adjusted price impact ratio of Karim *et al*. (2016) captures the public free-float factor which increases the predictive power of price impact, compared to existing price impact ratios such as the Illiquidity ratio of Amihud (2002). Due to the availability of data and simplicity, low-frequency measures of liquidity are widely used in research and practice. However, some limitations remain compared to high-frequency liquidity measures which are computed from intraday data. Thus, researchers are still seeking the best low-frequency liquidity measure.

The remainder of the paper is organized as follow. Section 2 discusses the transaction cost-based liquidity measures. Liquidity proxies which capture volume dimension are displayed in Section 3. Sections 4 and 5 consider the price impact and multidimension-based measures, respectively. The shortcomings of low-frequency liquidity measures are discussed in Section 6. Finally, Section 7 concludes the paper.

2. Transaction Cost-Based Measures

Transaction costs refer to the expenses associated with the execution of a trade. Trading costs can be separated into two main categories, namely, explicit and implicit costs. Explicit costs such as order processing costs, taxes, and brokerage fees are identifiable and known in advance of trading. Meanwhile, implicit costs are less observable, compared to explicit costs but can account for a large fraction of total transaction costs. Examples of components to implicit costs are bid–ask spreads, size of transaction, and timing of trade execution.

Following Marshall *et al.* (2011), spread is considered as the best transaction costs benchmark. Spread captures the transaction costs at the best bid and ask price and this cost is for the amount of security executed at the best bid and ask quote. Depth is also important to investors, which provides information about the amount that can be traded at a given price. When a trader needs to transact an order with the quantity being larger than the quantity of the best limit orders, the remaining portion may be filled at the second best bid or ask price. The difference in these executed prices and the traded quantities of stock at each price have impacts on transaction costs. Extant literature on market microstructure also shows that the bid–ask spreads are the most commonly used measure of trading costs as they capture nearly all of the costs associated with stock trading (Sarr and Lybek, 2002). Bid–ask spreads consist of three components including order processing, information asymmetry, and the inventory cost components. Ever since the late 1960s, spread components and their behavior are widely discussed by researchers in both theoretical and empirical literature (see, e.g., Demsetz, 1968; Stoll, 1978; Easley and O'Hara, 1987; Huang and Stoll, 1997; Gregoriou, 2013).

Market makers or dealers are also considered as liquidity suppliers, who provide immediacy of trade execution to the market by matching buy and sell orders (Demsetz, 1968). When order processing costs are high, dealers need to be compensated for this cost by posting relatively high bid and low ask prices. Meanwhile, inventory cost models claim that dealers in security markets may face risk when holding security as inventory due to the uncertainty about future returns as well as the time taken for the transaction to be executed (Ho and Stoll, 1981). In particular, unexpected changes in future stock price and market environment can lead to a potential loss for market makers. Another component of the bid–ask spread is asymmetric information. It happens when one party of a transaction has information about the true value of a security, whereas the other party does not. The informed party is more likely to trade with a larger quantity at any security price. Hence, market makers may face a potential loss when trading with investors who have private information due to the change in security's price. Moreover, it is uncertainty about who the informed trader is and when an information event exists. As a result, when quoting the bid and ask prices, dealers can increase the bid–ask spread to compensate for this potential loss.

High-frequency forms of bid–ask spread include quoted bid–ask spread, relative bid–ask spread, and effective bid–ask spread. The quoted bid–ask spread is a straightforward proxy of illiquidity as it capture the transaction cost dimension. The quoted spread measures the cost of completing a round trip (buy and sell) if trades are executed at the quoted prices (Bessembinder and Venkateraman, 2010). Another form of spread is the relative bid–ask spread. It is defined as the dollar bid–ask spread over the midpoint of closing bid and ask prices for the trading day. It overcomes the issue of quoted bid–ask spread being wider for large price stocks. This leads to a bias conclusion that large stocks are more illiquid than small securities.

The effective bid–ask spread is devised to capture trading costs when they occur within the ask and bid prices in a more efficient manner. It is defined as twice the absolute value of the subtraction between a transaction price and the midpoint of bid and ask quotes at the time of the transaction. Although bid–ask spreads have some advantages on measuring liquidity and are widely employed in research, they also have their shortcomings. The limit in obtaining trade and quote data in all stock markets as well as a tedious process of data to calculate high-frequency bid–ask spreads, raises the demand for alternative spread estimators. As a result, considerable emphasis has been placed on researching and proposing estimators of bid–ask spread, which are based on low-frequency data. In this section, we review the construction as well as advantages and disadvantages of some widely used estimators of bid–ask spreads. These include the Roll (1984) implicit effective spread, Zeros by Lesmond *et al.* (1999), High–Low spread of Corwin and Schultz (2012), Closing Percent Quoted Spread of Chung and Zhang (2014), and most recently spread measure of Abdi and Ranaldo (2017).

