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Is liquidity wasted? The zero-returns on the Warsaw Stock Exchange

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Abstract
The purpose of our study is to examine the dynamics of various liquidity proxies around specific price formation within intraday data. We examine the behavior of the measures representing price impact, depth of the market, its width and elasticity around intraday zero-return observations. Our sample is based upon quotations of blue chip stocks listed on the Warsaw Stock Exchange, one of the European emerging markets. This paper identifies an incoherent behavior of liquidity measures from different dimensions around intraday zero-returns. Although the transaction costs are lower and zero return configurations seem to offer better liquidity, this potential is not exploited as the trading activity measures decrease. The stock market is characterized by high resiliency as the observed changes in liquidity measures are short-term.

Keywords Liquidity · Intraday data · Market microstructure · Price configurations · Zero-return

1 Introduction

Stocks's liquidity surveys are a mainstream component of financial econometrics (Amihud and Mendelson 2015). There is a consensus on the issue that liquidity is an important price formation factor in both developed and emerging markets (Bekaert et al. 2007). However, changes in liquidity are driven by various factors (Das and Hanouna 2010; Yingyi 2019). There are at least four dimensions of liquidity mentioned in the literature: depth, width, immediacy of price reaction and resiliency (Mazza 2015). The depth as defined from the trading activity perspective is the ability of the market to absorb orders without significant impact on prices. The market width is described as the costs of reverting a position within an interval. Immediacy is defined as an impact on price, whereas resiliency is described as the speed at which liquidity reverts to 'normal' levels after an adverse liquidity shock (see e.g. Goyenko et al. 2009; Kyle 1985).

Several attempts have been made to relate the incidence of zero-returns to liquidity. One of the earliest was reported by Lesmond et al. (1999) who proposed a new liquidity measure

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called zero-return. A zero-return is calculated as the proportion of daily zero-returns over a given month. In Lesmond et al. (1999) it is argued that zero-returns appear when the transaction costs threshold is not exceeded. In other words, zero-returns are the outcomes of the impact of transaction costs on investors' decisions. In Lesmond et al. (1999) two groups of investors are considered: informed traders and liquidity (noise) investors. The former has the information advantage over the latter, which comes from the access to private information. The noise traders are uninformed, have no access to private information or cannot interpret public information properly (Easley et al. 1996; Bloomfield et al. 2005). In the case of informed traders, if profits from trades based on information are too little in relation to the transaction costs, they will choose not to trade. For liquidity investors, if the transaction costs are too high, they will also decide not to trade. In general, the higher are the transaction costs, the less liquidity is offered, and the higher number of zero-returns is observed. Henceforth a zero-return used to be considered as a relevant monthly proxy for illiquidity both on the developed (Lesmond et al. 1999) and the emerging markets (Bekaert et al. 2007).

More recently, literature has offered new insights into a relation between price changes and liquidity within the high-frequency framework. Mazza (2015) examines the behavior of various liquidity measures around the special price configuration that occurs when the high, the low, the open, and the close prices (HLOC) are the same. The study is conducted on the Euronext market and is based on 15-min data. The evidence shows that when sellers and buyers set prices of a given stock at the same level (HLOC prices are the same), and a consensus on the value of a security is achieved, liquidity significantly improves. This result is robust to the choice of liquidity measures.

The research presented in Mazza (2015) is conducted within intraday event study approach, which is well-suited for the examination of a reaction to particular events. Within similar methodology (Gomber et al. 2013) study the dynamics of liquidity proxied by the exchange liquidity measure (XLM) on the German stock market. They examine the reaction of XLM measure to two types of shocks: "endogenous", that come from high volume transactions, and "exogenous", that are represented by the arrival of public information. They conclude that the resiliency of the market after a big transaction is high, as in such cases the stock market quickly reverts to the previous price levels.

Another strand of the intraday event study literature is devoted to price jumps and liquidity measures (e.g. Hanousek et al. 2012; Będowska-Sójka 2017). The results across these studies indicate that huge changes of prices (jumps) are accompanied by the increase in transaction costs and decrease of a market depth. Although the dynamics of liquidity measures around jumps were already examined, to our best knowledge there is a gap in the literature considering the relation between zero-returns and liquidity in the intraday data.

