# Chapter 9
# Liquidity Proxies Based on Intraday Data: The Case of the Polish Order-Driven Stock Market

**Joanna Olbrys and Michal Mursztyn**

**Abstract** The objective of this paper is to estimate selected liquidity measures based on high-frequency intraday data and to examine their magnitude on the Warsaw Stock Exchange (WSE). We construct and analyze a panel of data which consists of daily proxies of five liquidity estimates for 53 WSE-traded companies divided into three size groups. Although the WSE is classified as an order-driven market with an electronic order book, the raw data set does not identify trade direction. Therefore, the trade classification Lee and Ready (J Finance 46(2):733–746, 1991) algorithm is employed to infer trade sides and to distinguish between so-called buyer- and seller-initiated trades. Moreover, the paper provides a robustness analysis of the obtained results with respect to the whole sample and three adjacent subsamples each of equal size: the precrisis, global financial crisis (GFC), and postcrisis periods. The constructed panel of data would be utilized in further investigation concerning commonality in liquidity on the Polish stock market.

**Keywords** Intraday data · Liquidity · Trade classification algorithm · Order-driven market · Global financial crisis

## 9.1 Introduction

The role of liquidity in empirical finance and market microstructure has grown over the last years influencing conclusions in asset pricing, corporate finance, and market efficiency. In his seminal work, Kyle (1985) argues that market liquidity is a slippery and elusive concept, in part because it encompasses a number of transactional properties of markets. For example, the inconsistent evidence of commonality in liquidity on various stock markets in the world might be attributed to the differences in market designs. It is important to distinguish between order-

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N. Tsounis, A. Vlachvei (eds.), *Advances in Panel Data Analysis in Applied Economic Research*, Springer Proceedings in Business and Economics,
https://doi.org/10.1007/978-3-319-70055-7_9

driven and quote-driven market structures because market structure determines how orders are transformed into trades and how this transformation affects liquidity. In an order-driven market, no designated market maker has an obligation to provide liquidity to the market. Traders and investors submit a limit order book to buy and sell shares, e.g., Harris (2003). Unfortunately, although the Warsaw Stock Exchange (WSE) is classified as an order-driven market with an electronic order book, the information of the best bid and ask price is not publicly available, e.g., Olbryś and Mursztyn (2015) and Nowak (2017).

It is important to note that direct measurement of liquidity, bid/ask spreads, other trading costs, etc. is difficult and even impossible as intraday trading data are not available free of charge in the case of most emerging stock markets. The lack of access to intraday trading data for emerging markets in general is a fact that is both widely known and amply commented in the literature, e.g., Lesmond (2005), Bekaert et al. (2007), and Olbryś (2014).

Measuring liquidity/illiquidity on the WSE is a crucial subject as Nowak and Olbryś (2016) documented cross-time and cross-security patterns in non-trading among the WSE-listed stocks. The empirical results reveal that a large number of the companies exhibit substantial non-trading problem, which means the lack of transactions over a particular period when the WSE is open for trading. Therefore, investors should recognize whether they have to take illiquidity risk into consideration in their financial decisions.

The goal of this paper is to estimate selected liquidity/illiquidity proxies derived from intraday data and to examine their magnitude on the WSE. We construct and analyze the panel of data which consists of daily estimations of five liquidity measures for 53 WSE-traded companies divided into three size groups. The high-frequency intraday data "rounded to the nearest second" covers the period from January 3, 2005, to June 30, 2015. As the raw data set does not identify a trade direction on the WSE, the trade classification Lee and Ready (1991) algorithm is employed to infer trade sides and to distinguish between so-called buyer- and seller-initiated trades (Olbryś and Mursztyn 2015). Moreover, the paper provides a robustness analysis of the obtained results with respect to the whole sample and three adjacent subsamples each of equal size: precrisis, crisis, and postcrisis periods. The global financial crisis (GFC) on the WSE is formally set based on the papers (Olbrys and Majewska 2014, 2015), in which the Pagan and Sossounov (2003) method for formal statistical identification of market states was employed.

To the best of the author's knowledge, the presented empirical results on the WSE are novel and have not been reported in the literature thus far. The constructed panel of data could be used in further investigation concerning commonality in liquidity on the WSE. It is worth to note that empirical market microstructure research has recently shifted its focus from the examination of liquidity of individual securities toward analyses of the common determinants and components of liquidity.

The remainder of the study is organized as follows. Section 9.2 describes the methodological background concerning the measurement of liquidity using intraday data. Section 9.3 presents a brief analysis of the obtained data panel and discusses the empirical results on the WSE. The last section summarizes the main findings with the conclusion.

| Nomenclature | |
|---|---|
| WSE | Warsaw Stock Exchange |
| GFC | The 2007–2009 global financial crisis |
| LR | The Lee and Ready (1991) trade side classification algorithm |
| %RS | Percentage relative spread |
| %ES | Percentage effective spread |
| %RealS | Percentage realized spread |
| %PI | Percentage price impact |
| %OR | Percentage order ratio |