2.1 *Roll (1984) Implicit Effective Spread*

Roll (1984) introduces an implicit spread based on the autocorrelation between the bid and ask prices as a proxy of stock liquidity. The implied spread is defined as:

$$Roll_i = 2\sqrt{-cov_i} \tag{1}$$

where $Roll_i$ is the implicit spread of stock i, cov_i is the first-order serial covariance of returns for stock i. The Roll estimator can be calculated using both daily and weekly data.

As noted by Roll (1984) under assumptions of an efficient market where relevant information is reflected quickly and accurately on prices, the quoted spread is constant and the average of bid–ask prices fluctuates randomly. The quoted bid–ask spread fails to capture the true transaction costs as most trades are executed within the bid and ask prices. These things motivate Roll (1984) to use the serial correlation of price changes to propose implicit spread as a proxy for liquidity. He also discovers that his proxy is strongly correlated to firm size, thus it supports the argument that the implicit spread captures the transaction cost dimension. It is argued that implicit effective spread can be obtained easily as it only requires transaction price data without information about the bid–ask spread and order flow. Other studies employ implicit effective spread as a proxy for liquidity, see, for instance, Lesmond (2005) and Fong *et al.* (2017).

Nevertheless, the implicit effective spread is undefined if serial covariance is positive. Reinganum (1990) shows that 41% of the security serial covariance are positive. To deal with this issue, Roll (1984) suggests that the sign of covariance is preserved after taking the square root, but the implicit effective spread will be recorded as a negative number. Meanwhile, Hasbrouck (2009) sets the spread equal to zero if the serial covariance is positive. Another problem is that for days with no trade, the midpoint of the closing bid and ask prices is still reported by the stock exchange. It leads to a bias in the estimated trading expense as the midpoint realizations do not contain the cost (Hasbrouck, 2009).

The Roll (1984) model is the first model which employs price data to estimate the effective spread. Since then, several models have been introduced. For example, Lesmond *et al.* (1999) propose a model to estimate transaction costs using daily security returns only. Compared with Roll (1984), they introduce an estimator based on occurrence of zero returns. More recently, Abdi and Ranaldo (2017) develop a new estimator using closing high and low prices over two consecutive days. The Abdi and Ranaldo (2017) model unlike the autocovariance measure of Roll (1984), is independent of trade direction dynamics and uses daily high–low spreads which are available over long time horizons. Other models are reported in Hasbrouck (2009), Corwin and Schultz (2012), Fong *et al.* (2017), and Ibrahim and Kalaizoglou (2016).

2.2 *Zeros by Lesmond et al. (1999)*

Lesmond *et al*. (1999) introduce another liquidity proxy which captures the frequency of zero return days. In particular, it is defined as the ratio of number of days with zero return divided by the total number of observable days. The percentage of daily zero returns can be obtained for a period of a month or a year, by computing the following formula:

$$Zeros_{it} = \frac{Zero\ daily\ returns_{it}}{D_{it}} \tag{2}$$

where $Zeros_{it}$ is the frequency of days with return equal to zero for security i, over period of time t, $Zero\ daily\ returns_{it}$ is the number of zero return days of security i over the period of time t, and D_{it} is the number of available trading days.

According to Lesmond *et al*. (1999), frequency of zero daily return could be a measure of liquidity with some explanations. First, a higher illiquid stock faces more difficulty to trade, increasing the probability of these stocks having days with zero volume and return. Second, when trading cost is high and it is not compensated fully by gains from trading, investors with private information are less likely to trade. Hence, it leads to days with zero returns. A security with low transaction costs will have more frequent price movement and less zero returns, compared to a security with high transaction costs. Essentially, a zero return observation is a consequence of high transaction costs, thus the proportion of days with zero return in a period is used as a simple proxy for transaction costs. The higher the value of *Zeros*, the larger total transaction costs are.

The benefit of *Zeros* is that it provides estimates of transaction cost regardless of time period, stock exchange, or firms by only using time-series daily return data. It allows transaction costs to be obtained more easily and inexpensively. In addition, this measure is arguably stronger then the effective spread of Roll (1984), as the model of Roll cannot provide estimates for more than half of the firms listed on the NYSE/AMEX exchange (Harris, 1990).