This study is aimed to examine liquidity dynamics at the time of the appearance of zero-returns, that is when consecutive close prices in short time periods are the same. The principal evidence is that around the occurrence of a zero-return the liquidity measures from different dimensions show significant changes, but their behavior is incoherent. We extend the examination of zero-returns which is a well-known proxy for daily or monthly illiquidity Lesmond et al. (1999). Within the high-frequency framework we obtain a more precise picture of what happens when zero-returns appear. We find that in a zero-return interval spreads decrease what signals lower transaction costs and as such should be exploited by traders. However, both volume and the number of transactions within a 10-min interval may decrease by as much as 30%. Such results suggest that although in zero-return interval liquidity measured by transaction costs improves, traders are not willing to trade. As different liquidity measures display incoherent reactions, it is difficult to determine if overall liquidity has improved or weakened. The lack of transactions at the time of lower spreads indicate that investors refrain from trading, but only for short time interval. The incoherence of the dynamics of liquidity measures is unusual as it has not been evidenced at any other event considered in the literature as jumps (Hanousek et al. 2012) or HLOC configurations (Mazza 2015).

Our research focuses on one of the quickly growing emerging markets, the Warsaw Stock Exchange (henceforth WSE). As Bekaert et al. (2007) claim the effects of liquidity might be particularly strong on such markets. We use the unique database created from tick-by-tick data which allows us to calculate liquidity measures in four dimensions. There is a strong periodicity not only in the liquidity measures, but also with respect to the occurrence of the special price configurations. We focus on the dynamics of liquidity measures at times of the zero-returns, including two special cases where either the low or the high price are the same as the close one. So far, the overall dependencies between price dynamics and different liquidity characteristics on the WSE are partially examined (Będowska-Sójka and Jumps 2016) and the issue of relation between zero-returns and liquidity has yet to be raised.

The rest of the paper is organized as follows: Sect. 2 contains data presentation and describe process of filtering tick-by-tick data and sample construction. Section 3 describes the methodology of the calculation of the liquidity measures used in the study. It also includes a description of the periodicity filters applied to the series as well as the introduction to event study methodology. Section 4 presents the results of empirical research. Section 5 concludes and sets some further issues.

2 Data

We use a sample of 20 stocks listed on the Warsaw Stock Exchange and belonging to WIG20, the Polish blue chip index. This exchange operates as an open limit order book market, where market participants submit both market orders and limit orders. Such markets' organization guarantee full transparency for market participants. There exists a continuous double auction mechanism where submitted orders are displayed in the order book and matched automatically (Sun et al. 2019). Thus, the market operates without any market makers, matching orders are based on their price and time priority. Trading hours are from 9:00 AM till 4:50 PM (CET).

We have tick-by-tick data for 61 trading days from January 4, 2016 to April 4, 2016.[1] We consider the stocks that are the constituents of the WIG20 in the end of 2015. The beginning of the year is chosen as this period does not include any extraordinary corporate actions such as dividend payouts or stock repurchases. Our database is built using data from the electronic limit order book operated by the Universal Trading Platform system. We have both price and volumes of each trade as well as the best bid and ask offers that appear in the order book during each trading day. We exclude those orders that are made at the time of an auction (fixing) at the beginning and the end of the day, because of their differences in the price setting mechanism. The raw data comprise between 45221 and 468715 entries for each stock. These entries are filtered according to the cleaning procedure presented in Barndorff-Nielsen et al. (2009). We construct the database for equally sampled data at 10-min intervals and calculate various liquidity measures as well as obtain high-low-open-close prices for all stocks throughout the sample period. With equally sampled data we obtain 47 intervals per day, starting from 9:10 AM and ending up on 4:50 PM. This sampling frequency allows the observation of intraday dynamics and avoids microstructure noise impact. We also considered

[1] Similar sample length with respect to the number of days is used in Mazza (2015), while in Gomber et al. (2013) the sample period consists of 21 days.