## 9.2 Measuring Liquidity/Illiquidity Using Intraday Data

There is a growing body of empirical literature concerning direct measurement of liquidity based on intraday transaction data. Specifically, there has been quite extensive research on various versions of a bid/ask spread. The related literature indicates that different versions of a bid/ask spread are proper measures for stock illiquidity because they approximate the cost of immediate execution of a trade. In this research, percentage relative spread, percentage effective spread, and percentage realized spread are employed. It is worth to note that sometimes the same spread measure has different names. For example, relative spread is sometimes referred to as inside bid/ask spread, e.g., Levin and Wright (1999) and Acker et al. (2002), or as proportional (quoted) spread, e.g., Corwin (1999), Chordia et al. (2000, 2001), Chung and Van Ness (2001), Korajczyk and Sadka (2008), and Hameed et al. (2010). As for effective spread, the nomenclature is not unambiguous either. For example, in his seminal work Roll (1984) introduces the estimator of effective bid/ask spread in an efficient market, but he does not utilize intraday transaction data. Moreover, there are at least two basic versions of an effective spread derived from intraday data. One of them is calculated using a quote midpoint in the denominator, e.g., Corwin (1999), Finucane (2000), and Theissen (2001), while the second is computed using a transaction price, e.g., Chordia et al. (2000), Peterson and Sirri (2003), and Chakrabarty et al. (2007).

The literature is far too vast to give a complete citation list. Therefore, Table 9.1 presents a brief literature review concerning various versions of liquidity/illiquidity proxies based on the bid/ask spread concept. It is worth to note that both relative and effective spreads have been explored quite extensively, but relatively little empirical research has been conducted using realized spread. Realized spread is a temporary component of effective spread, which is defined as the amount earned by a dealer or other supplier of immediacy, e.g., Huang and Stoll (1996) and Theissen (2001). Realized spread is sometimes referred to as a price reversal component since a dealer takes profits only if price reverses.

Moreover, a price impact estimate is employed in our study. According to the literature, a proxy of price impact measures the sensitivity of a stock's price to trades (Stoll 2000, p. 1495), and most of researchers derive price impact from intraday

**Table 9.1** Summarized literature review: selected papers including various empirical applications of relative spread, effective spread, and realized spread

| The authors | Relative spread | Effective spread | Realized spread |
|---|---|---|---|
| Lee, Mucklow, and Ready (1993) | – | + | – |
| Lin, Sanger, and Booth (1995) | + | + | – |
| Huang and Stoll (1996) | – | + | + |
| Kluger and Stephan (1997) | + | – | – |
| Corwin (1999) | + | + | – |
| Levin and Wright (1999) | + | – | – |
| Brockman and Chung (2000) | + | – | – |
| Elyasiani, Hauser, and Lauterbach (2000) | + | – | – |
| Van Ness, Van Ness, and Pruitt (2000) | + | + | – |
| Chordia, Roll, and Subrahmanyam (2000) | + | + | – |
| Finucane (2000) | – | + | – |
| Stoll (2000) | – | + | – |
| Theissen (2001) | + | + | + |
| Chordia, Roll, and Subrahmanyam (2001) | + | + | – |
| Chung and Van Ness (2001) | + | – | – |
| Acker, Stalker, and Tonks (2002) | + | – | – |
| Piwowar and Wei (2003) | + | + | – |
| Peterson and Sirri (2003) | + | + | – |
| von Wyss (2004) | + | + | + |
| Chakrabarty, Li, Nguyen, and Van Ness (2007) | – | + | – |
| Korajczyk and Sadka (2008) | + | + | – |
| Pukthuanthong-Le and Visaltanachoti (2009) | + | – | – |
| Goyenko, Holden, and Trzcinka (2009) | + | + | + |
| Hameed, Kang, and Viswanathan (2010) | + | – | – |
| Olbrys and Mursztyn (2017) | + | – | – |
| Olbryś (2017) | + | – | – |

transaction data, e.g., Chakrabarty et al. (2007), von Wyss (2004), and Coppejans et al. (2004). Kyle (1985) provides a theoretical model for such a measure based on the adverse information conveyed by a trade. Price impact could be defined as the increase (decrease) in the quote midpoint over a time interval beginning at the time of the buyer- (seller-) initiated trade. This is the permanent price change of a given transaction, or equivalently, the permanent component of effective spread, e.g., Goyenko et al. (2009, p. 156).

Furthermore, order ratio as an order imbalance indicator is utilized in this research. Order imbalance has important influence on stock liquidity, considerably even more important than volume. Therefore, order imbalance indicators could be employed among other liquidity and trading activity measures to estimate liquidity. The literature proposes various proxies of order imbalance, e.g., Chan, Fong (2000), Ranaldo (2001), Chordia et al. (2002, 2005), von Wyss (2004), Korajczyk and

Sadka (2008), Pukthuanthong-Le and Visaltanachoti (2009), Nowak (2017), Olbrys and Mursztyn (2017), and Olbryś (2017). In this study, percentage order ratio is employed.

### 9.2.1 Selected Spread Proxies Derived from Intraday Data

In this research, we utilize the high-frequency data "rounded to the nearest second." The data set contains the opening, high, low, and closing (OHLC) prices and volume for a security over one unit of time. In measuring spread proxies, high, low, and closing prices are needed.