Furthermore, Lesmond *et al*. (1999) report a positive relationship between zero daily return and spread measures including quoted bid–ask spread and Roll (1984) measure. Being consistent with this finding, using a sample of 19 emerging markets, Bekaert *et al*. (2007) provide evidence that zero daily return is positively associated with bid–ask spread across all countries and negatively with turnover ratio. The wide employment of this measure in the academic literature also confirms the usefulness of it for the U.S. market (Goyenko *et al*., 2009; Fong *et al*., 2017) as well as for global financial markets (Lesmond, 2005; Chai *et al*., 2010; Lee, 2011).

Nevertheless, being similar to other liquidity proxies, *Zeros* also comes with limitations. In particular, Bekaert *et al*. (2007) claim that days with zero returns may suggest other information associated with the equity market instead of stock liquidity. For instance, the days with zero returns are automatically observed with a lower level for a market with larger stocks. Furthermore, no trading days can occur due to a lack of information flow.

2.3 *High–Low Spread of Corwin and Schultz (2012)*

Corwin and Schultz (2012) propose a new estimator of bid–ask spread called High–Low spread, which uses daily high and low prices only. They argue that "the sum of the price ranges over 2 consecutive single days reflect 2 days' volatility and twice the spread, while the price range over one 2-day period reflects 2 days' volatility and one spread." It allows them to derive an estimate of bid–ask spread as a function of the high to low price ratio. In particular, the High–Low spread is given by:

$$S_t = \frac{2\left(e^{\alpha t} - 1\right)}{1 + e^{\alpha t}} \tag{3}$$

$$\alpha_t = \frac{\sqrt{2\beta_t} - \sqrt{\beta_t}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma_t}{3 - 2\sqrt{2}}} \tag{4}$$

$$\beta_t = (h_{t+1} - l_{t+1})^2 + (h_t - l_t)^2 \tag{5}$$

$$\gamma_t = (\max\{h_{t+1}, h_t\} - \min\{l_{t+1}, l_t\})^2 \tag{6}$$

where S_t is the High–Low spread of stock in day t, h_t and l_t are the observed high and low stock prices in day t, respectively. For a sample of D days, the High–Low spread are obtained by averaging the above two-day estimator. The negative two-day estimates are set to zero.

Corwin and Schultz (2012) argue that the stock's volatility and its bid–ask spread can be reflected by the daily price range as the high (low) prices are almost always buyer (seller) initiated. Hence, the High–Low spread is proposed as an estimator of stock liquidity. The major merit of the High–Low spread is that it has a relative low standard deviation in low-frequency data, which makes it a reliable proxy when only low-frequency data are available (Bleaney and Li, 2015). Moreover, this spread is also easy to compute and it is not computer-time–intensive. Thus, this liquidity measure is suitable for large samples over long time periods.

Using a U.S. sample from 1993 and 2006, Corwin and Schultz (2012) report that their High–Low spread is strongly correlated with the TAQ effective spread (correlation of 0.892). They also suggest that it outperforms other low-frequency spread measures, such as the Roll (1984) and the effective stick estimator of Holden (2009).

The major shortcoming of High–Low spread is that this method needs an adjustment for nontrading periods, such as holidays and weekends. This is because Corwin and Schultz (2012) assume that the stock trades continuously while the market opens. Another assumption is that stock values do not change while the market is closed. In practice, these assumptions are violated, decreasing the accuracy of the High–Low spread.

2.4 *Closing Percent Quoted Spread of Chung and Zhang (2014)*

An alternative low-frequency estimator of bid–ask spread is the Closing Percent Quoted Spread, which is introduced by Chung and Zhang (2014). This measure is constructed using daily closing bid and ask prices only and is regarded a good proxy of effective spread. Closing Percent Quoted Spread is calculated as below:

$$Closing\ Percent\ Quoted\ Spread_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{Closing\ ask_{idt} - Closing\ bid_{idt}}{(Closing\ ask_{idt} + Closing\ bid_{idt})/2} \tag{7}$$

where $Closing\ Percent\ Quoted\ Spread_{it}$ is the Closing Percent Quoted Spread of stock i in the period of time t, D_{it} is the number of trading days in time t, $Closing\ ask_{idt}$ and $Closing\ bid_{idt}$ are closing ask and bid prices of stock i in day d, respectively.

Closing Percent Quoted Spread is straightforward to compute and suitable for long time horizons, as it only requires daily closing ask and bid prices. Compared to prior liquidity proxies, it is relatively easier to calculate for both researchers and practitioners as this measure does not require a sophisticated estimation procedure or large computational efforts.

Using a U.S. sample, Chung and Zhang (2014) compare the performance of their spread with previous low-frequency spread estimators such as the Roll (1984) implicit effective spread and the *Zeros* measure of Lesmond *et al.* (1999). They imply that Closing Percent Quoted Spread provides a more thorough approximation of TAQ spread, compared to other liquidity measures in a cross-sectional setting. Furthermore, their spread measure is also highly correlated with the TAQ-based spread using both time-series and cross-sectional data, especially for NASDAQ stocks. When comparing different liquidity measures on 42 stock exchanges around the world, Fong *et al*. (2017) suggest that Closing Percent Quoted Spread is the best percent-cost proxy.

2.5 *AR Spread of Abdi and Ranaldo (2017)*

Recently, Abdi and Ranaldo (2017) propose a new proxy (hereafter, AR) to measure stock liquidity which captures the transaction cost dimension. Formally, it can be defined as follows:

$$AR_{it} = 2\sqrt{E\left[(c_{it} - \eta_{it})(c_{it} - \eta_{it+1})\right]} \tag{8}$$

where AR_{it} is the Abdi and Ranaldo (2017) spread estimator of stock i in day t, c_{it} is the close log-price of stock i, η is the midpoint of the daily high and low log-price of stock i. Formally, it is given by:

$$\eta_{it} = \frac{h_{it} + l_{it}}{2} \tag{9}$$

The AR spread over a period of time is calculated as the average of daily measures. AR spread also has the benefit of data availability as it only uses close, high, and low prices. Despite being built based on the estimators of Roll (1984) and Corwin and Schultz (2012), the liquidity measure of Abdi and Ranaldo (2017) has some other advantages. First, it is independent of trade direction dynamics and thus, it does not rely on bid–ask bounces to capture the effective spread like Roll (1984). Moreover, unlike Corwin and Schultz (2012) AR spread does require adjustment for nontrading periods.

According to Abdi and Ranaldo (2017), the AR spread has the highest correlations with TAQ effective spread, compared to other low-frequency estimates. Furthermore, their measure also improves the systematic liquidity risk and commonality measurement of liquidity.

In summary, the five low-frequency proxies discussed in this section are good estimators of bid–ask spread. These estimators are also used to measure stock liquidity as they are useful in capturing market makers' reaction to news. However, they are not good at encapsulating long-run financial stability. Hence, we need to use other liquidity measures such as price impact ratios in order to approximate financial stability.

3. Volume-Based Measures

Volume-based liquidity measures distinguish between liquid and illiquid securities by the amount of transactions. There is a close link between bid–ask spread and volume. A transaction can execute when the bid and ask price meet, thus large bid–ask spread implies a low volume of security whereas small bid–ask spread leads to a high trading volume of that stock. Meanwhile, there is also a causal effect of trading volume on spread. Small trading volume adds more liquidity to stocks and hence helps improve price accuracy and reduces spread (Sarkissian, 2016). Easley and O'Hara (1992) also suggest that volume has a positive impact on the size of spread. All else being equal, the greater volume leads to the larger spread due to the information component of the bid–ask spread.

According to Sarr and Lybek (2002), volume-based measures capture breadth and depth characteristics of a market or an asset. They are useful in measuring market breadth, which means that orders are both numerous and large in volume. Moreover, the number of transactions also provides valuable information for market dealers. Indeed, when there are large number of orders from both the selling and buying sides of the market, dealers are able to execute orders without taking risky inventory positions. As a result, volume-based measures are frequently used to measure liquidity. The common measures in this category are trading volume and turnover ratio.

3.1 *Trading Volume*

Trading volume is a straightforward proxy of liquidity. It is calculated as an amount of traded shares between market makers in buying and selling activities for a security *i* in a period *t*. Trading volume is usually calculated as dollar trading volume with the following formula:

$$DVol_{it} = \sum_{j=1}^{n} P_{ikt} \quad \times \; Vol_{ikt} \tag{10}$$

where $DVol_{it}$ is the trading volume of a security *i* over time period *t*. It is calculated as the sum of the dollar value of *n* transactions of stock *i* at period $t.P_{ikt}$ and Vol_{ikt} are price and quantity of stock *i* for transaction *k* at time period *t*, respectively.

Alternatively, trading volume can be measured as the logarithm of the annual number of shares traded times the logarithm of closing price at the end of a calendar year as in Gregoriou and Nguyen (2010). When investigating the correlation between trading volume and average returns, Brennan *et al*. (1998) observe that they are negatively correlated, which is consistent with the notion that there is influence of liquidity measures on stock returns (Amihud and Mendelson, 1986b). Supporting this finding, Chordia *et al*. (2001) also provide evidence for the negative correlation between security returns and both the level and the variability of trading activities after book to market, size, and momentum effects have been controlled. Moreover, trading volume does matter in the adjustment of security price to information (Easley and O'Hara, 1992) and is a major determinant of the liquidity part of pricing (O'Hara, 2003).