The midpoint price $P_t^{\mathrm{mid}}$ at time $t$ is calculated as the arithmetic mean of the best ask price $P_t(a)$ and the best bid price $P_t(b)$ at time $t$. Considering that the bid and ask prices are not made public on the WSE, the midpoint price at time $t$ is rounded by the arithmetic mean of the lowest price $P_t^L$ and the highest price $P_t^H$ at time $t$, which approximate the best ask price and the best bid price, respectively (Olbryś and Mursztyn 2015, p. 43):

$$P_t^{\mathrm{mid}} = \frac{P_t^H + P_t^L}{2} \tag{9.1}$$

The transaction price $P_t$ at time $t$ is approximated by the closing price.

**Percentage Relative Spread** The percentage relative spread value is given by Eq. (9.2):

$$\%RS_t = \frac{100 \cdot \left(P_t^H - P_t^L\right)}{P_t^{\mathrm{mid}}} \tag{9.2}$$

where $P_t^H, P_t^L$ are the highest and lowest prices at time $t$, respectively, while the midpoint price $P_t^{\mathrm{mid}}$ at time $t$ is given by Eq. (9.1). Percentage relative spread is in fact a measure of illiquidity. A wide percentage relative spread value denotes low liquidity. Conversely, a narrow percentage relative spread value denotes high liquidity. The %RS at time $t$ is equal to zero when $P_t^H = P_t^L$. Daily percentage relative spread value is calculated as a volume-weighted average of percentage relative spreads computed over all trades within a day.

**Percentage Effective Spread** The percentage effective spread value is obtained by relating the transaction price to the midpoint of the bid and ask quote and it is given by Eq. (9.3):

$$\%ES_t = \frac{200 \cdot \left|P_t - P_t^{\mathrm{mid}}\right|}{P_t^{\mathrm{mid}}} \tag{9.3}$$

where the midpoint price $P_t^{\mathrm{mid}}$ at time $t$ is given by Eq. (9.1), while the transaction price $P_t$ at time $t$ is approximated by the closing price. Similarly to percentage relative spread, percentage effective spread is an illiquidity measure. A wide percentage effective spread value denotes low liquidity. Conversely, a narrow percentage effective spread value denotes high liquidity. The %ES at time $t$ is equal to zero when $P_t = P_t^{\text{mid}}$. Daily percentage effective spread value is calculated as a volume-weighted average of percentage effective spreads computed over all trades within a day.

### *9.2.2 Trade Side Classification Algorithm*

To calculate several liquidity/illiquidity measures using intraday data, it is essential to recognize the side initiating the transaction and to distinguish between so-called buyer- and seller-initiated trades. The WSE is classified as an order-driven market with an electronic order book, but information of the best bid and ask price is not publicly available. In fact, even the nonproprietary financial databases that provide information on trades and quotes do not identify the trade direction. As a consequence, the researchers rely on indirect trade classification rules to infer trade sides. There are some trade classification procedures described in the literature, but the Lee and Ready (1991) algorithm (LR) remains the most frequently used (Chakrabarty et al. 2012, p. 468). The LR algorithm proceeds in three steps (Theissen 2001, p. 148):

1. Transactions that occur at prices higher (lower) than the quote midpoint are classified as buyer-initiated (seller-initiated) trades.
2. Transactions that occur at a price that equals the quote midpoint but is higher (lower) than the previous transaction price are classified as being buyer-initiated (seller-initiated).
3. Transactions that occur at a price that equals both the quote midpoint and the previous transaction price but is higher (lower) than the last different transaction price are classified as buyer-initiated (seller-initiated) trades.

In this paper, the LR procedure is employed as Olbryś and Mursztyn (2015) indicated that this algorithm performs quite well on the WSE, the empirical results turn out to be robust to the choice of the sample and do not depend on a firm size.

### *9.2.3 Some Liquidity Proxies Supported by the Trade Side Classification Algorithm*

As mentioned in the previous section, to compute some liquidity estimates using intraday data, it is essential to distinguish between the buyer- and seller-initiated trades. In this research, three alternative estimates of liquidity, supported by the trade side classification algorithm, are employed: (1) percentage realized spread, (2) percentage price impact, and (3) percentage order ratio as an order imbalance indicator. Both the realized spread and price impact proxies are treated as effective spread components, and they are calculated over a time interval beginning at the moment of the buyer- or seller-initiated transaction. For example, Goyenko et al. (2009, p. 156) employ a 5-min interval, and the subscript $t + 5$ means the trade 5-min after the trade $t$. Chakrabarty et al. (2007, p. 3820) use the subscript $t + 10$ which means the trade 10-min after the trade $t$. Theissen (2001, p. 159) proposes more general approach and the subscript $t + \tau$. In this study, the subscript $t + 5$ means the fifth trade after the trade $t$, as Nowak and Olbryś (2016) documented that a large number of the WSE-listed companies exhibit substantial non-trading problem, i.e., the lack of transactions over a particular period when the WSE is open for trading.

**Percentage Realized Spread** The percentage realized spread value, which is a temporary component of the effective spread, is given by Eq. (9.4):

$$\%\text{Real S}_t = \begin{cases} 200 \cdot \ln \frac{P_t}{P_{t+5}}, \text{when the trade } t \text{ is classified as a buyer-initiated} \\ 200 \cdot \ln \frac{P_{t+5}}{P_t}, \text{when the trade } t \text{ is classified as a seller-initiated} \end{cases} \tag{9.4}$$

where the transaction price $P_t$ at time $t$ is approximated by the closing price. The price $P_{t+5}$ is the closing price of the fifth trade after the trade $t$. The %RealS at time $t$ is equal to zero when $P_t = P_{t+5}$. The post-trade revenues earned by the dealer (or other supplier of liquidity) are estimated on the basis of actual post-trade prices. Daily percentage realized spread value is calculated as a volume-weighted average of percentage realized spreads computed over all trades within a day. Moreover, daily percentage realized spread value is defined as equal to zero when all transactions within a day are unclassified.

**Percentage Price Impact** The proxy of price impact focuses on the change in a quote midpoint after a signed trade, and it is given by Eq. (9.5):

$$\%PI_t = \begin{cases} 200 \cdot \ln \frac{P_{t+5}^{\text{mid}}}{P_t^{\text{mid}}}, \text{when the trade } t \text{ is classified as a buyer-initiated} \\ 200 \cdot \ln \frac{P_t^{\text{mid}}}{P_{t+5}^{\text{mid}}}, \text{when the trade } t \text{ is classified as a seller-initiated} \end{cases} \tag{9.5}$$

where the midpoint price $P_t^{\text{mid}}$ at time $t$ is given by Eq. (9.1), while $P_{t+5}^{\text{mid}}$ is the quote midpoint of the fifth trade after the trade $t$. Price impact could be defined as the increase (decrease) in the midpoint over a five-trade interval beginning at the time of buyer- (seller-) initiated transaction. The %PI at time $t$ is equal to zero when $P_t^{\text{mid}} = P_{t+5}^{\text{mid}}$. Daily proxy of percentage price impact value is calculated as a volume-weighted average of percentage price impact estimates computed over all trades within a day. Moreover, daily percentage price impact value is defined as equal to zero when all transactions within a day are unclassified.

**Percentage Order Ratio** The percentage order ratio as daily order imbalance indicator is given by the following Eq. (9.6):

$$\%\text{OR} = 100 \cdot \frac{\left| \sum_{i=1}^{m} \text{VBuy}_i - \sum_{j=1}^{k} \text{VSell}_j \right|}{\sum_{n=1}^{N} V_n} \tag{9.6}$$

where the sums $\sum_{i=1}^{m} \text{VBuy}_i$, $\sum_{j=1}^{k} \text{VSell}_j$, $\sum_{n=1}^{N} V_n$ denote daily cumulated trading volume related to transactions classified as buyer- or seller-initiated trades, and daily cumulated trading volume for all transactions, respectively. The OR indicator captures imbalance in the market since it rises as the difference in the numerator becomes large. According to the literature, a high order ratio value denotes low liquidity. Conversely, a small order ratio value denotes high liquidity. The OR indicator is equal to zero when the numerator is equal to zero. It happens when daily cumulated trading volumes related to transactions classified as buyer- or seller-initiated trades are equal. Moreover, the daily order ratio value is defined as equal to zero in two cases: (1) when all transactions within a day are unclassified, or (2) when total daily trading volume in the denominator is equal to zero.

## 9.3 Data Description and Empirical Results on the WSE

As mentioned in previous section, we utilize the database containing the high-frequency data "rounded to the nearest second" (available at www.bossa.pl) for 53 WSE-traded stock divided into three size groups, in the period from January 3, 2005 to June 30, 2015. When forming the database, we included only those securities which existed on the WSE for the whole sample period since December 31, 2004, and were not suspended. All companies entered into the database (147) were sorted according to their market capitalization at the end of each year. Next, the stocks were divided into three size groups based on the breakpoints for the bottom 30% (small companies), middle 40% (medium companies), and top 30% (big companies) (Fama and French 1993). The companies that remained in the same group during the period investigated were selected. Finally, the 53 WSE-listed companies were gathered into separate groups, specifically: 27 firms into the BIG group, 18 firms into the MEDIUM group, and 8 firms into the SMALL group (Nowak and Olbryś 2016).

We construct and analyze the panel of data which consists of daily proxies of five liquidity/illiquidity estimates presented in Sect. 9.2. As the intraday data set is large, special programs in the C++ programming language have been implemented to reduce the time required for calculations.

To verify the robustness of the obtained empirical results, the research is provided over the whole sample (2626 trading days) and three adjacent subsamples each of equal size (436 trading days): (1) the precrisis period September 6, 2005, to May 31, 2007; (2) the crisis period June 1, 2007, to February 27, 2009; and (3) the postcrisis period March 2, 2009, to November 19, 2010 (Olbrys and Mursztyn 2015; 2017). The global financial crisis on the WSE is formally set based on the papers (Olbryś and Majewska 2014; 2015), in which the Pagan and Sossounov (2003) method for formal statistical identification of market states was employed.

### *9.3.1 Summarized Results of Liquidity Estimates*

Tables 9.2, 9.3, and 9.4 present summarized results of the average daily values of five liquidity proxies described in Sect. 9.2, for each WSE-traded company entering the size group (i.e., BIG, MEDIUM, or SMALL, respectively). These results are worth of a comment. In general, the values of all liquidity estimates rather do not depend on a firm size and turn out to be robust to the choice of the period. Moreover, we observe the lower values of illiquidity proxies (i.e., %RS, %ES, %OR) for the most liquid big companies with the largest market capitalization (namely, KGH, OPL, PEO, PKN, PKO), regardless of the subsample choice.