Trading volume captures the trading activity of liquidity components, and by implication it is considered as a proxy for liquidity. Stoll (1978) suggests that dollar trading volume has a positive relationship to the holding cost of dealers. Hence, it is an influential determinant of liquidity. The higher trading volume, the lower security illiquidity. Furthermore, Chordia *et al*. (2000) also show strong correlation between trading volume and quoted depth, and other proxies of liquidity. Although being popular in application (Lee, 1993; Chordia *et al*., 2001; Becker-Blease and Paul, 2006), trading volume is considered as an inappropriate liquidity measure due to the double counting issue.

3.2 *Turnover Ratio*

Another volume-based measure of liquidity is turnover ratio. It can be calculated as the number of traded shares divided by the number of shares outstanding.

$$Turnover_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{Vol_{idt}}{Shrout_{idt}} \tag{11}$$

where $Turnover_{it}$ is the turnover ratio of stock *i* over time period *t*. D_{it} is the number of trading days. Vol_{idt} and $Shrout_{idt}$ are the daily number of shares traded and daily number of shares outstanding of stock *i*, respectively.

According to Easley and O'Hara (1992) and Engle and Russell (1998), trading frequency carries information of the market and bears a significant weighting on liquidity. Turnover captures trading frequency, thus when liquidity is not examined directly, one can use this rate as a method to measure stock liquidity. Moreover, turnover ratio is considered to be a more suitable liquidity measure compared to trading volume as it accounts for market capitalization of stocks (Gabrielsen *et al*., 2011). Turnover ratio is easy to obtain because of the availability of data on a monthly and daily basis. This allows the capturing of liquidity for numerous stocks over a long time period. Due to these advantages of turnover ratio, it is employed as a proxy of liquidity in other research such as Rouwenhorst (1999), Chordia *et al*. (2001), Nguyen *et al*. (2007), and Brown *et al*. (2009). Using both time-series and cross-sectional regressions tests, Nguyen *et al*. (2007) show evidence for the significance and negative correlation between turnover and asset returns, whereas Rouwenhorst (1999) and Brown *et al*. (2009) provide inconsistent results.

On the other hand, Lee and Swaminathan (2000) argue that turnover ratio may provide information other than liquidity. They find a low degree of correlation between this ratio and firm size and relative spread. Furthermore, they provide evidence that turnover relates to stock's past performance as firms with low past turnover rates earn higher future return. Lesmond (2005) argues that there is a scaling problem with turnover as this measure is likely to be nonlinear with respect to the bid–ask spread. Hence, turnover may be a less than perfect liquidity approximation.

Together with above advantages and disadvantages of volume-based measures (i.e., trading volume and turnover ratio) as a proxy for liquidity, there is still an issue which arises from using both measures. According to Gabrielsen *et al*. (2011), volume-based liquidity measures fail to show how price changes by the arrival of sudden orders. These proxies are not built based on theoretical models of market maker behavior, thus they only capture the past performance of prices and volume changes. Hence, they suggest that these measures are only a useful starting point in the analysis process.

4. Price Impact-Based Measures

4.1 *Amihud (2002) Illiquidity Ratio*

The illiquidity measure introduced by Amihud (2002) is the most commonly used price impact ratio in the finance literature. In particular, illiquidity ratio reflects the sensitivity of average absolute daily price to $1 trading volume for a stock, it is also referred to as the return to volume ratio. The average of daily impacts over a sample period is calculated as follows:

$$RtoV_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{idt}|}{Dvol_{idt}} \tag{12}$$

where $RtoV_{it}$ is the illiquidity ratio of stock i in the period t, D_{it} is the number of trading days in the period t for stock i, R_{idt} is the return of stock i on day d in the period t, and $Dvol_{idt}$ is the dollar volume of stock i on day d in the period t. The stock is said to be illiquid if the return to volume $RtoV$ ratio is high. It implies that stock price moves in a great capacity when there is little volume change.

The Amihud (2002) illiquidity ratio exhibits some advantages over other liquidity measures. First, this ratio is computed using readily available data on daily return and volume. It allows researchers to compute the illiquidity ratio for days over long time periods for most financial markets. The detailed transaction data in some markets, especially emerging markets are not widely available, which limits the usage of trading cost-based liquidity measures in academic research. Therefore, the illiquidity ratio provides a proxy from available data for these markets to deal with this issue. Second, return to volume ratio captures the effects of trading volume on the movements of security prices and transforms it into transaction costs (Acharya and Pedersen, 2005). It can be seen from the ratio's formula that higher trading volume leads to a lower illiquidity ratio. Meanwhile, Lou and Shu (2017) suggest that the value of the Amihud return to volume ratio is its correlation with trading volume, which enables this ratio to measure price impact comprehensively via its trading volume component.