Moreover, one can observe in Tables 9.2, 9.3, and 9.4 that average daily estimations of realized spread (%RealS) are positive for almost all stocks from three size groups, except for isolated cases. These findings are rather consistent with the literature because the existence of a bid/ask spread has several consequences in time series properties, and one of them is the bid/ask bounce, e.g., Roll (1984) and Tsay (2010). According to definition (4), realized spread is in fact a percentage logarithmic rate of return. As a price reversal component of a bid/ask spread the realized spread is usually positive since an investor realizes earnings only if price reverses. A small positive realized spread value informs about higher liquidity, while a high positive realized spread value denotes lower liquidity. Furthermore, the evidence is that average daily estimations of price impact (%PI) are negative in most cases, which is a probable consequence of the fact that both the realized spread and price impact proxies are treated as the effective bid/ask spread components complementing each other, e.g., Glosten (1987) and Huang and Stoll (1996, 1997).

Tables 9.2, 9.3, and 9.4 are based on (1) the whole sample period $P_1$ (3.01.2005 to 30.06.2015), (2) the precrisis period $P_2$ (6.09.2005 to 31.05.2007), (3) the global financial crisis period $P_3$ (1.06.2007 to 27.02.2009), and the postcrisis period $P_4$ (2.03.2009 to 19.11.2010). Ticker symbols are in alphabetical order according to the company's full name.

**Table 9.2** The BIG group – the average daily values of five liquidity proxies: %RS (2), %ES (3), %RealS (4), %PI (5), and %OR (6)

| | %RS | | | | %ES | | | | %RealS | | | | %PI | | | | %OR | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| BIG | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_1$ | $P_2$ | $P_3$ | $P_4$ |
| BHW | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.09 | 0.14 | 0.11 | 0.11 | −0.06 | −0.11 | −0.07 | −0.07 | 38.4 | 46.9 | 47.0 | 49.2 |
| BPH | 0.10 | 0.02 | 0.06 | 0.10 | 0.10 | 0.02 | 0.06 | 0.10 | 0.14 | 0.07 | 0.16 | 0.20 | −0.07 | −0.05 | −0.11 | −0.11 | 40.1 | 32.9 | 40.7 | 40.0 |
| BNP | 0.09 | 0.15 | 0.20 | 0.02 | 0.09 | 0.15 | 0.20 | 0.02 | 0.03 | 0.01 | 0.06 | −0.001 | −0.01 | 0.03 | −0.02 | 0.001 | 31.0 | 26.7 | 38.3 | 16.0 |
| BOS | 0.11 | 0.12 | 0.08 | 0.14 | 0.11 | 0.12 | 0.08 | 0.13 | 0.04 | 0.01 | 0.007 | 0.06 | −0.01 | −0.001 | −0.01 | −0.03 | 34.2 | 30.9 | 27.9 | 34.7 |
| BDX | 0.08 | 0.10 | 0.07 | 0.06 | 0.07 | 0.10 | 0.07 | 0.06 | 0.11 | 0.03 | 0.15 | 0.10 | −0.06 | 0.04 | −0.09 | −0.05 | 42.8 | 52.8 | 47.1 | 44.7 |
| BZW | 0.04 | 0.03 | 0.03 | 0.03 | 0.04 | 0.03 | 0.03 | 0.03 | 0.07 | 0.09 | 0.08 | 0.07 | −0.04 | −0.06 | −0.05 | −0.04 | 30.7 | 31.9 | 24.7 | 26.4 |
| DBC | 0.10 | 0.09 | 0.08 | 0.12 | 0.10 | 0.09 | 0.08 | 0.12 | 0.09 | 0.12 | 0.07 | 0.12 | −0.04 | −0.05 | −0.03 | −0.07 | 43.6 | 41.3 | 49.0 | 41.3 |
| ECH | 0.08 | 0.09 | 0.07 | 0.10 | 0.08 | 0.09 | 0.07 | 0.09 | 0.16 | 0.10 | 0.17 | 0.22 | −0.10 | −0.04 | −0.10 | −0.14 | 44.6 | 47.5 | 39.6 | 43.2 |
| GTN | 0.06 | 0.04 | 0.04 | 0.03 | 0.05 | 0.04 | 0.04 | 0.03 | 0.11 | 0.15 | 0.08 | 0.07 | −0.06 | −0.11 | −0.04 | −0.04 | 27.4 | 25.9 | 29.1 | 25.2 |
| GTC | 0.05 | 0.05 | 0.04 | 0.03 | 0.05 | 0.05 | 0.03 | 0.03 | 0.09 | 0.11 | 0.05 | 0.08 | −0.05 | −0.07 | −0.02 | −0.05 | 30.1 | 33.1 | 24.8 | 26.0 |
| ING | 0.06 | 0.06 | 0.09 | 0.06 | 0.06 | 0.06 | 0.09 | 0.05 | 0.10 | 0.13 | 0.09 | 0.09 | −0.05 | −0.08 | −0.03 | −0.04 | 48.0 | 57.6 | 53.2 | 43.4 |
| KTY | 0.07 | 0.04 | 0.07 | 0.08 | 0.07 | 0.04 | 0.06 | 0.08 | 0.13 | 0.22 | 0.13 | 0.09 | −0.08 | −0.18 | −0.09 | −0.04 | 46.0 | 44.2 | 50.6 | 48.9 |
| KGH | 0.02 | 0.02 | 0.03 | 0.03 | 0.02 | 0.02 | 0.03 | 0.03 | 0.02 | 0.02 | 0.03 | 0.03 | 0.000 | 0.000 | −0.01 | −0.007 | 17.0 | 16.7 | 18.9 | 18.5 |
| LPP | 0.08 | 0.09 | 0.11 | 0.09 | 0.08 | 0.09 | 0.10 | 0.09 | 0.09 | 0.05 | 0.19 | 0.12 | −0.05 | −0.01 | −0.12 | −0.08 | 45.8 | 53.0 | 48.8 | 51.7 |

| | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| MBK | 0.03 | 0.04 | 0.03 | 0.04 | 0.03 | 0.04 | 0.03 | 0.04 | 0.07 | 0.13 | 0.06 | 0.08 | −0.04 | −0.10 | −0.03 | −0.04 | 29.3 | 39.6 | 28.0 | 24.2 |
| MIL | 0.05 | 0.07 | 0.05 | 0.06 | 0.05 | 0.07 | 0.04 | 0.05 | 0.11 | 0.15 | 0.13 | 0.10 | −0.07 | −0.09 | −0.09 | −0.05 | 35.2 | 38.0 | 39.0 | 29.8 |
| MOL | 0.07 | 0.07 | 0.08 | 0.09 | 0.07 | 0.07 | 0.07 | 0.09 | 0.07 | 0.17 | 0.14 | 0.04 | −0.04 | −0.11 | −0.11 | −0.02 | 46.6 | 43.6 | 49.2 | 49.5 |
| NET | 0.05 | 0.03 | 0.07 | 0.06 | 0.05 | 0.03 | 0.07 | 0.05 | 0.12 | 0.15 | 0.13 | 0.13 | −0.08 | −0.11 | −0.07 | −0.08 | 36.5 | 29.2 | 42.3 | 39.4 |
| OPL | 0.02 | 0.01 | 0.02 | 0.02 | 0.02 | 0.01 | 0.02 | 0.02 | 0.04 | 0.04 | 0.04 | 0.04 | −0.02 | −0.03 | −0.02 | −0.04 | 21.4 | 19.6 | 20.1 | 21.7 |
| ORB | 0.08 | 0.05 | 0.05 | 0.10 | 0.08 | 0.05 | 0.05 | 0.10 | 0.13 | 0.17 | 0.10 | 0.17 | −0.08 | −0.12 | −0.07 | −0.10 | 49.8 | 45.2 | 48.9 | 51.2 |
| PEO | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.03 | 0.03 | 0.04 | 0.04 | −0.008 | −0.02 | −0.02 | −0.02 | 21.1 | 24.2 | 21.0 | 21.1 |
| PKN | 0.02 | 0.01 | 0.02 | 0.02 | 0.02 | 0.01 | 0.02 | 0.02 | 0.02 | 0.02 | 0.03 | 0.02 | 0.001 | −0.004 | −0.01 | −0.004 | 18.8 | 18.9 | 19.5 | 20.3 |
| PKO | 0.02 | 0.01 | 0.02 | 0.02 | 0.02 | 0.01 | 0.02 | 0.02 | 0.03 | 0.04 | 0.03 | 0.03 | −0.01 | −0.03 | −0.14 | −0.08 | 19.5 | 23.3 | 20.5 | 19.7 |
| STP | 0.14 | 0.12 | 0.14 | 0.12 | 0.13 | 0.12 | 0.13 | 0.12 | 0.14 | 0.16 | 0.22 | 0.16 | −0.07 | −0.08 | −0.10 | −0.31 | 44.7 | 43.0 | 47.5 | 45.8 |
| SNS | 0.07 | 0.11 | 0.08 | 0.07 | 0.06 | 0.11 | 0.07 | 0.06 | 0.12 | 0.12 | 0.20 | 0.20 | −0.07 | −0.03 | −0.13 | −0.14 | 31.7 | 40.9 | 37.8 | 34.4 |
| TVN | 0.04 | 0.03 | 0.03 | 0.04 | 0.04 | 0.03 | 0.03 | 0.03 | 0.08 | 0.09 | 0.08 | 0.08 | −0.05 | −0.06 | −0.06 | −0.05 | 27.2 | 28.4 | 25.2 | 26.1 |
| ZWC | 0.14 | 0.12 | 0.22 | 0.17 | 0.13 | 0.12 | 0.22 | 0.16 | 0.03 | 0.03 | 0.04 | 0.03 | −0.01 | −0.01 | 0.003 | 0.001 | 38.8 | 41.1 | 41.6 | 42.3 |
| *Mean* | *0.06* | *0.06* | *0.07* | *0.07* | *0.06* | *0.06* | *0.07* | *0.06* | *0.08* | *0.09* | *0.10* | *0.10* | *−0.05* | *−0.06* | *−0.06* | *−0.07* | *34.8* | *36.2* | *36.3* | *34.6* |