In spite of the fact that return to volume ratio is a useful and convenient measure for illiquidity, there are still some limitations. First, it is associated with a significant size bias. Cochrane (2005) argues that for two stocks with the same turnover, the stock with larger market capitalization is automatically less illiquidity only because of its size. As a consequence, the illiquidity ratio is incomparable across stocks with different market values (Florackis *et al*., 2011). Second, Florackis *et al*. (2011) also argue that it fails to reflect the trading frequency aspect of liquidity. They suggest that trading frequency is becoming a dominant issue and it affects the required premium. However, Amihud's ratio assumes that trading frequency is similar across stocks and thus it should not have influence on liquidity premia.

This assumption is unrealistic due to the considerable cross-sectional and time-series variation of trading frequency (Datar *et al*., 1998).

4.2 *Florackis et al. (2011) Price Impact Ratio*

Florackis *et al*. (2011) introduce a new price impact ratio to capture liquidity. In particular, it is proposed as an alternative to the Amihud (2002) illiquidity ratio.

According to Florackis *et al*. (2011), there are two main limitations of the Amihud (2002) return to volume ratio, namely, cross-sectional size bias and the assumption of similar trading frequency across stocks. It is noticeable that the trading volume which appears in the denominator of the Amihud (2002) ratio is very highly correlated with the market value of stocks. Furthermore, Florackis *et al*. (2011) argue that return to volume ratio fails to account for the trading frequency of securities. Datar *et al*. (1998) find that trading frequency has a strong effect on asset pricing.

Florackis *et al*. (2011) develop a new liquidity measure defined as the absolute return scaled by the turnover ratio (henceforth RtoTR). Formally, it is defined as the following:

$$RtoTR_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{idt}|}{TR_{idt}} \tag{13}$$

where $RtoTR_{it}$ is the return to turnover ratio of stock i in a period of time t, D_{it} is the number of valid trading days of security i over time t, R_{idt} is the daily return of security i in day d, and TR_{idt} is the turnover ratio of security i in day d.

It can be seen from the formulas of the RtoV and RtoTR ratios that trading volume in the denominator of the former is substituted by turnover ratio in the latter. As a result, RtoTR ratio has a similar intuitive interpretation that reflects the change in stock price to 1% of turnover ratio.

As highlighted by Florackis *et al*. (2011), this new measure not only takes into account the benefits of the Amihud (2002) illiquidity ratio but it also has some other appealing features. In particular, their liquidity proxy inherits the easy access and data availability of the Amihud ratio. Furthermore, the RtoTR ratio overcomes one of the big drawbacks of the Amihud (2002) return to volume ratio, namely the size bias as there is no empirical association between firm size and turnover ratio.

They argue that return to turnover ratio is more comprehensive because it combines trading costs and frequency effects. According to proposition 1 of Amihud *et al*. (2005), the expected return on security i for a risk-neutral investor is given by the following equation:

$$E\left(r^i\right) = r^f + \mu \frac{C^i}{P^i} \tag{14}$$

Where C^i and P^i represent the transaction costs and price of asset i, respectively, and μ is the trading intensity of the investor. It can be seen that both transaction cost and trading frequency positively correlate with expected return. Therefore, asset prices are affected by a compound effect of both aspects, not each aspect in isolation.

4.3 *Free-Float–Adjusted Price Impact Ratio*

An alternative price impact ratio is developed by Karim *et al*. (2016). It is a modification of the Florackis *et al*. (2011) RtoTR ratio, with the consideration of the free-float factor. The new liquidity measure is given by:

$$RtoTRF_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{idt}|}{TRF_{idt}} \tag{15}$$

where $RtoTRF_{it}$ is return to turnover ratio adjusted with the public free-float factor of stock i over time period t, D_{it} is the number of available trading days for security i for the period of time t, R_{idt} is daily return of stock i, and RTF_{idt} is the corresponding turnover ratio captured by the free-float percentage. RTF_{idt} is calculated as trading volume divided by the multiplication of the number of share outstanding and the public free-float factor.

Formally, compared to the RtoTR ratio of Florackis *et al*. (2011), the new liquidity proxy replaces the turnover ratio in the denominator component by adjusted turnover ratio controlling for the public free-float factor. The adjusted turnover ratio increases the encapsulation power of price impact, which is defined as the ability of the ratio to approximately capture the cross-sectional variability of the turnover ratio of the security. Lam *et al*. (2011) argue that the free-float factor and liquidity are correlated together as the higher supply of the stock makes it easier to trade. Hence, they suggest that measures should consider the supply ability of stock to truly capture the liquidity.

As argued by Karim *et al*. (2016), the RtoTRF ratio inherits some benefits of the RtoTR ratio of Florackis *et al*. (2011). First, data for calculating the new ratio are simple and available to obtain. Second, it is free of size bias as we explained earlier. Furthermore, the denominator of the RtoTRF ratio includes turnover ratio which controls for the impact of trading frequency on asset pricing. The new liquidity proxy RtoTRF not only inherits the benefits of the RtoTR ratio, it also has additional appealing features. In particular, the RtoTRF ratio appeals in term of the “real supply” of available shares to the public by taking into account the public free-float factor. The number of shares outstanding is not the stock supply to the public, which implies that the turnover alone does not indicate the real number of shares traded. Therefore, the proposed measure is expected to be more suitable in estimating the price impact aspect of stock liquidity.

In order to test the advantages of the RtoTRF ratio, Le and Gregoriou (2018) examine the relation between liquidity and asset prices using three different price impact ratios including RtoV, RtoTR, and RtoTRF for comparison purposes. Using a sample of all U.S. public companies over the period from 1997 to 2017, they show that the free-float–adjusted price impact ratio is superior to the other two price impact ratios. In particular, they argue that more liquid stocks (low RtoTR or RtoTRF ratios) yield higher returns than less liquid stocks. It can be explained by a trading frequency argument, liquid stocks may get traded more frequently and thus they have greater returns. This finding is also robust to the global financial crisis over the time period 2007–2009.

5. Multidimension-Based Measure

5.1 *Turnover-Adjusted Number of Zero Daily Trading Volume (Liu, 2006)*

Liu (2006) introduces a turnover-adjusted number of day with zero trading volume liquidity measure. Liu (2006)’s liquidity proxy of a security is calculated using the equation below:

$$LM_{it} = \left[NoZV_{it} + \frac{1/(turnover_{it})}{Deflator} \right] \times \frac{21}{NoTD_t} \tag{16}$$

where LM_{it} is the turnover-adjusted number of zero daily trading volume of stock i in month t, $NoZV_{it}$ is the number of days with zero volume of stock i in month t, $Turnover_{it}$ is the sum of daily turnover of stock i in month t, $NoTD_t$ is the total number of trading days in the market in month t, and *Deflator* is 480000 as suggested by Liu (2006). Deflator is chosen to make sure that $0 < \frac{1/(\times month\ turnover)}{Deflator} < 1$. Thus, stocks with similar days of zero volume may be further distinguished.

Liu (2006)’s measure takes into account multiple dimensions of liquidity including trading quantity, trading speed, and trading cost with a particular focus on trading speed. More specifically, the figure of days with zero volume reflects the continuity of trading as well as the potential delay or challenge in executing an order. A stock with higher number of zero daily volume is less likely to be traded and thus less liquid. The role of daily zero volume in this measure is similar to the number of days with zero returns in Lesmond *et al*. (1999), and thus this measure captures the trading cost dimension. Furthermore, for stocks with the same number of days with zero volume, turnover ratio is used to distinguish the liquidity level between them.

As noted by Liu (2006), this new measure is highly related to other liquidity proxies such as turnover ratio and return to volume ratio. Other studies employ the Liu (2006) measure in investigating stock liquidity such as Chai *et al*. (2010) and Lam and Tam (2011).

6. Issues in Low-Frequency Liquidity Measurement

One of the main benefits of using low-frequency data to calculate liquidity is that it saves significant computation time compared to using high-frequency data (intraday data) (Holden *et al*., 2014). The daily data are also available over long time horizons for most stock exchanges. Hence, low-frequency liquidity measures are applied in many academic studies. Specifically, asset pricing literature has shown that liquidity is a priced risk factor not only in the U.S. market (see Chordia *et al*., 2000; Acharya and Pedersen, 2005; Hasbrouck, 2009), but also for emerging markets (Bekaert *et al*., 2007). Hence, a high-performing low-frequency proxy of liquidity will provide a very valuable contribution to the asset pricing literature. It motivates researchers to propose and introduce new low-frequency liquidity proxies of high-frequency measures. For instance, due to the lack of long-term intraday data and computational difficulties in calculating bid–ask spread, Roll (1984) implicit effective spread and *Zeros* of Lesmond *et al*. (1999) mentioned above are the first measures to estimate transaction costs using price data and daily data. Hasbrouck (2009) develops an alternative proxy for the effective spread with a Gibbs procedure whereas Holden (2009) also introduces an extended Roll (1984) model. Chung and Zhang (2014) suggest a percent-cost proxy called “Closing Percent Quoted Spread” using closing ask and bid prices only and most recently the AR spread is introduced by Abdi and Ranaldo (2017).