**Table 9.3** The MEDIUM group – the average daily values of five liquidity proxies: %RS (2), %ES (3), %RealS (4), %PI (5), and %OR (6)

| | %RS | | | | %ES | | | | %RealS | | | | %PI | | | | %OR | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| MEDIUM | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_1$ | $P_2$ | $P_3$ | $P_4$ |
| ALM | 0.17 | 0.16 | 0.14 | 0.18 | 0.17 | 0.16 | 0.14 | 0.17 | 0.22 | 0.26 | 0.20 | 0.23 | −0.13 | −0.14 | −0.12 | −0.09 | 42.9 | 38.7 | 46.6 | 36.8 |
| AMC | 0.12 | 0.15 | 0.15 | 0.15 | 0.12 | 0.15 | 0.15 | 0.14 | 0.17 | 0.21 | 0.25 | 0.17 | −0.08 | −0.09 | −0.14 | −0.06 | 37.3 | 37.3 | 40.0 | 27.0 |
| ATG | 0.17 | 0.16 | 0.16 | 0.15 | 0.17 | 0.16 | 0.16 | 0.15 | 0.12 | 0.03 | −0.003 | 0.04 | −0.04 | 0.02 | 0.04 | 0.01 | 43.7 | 42.8 | 47.3 | 50.3 |
| ATM | 0.13 | 0.15 | 0.14 | 0.14 | 0.13 | 0.15 | 0.14 | 0.14 | 0.16 | 0.19 | 0.25 | 0.16 | −0.10 | −0.10 | −0.16 | −0.09 | 44.3 | 45.2 | 43.3 | 42.2 |
| CNG | 0.12 | 0.10 | 0.12 | 0.12 | 0.12 | 0.10 | 0.12 | 0.11 | 0.14 | 0.17 | 0.08 | 0.18 | −0.08 | −0.11 | 0.004 | −0.11 | 44.4 | 37.3 | 49.9 | 46.8 |
| COL | 0.16 | 0.15 | 0.18 | 0.13 | 0.15 | 0.15 | 0.18 | 0.12 | 0.17 | 0.04 | 0.20 | 0.19 | −0.07 | 0.02 | −0.08 | −0.08 | 37.2 | 47.0 | 40.1 | 24.8 |
| IND | 0.12 | 0.15 | 0.11 | 0.17 | 0.12 | 0.15 | 0.11 | 0.17 | 0.09 | 0.10 | 0.08 | 0.20 | −0.05 | −0.04 | −0.06 | −0.14 | 43.7 | 45.1 | 46.4 | 46.2 |
| IPL | 0.13 | 0.15 | 0.14 | 0.13 | 0.13 | 0.15 | 0.14 | 0.13 | 0.11 | 0.17 | 0.08 | 0.10 | −0.04 | −0.06 | −0.02 | −0.03 | 44.7 | 37.9 | 42.0 | 41.6 |
| LTX | 0.13 | 0.15 | 0.13 | 0.16 | 0.13 | 0.15 | 0.13 | 0.15 | 0.15 | 0.17 | 0.18 | 0.19 | −0.06 | −0.03 | −0.06 | −0.08 | 33.7 | 28.5 | 28.4 | 33.0 |
| MCI | 0.13 | 0.13 | 0.13 | 0.14 | 0.12 | 0.13 | 0.12 | 0.12 | 0.16 | 0.20 | 0.15 | 0.12 | −0.05 | −0.08 | −0.03 | −0.01 | 24.9 | 24.4 | 24.7 | 17.4 |
| MNI | 0.17 | 0.14 | 0.15 | 0.11 | 0.16 | 0.14 | 0.14 | 0.10 | 0.21 | 0.23 | 0.20 | 0.15 | −0.09 | −0.10 | −0.09 | −0.06 | 34.1 | 26.8 | 27.8 | 40.8 |
| PEK | 0.14 | 0.14 | 0.12 | 0.16 | 0.14 | 0.14 | 0.12 | 0.16 | 0.14 | 0.23 | 0.22 | 0.07 | −0.08 | −0.14 | −0.16 | −0.03 | 43.4 | 40.7 | 45.8 | 47.5 |
| PUE | 0.18 | 0.19 | 0.22 | 0.20 | 0.18 | 0.19 | 0.22 | 0.20 | 0.05 | 0.02 | 0.06 | 0.08 | −0.01 | 0.02 | −0.02 | −0.03 | 41.5 | 42.1 | 38.6 | 42.6 |
| SKA | 0.11 | 0.14 | 0.10 | 0.10 | 0.11 | 0.14 | 0.10 | 0.10 | 0.02 | 0.04 | 0.08 | −0.02 | 0.000 | −0.01 | −0.07 | −0.04 | 43.9 | 43.6 | 43.3 | 45.6 |
| STF | 0.13 | 0.12 | 0.16 | 0.15 | 0.13 | 0.12 | 0.16 | 0.15 | 0.13 | 0.18 | 0.19 | 0.17 | −0.06 | −0.08 | −0.07 | −0.09 | 40.9 | 28.1 | 39.4 | 42.2 |
| STX | 0.13 | 0.11 | 0.14 | 0.09 | 0.12 | 0.11 | 0.12 | 0.07 | 0.19 | 0.17 | 0.15 | 0.18 | −0.10 | −0.06 | −0.03 | −0.11 | 30.5 | 24.0 | 18.4 | 28.2 |
| TIM | 0.16 | 0.14 | 0.14 | 0.15 | 0.16 | 0.14 | 0.14 | 0.15 | 0.11 | 0.20 | 0.15 | 0.06 | −0.05 | −0.10 | −0.09 | −0.01 | 43.4 | 38.4 | 46.2 | 47.5 |
| VST | 0.15 | 0.11 | 0.11 | 0.16 | 0.13 | 0.11 | 0.11 | 0.14 | 0.20 | 0.07 | 0.20 | 0.19 | −0.09 | −0.01 | −0.12 | −0.07 | 36.1 | 47.9 | 49.9 | 23.4 |
| *Mean* | *0.14* | *0.14* | *0.14* | *0.14* | *0.14* | *0.14* | *0.14* | *0.14* | *0.14* | *0.15* | *0.16* | *0.14* | *−0.06* | *−0.06* | *−0.07* | *−0.06* | *39.5* | *37.5* | *39.9* | *38.0* |