Thus far, a wide range of researchers have applied these low-frequency estimators in their analysis. However, the question is how well these measures capture standard benchmarks which are calculated from intraday data and whether they really measure liquidity. In order to answer this question, several studies have evaluated the performance of these low-frequency liquidity measures in stock markets. For example, Goyenko *et al*. (2009) compare a large number of widely used liquidity proxies to liquidity benchmarks from high-frequency data. Using a U.S. data sample, they discover that both monthly and annual low-frequency proxies are good at capturing high-frequency measures of transaction costs. Chung and Zhang (2014) report that Closing Percent Quoted Spread performs better than the Roll (1984) and Zeros estimator in the U.S. market. The most comprehensive study is conducted by Fong *et al*. (2017), who investigate liquidity proxies worldwide. They extend the study of Goyenko *et al*. (2009) by comparing a wide range of monthly liquidity measures calculated from daily data to the high-frequency liquidity measures. These are computed from the new global intraday equity database entitled Thomson Reuters Tick History (TRTH). Their sample includes intraday data for 42 markets around the world. They find that the daily version of the Amihud price impact ratio is the best daily proxy for cost-per-volume, whereas Closing Percent Quoted Spread is the best daily percent-cost proxy.

Nevertheless, Jahan-Parvar and Zikes (2019) have established that low-frequency liquidity measures do not really capture transaction costs. They compare some popular daily data-based measures of transaction costs with their high-frequency data-based measures. They argue that low-frequency measures are highly upwardly bias and imprecise for U.S. equities and foreign exchange rates. They also suggest that caution is need when applying these measures to asset pricing. Even though numerous proxies have been developed to measure low-frequency stock liquidity, their accuracy and ability to capture transaction costs can be improved further. Avenues of future research should be along the lines of developing low-frequency liquidity measures that are free of bias.

Another limitation of low-frequency liquidity measures is that they fail to capture market microstructure noise. Noise in transaction data is prevalent at high frequency (Aït-Sahalia and Yu, 2009). Market microstructure noise includes a range of frictions that arise due to the imperfection of the trading process such as bid–ask bounces, price changes' discreteness, inventory holdings, price impacts of large orders, and other source of friction. These noises bias the results of empirical asset pricing. Moreover, according to Zhang *et al*. (2005), market microstructure noise has different behavior over alternative frequencies with very high-frequency data mostly composed of market microstructure noise. Awartani *et al*. (2009) study the changes in microstructure noise due to sampling frequency and suggest that noise has a statistically significant effect on volatility estimators at frequencies of 2–3 minutes or higher. Therefore, high-frequency liquidity measures are better in reflecting market frictions.

7. Conclusion

This paper reviews the literature on liquidity measures. Although some proxies are proposed to measure stock liquidity, the jury is still out on the best approximation of liquidity. Many studies in both developed markets such as the United States, the United Kingdom and emerging markets are conducted to test the accuracy of different liquidity measures. In this study, we focus on low-frequency liquidity measures which are based on low-frequency data (daily data). Due to the availability of low-frequency data, especially for developing markets, these measures are widely used in the academic literature when examining liquidity of stocks.

We review liquidity measures in four groups which capture one or more dimensions of liquidity, including trading cost, price impact, trading volume, and multidimension measures. For each liquidity proxy, we discuss the advantages and disadvantages. The paper suggests that liquidity measures which capture the trading cost dimension are good estimators of bid–ask spread but they are not good at encapsulating long-run financial stability, compared to price impact ratios. Moreover, recent measures are proposed to overcome the disadvantages of prior proxies. For example, compared to other bid–ask spread proxies, the Closing Percent Quoted Spread of Chung and Zhang (2014) provides a more thorough approximation of TAQ spread and is highly correlated with the TAQ-based spread using both time-series and cross-sectional data. We also review how liquidity relates to asset pricing using evidence from various proxies of liquidity in different stock markets. The asset pricing literature has shown that liquidity is a priced risk factor not only in the U.S. market, but also for emerging markets. Finally, we discuss the main issue when using daily data to compute stock liquidity. Jahan-Parvar and Zikes (2019) have argued that low-frequency liquidity measures do not really capture transaction costs as they are highly upwardly bias and imprecise for U.S. equities and foreign exchange rates. In addition, low-frequency liquidity measures fail to capture market microstructure noise, thus leading to the bias in the results of empirical asset pricing. Even though the liquidity approximations discussed in this review are widely used, the literature is not convinced by their ability to capture standard liquidity benchmarks calculated from intraday data. It is still an open question and will continue to be an avenue for future research in liquidity.

Note

1. *Zeros* is a liquidity measure proposed by Lesmond *et al*. (1999) using daily data. It captures the transaction cost dimension based on the frequency of zero return.

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