**Table 9.4** The SMALL group – the average daily values of five liquidity proxies: %RS (2), %ES (3), %RealS (4), %PI (5), and %OR (6)

| | %RS | | | | %ES | | | | %RealS | | | | %PI | | | | %OR | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| SMALL | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_1$ | $P_2$ | $P_3$ | $P_4$ |
| APL | 0.17 | 0.25 | 0.33 | 0.25 | 0.17 | 0.25 | 0.33 | 0.25 | 0.17 | 0.31 | 0.27 | 0.29 | −0.07 | −0.11 | −0.10 | −0.14 | 29.0 | 31.4 | 32.5 | 29.8 |
| BDL | 0.16 | 0.19 | 0.21 | 0.15 | 0.15 | 0.19 | 0.20 | 0.13 | 0.25 | 0.22 | 0.29 | 0.24 | −0.15 | −0.06 | −0.12 | −0.14 | 29.2 | 25.9 | 24.6 | 29.5 |
| EFK | 0.23 | 0.28 | 0.21 | 0.16 | 0.23 | 0.28 | 0.20 | 0.16 | 0.14 | 0.32 | 0.21 | 0.005 | −0.07 | −0.12 | −0.13 | 0.02 | 42.3 | 35.9 | 42.4 | 47.9 |
| ENP | 0.24 | 0.29 | 0.31 | 0.25 | 0.24 | 0.29 | 0.30 | 0.24 | 0.24 | 0.46 | 0.28 | 0.29 | −0.13 | −0.23 | −0.12 | −0.17 | 37.8 | 29.8 | 31.5 | 37.5 |
| KMP | 0.21 | 0.32 | 0.23 | 0.24 | 0.20 | 0.32 | 0.23 | 0.24 | 0.26 | 0.38 | 0.33 | 0.40 | −0.14 | −0.13 | −0.19 | −0.25 | 33.2 | 32.7 | 34.5 | 35.5 |
| MZA | 0.19 | 0.28 | 0.24 | 0.17 | 0.19 | 0.28 | 0.24 | 0.17 | 0.20 | 0.41 | 0.27 | 0.11 | −0.12 | −0.21 | −0.15 | −0.05 | 35.9 | 32.8 | 39.0 | 33.1 |
| PLA | 0.20 | 0.19 | 0.24 | 0.22 | 0.20 | 0.19 | 0.24 | 0.21 | 0.15 | 0.26 | 0.20 | 0.24 | −0.06 | −0.11 | −0.04 | −0.14 | 35.8 | 31.5 | 32.1 | 34.8 |
| SME | 0.25 | 0.34 | 0.20 | 0.29 | 0.25 | 0.34 | 0.20 | 0.29 | 0.15 | 0.45 | 0.04 | 0.12 | −0.06 | −0.22 | 0.03 | −0.06 | 41.5 | 37.6 | 39.1 | 43.2 |
| *Mean* | *0.21* | *0.27* | *0.25* | *0.22* | *0.20* | *0.27* | *0.24* | *0.21* | *0.20* | *0.35* | *0.24* | *0.21* | *−0.10* | *−0.17* | *−0.09* | *−0.13* | *35.6* | *32.2* | *34.5* | *36.4* |

## 9.4 Conclusion

The aim of this paper was to compute and to analyze the following liquidity proxies derived from intraday data on the WSE: (1) percentage relative spread, (2) percentage effective spread, (3) percentage realized spread, (4) percentage price impact, and (5) percentage order ratio. A panel of data consisted of daily estimates of five liquidity measures for 53 WSE-listed companies divided into three size groups was constructed. As the information about trade side is essential for estimation of some liquidity measures, the Lee and Ready (1991) algorithm was employed to infer trade sides and to distinguish between the buyer- and seller-initiated trades. Moreover, the paper provided a robustness analysis of empirical findings with respect to the whole sample and three adjacent subsamples each of equal size: precrisis, crisis, and postcrisis periods. The results revealed that values of all liquidity estimates rather do not depend on a firm size and turn out to be robust to the choice of the period.

The constructed panel of data would be utilized in further investigation concerning commonality in liquidity on the WSE. It is important to note that empirical market microstructure research has recently shifted its focus from the examination of liquidity of individual securities toward analyses of the common determinants and components of liquidity. Beginning with Chordia et al. (2000), the identification of the common determinants of liquidity, or commonality in liquidity, emerged as a new and fast growing strand of the literature on liquidity.

**Acknowledgments** This study was supported by the grant "Comparative research on commonality in liquidity on the Central and Eastern European stock markets" from the National Science Center, Poland, No. 2016/21/B/HS4/02004.

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