Table 1 Basic characteristics of the stocks included in the sample

No.	Ticker	Price	MV (PLN)	Share (%)	All quotes	Filt.quotes
1	PKO	27.33	23,438,017	14.40	258,351	97,075
2	PKN	67.85	21,033,364	12.92	383,503	123,089
3	PZU	34.02	19,039,973	11.69	243,308	84,218
4	PEO	143.5	18,794,482	11.54	165,033	55,887
5	PGE	12.79	9,951,630	6.11	190,259	67,964
6	KGH	63.49	8,660,671	5.32	468,715	171,406
7	BZW	284	8,620,252	5.29	154,283	70,041
8	PGN	5.14	8,369,416	5.14	95,055	36,898
9	LPP	5 555	7,104,909	4.36	45,221	19,973
10	CPS	20.88	4,475,983	2.75	80,632	32,790
11	ACP	56.8	4,255,286	2.61	69,617	28,110
12	OPL	6.56	4,246,662	2.61	98,080	38,643
13	MBK	314	4,045,890	2.49	63,066	30,530
14	EUR	48.5	3,788,093	2.33	136,731	48,976
15	ALR	66.5	3,615,007	2.22	76,935	32,030
16	CCC	138.55	3,510,857	2.16	136,371	48,975
17	TPE	2.88	3,005,539	1.85	128,690	43,234
18	ENG	12.64	2,537,354	1.56	105,895	51,122
19	ENA	11.3	2,419,081	1.49	77,814	31,390
20	SNS	3.81	1,892,389	1.16	59,520	27,523

Ticker is a company ticker, *Price* is given in Polish zloty (PLN) at the end of 2015, *MV* stands for the market value (in thousands) at the end of 2015, *Share (%)* stands for the fraction of shares in the WIG20 index portfolio in 4 quarter in 2015, *All quotes* informs what is the number of quotes within the sample period and *Filt.quotes* shows the number of quotations after filtering the data (mistakes, double recordings etc.)

higher frequency (2-min or 5-min intervals) but for the majority of stocks included in the WIG20 index the higher frequency introduced too many zeros in the dataset.

Table 1 shows the basic information about the stocks included in the sample. Namely, the tickers of the stocks, the prices at the end of 2015, the market capitalization, the weights in the WIG20 index, the number of all quotes within the sample period and number of quotes after filtering the data. The decrease in number of quotes results mainly from the fact that filters aggregate the quotations observed in one time-stamp (one second). The minimum tick size differs across stocks ranging from 0.01 to 5 Polish złoty (PLN) depending on the stock's prices ranges. We find substantial cross-sectional differences between the stocks in the index that are reflected in the index weights. There are: four big stocks with relatively higher capitalization (weights over 10%), five medium stocks with weights from 4.36 to 6.11%, and eleven small stocks with weights lower than 3%. Although all the stocks are gathered into one index, individually they represent quite a diverse collection of the stocks.

3 Methodology

We calculate several measures of liquidity and within event study methodology examine, if liquidity shows any pronounced behavior during periods of special configurations' occurrence. We consider the configurations in the similar spirit to Mazza (2015): (1) there is no change in the prices within 10 min period, that is the closing prices in the sequential intervals are the same, $C_t = C_{t-1}$ (zero-return case, henceforth CC), (2) a zero-return is observed with the close price equal to the maximum (high) price, $C_t = C_{t-1} = H_t$, (CCH), and (3) a zero-return is observed with the close price equal to the minimum (low) price, $C_t = C_{t-1} = L_t$, (CCL). The CCH and CCL are special cases of CC and might show the specifics of the different demand-supply situations.

3.1 Liquidity measures

We consider a few liquidity measures focused on the different aspects of liquidity that are commonly used in the literature (e.g. Gomber et al. 2013; Boudt and Petitjean 2014; Mazza 2015; Yingyi 2019). Firstly, to assess the market width we consider three spreads:

– Bid-ask spread with last price (BAS):

$$BAS_t = \frac{\sum_{k=1}^{N_k} volume_k \frac{p_k^A - p_k^B}{p_k} \cdot c}{volume_t}, \tag{1}$$

where p_k^A is an ask price, p_k^B is a bid price, and p_k is price of transaction k, c is a constant equal to 20,000, $volume_k$ is a number of shares traded with a given price p_k, N_k is a number of all transactions within an interval t and $volume_t$ is a sum of volumes within given interval.

– Weighted quoted spread (WQS):

$$WQS_t = \frac{\sum_{k=1}^{Q} M_k (q_k^A + q_k^B)}{\sum_{k=1}^{Q} (q_k^A + q_k^B)}, \tag{2}$$

where $M_k = 2(p_k^A - p_k^B)/(p_k^A + p_k^B)$, q_k^A and q_k^B are the quantity of the best ask and bid offers, while Q is the number of offers within the given period of time.

– Weighted effective spread (WES):

$$WES_t = \frac{\sum_{k=1}^{N_i} ES_k (q_k^A + q_k^B)}{\sum_{k=1}^{N_i} (q_k^A + q_k^B)}, \tag{3}$$

where

$$ES_k = \frac{2DIR_k \left(p_k - \frac{p_k^A + p_k^B}{2} \right)}{\frac{p_k^A + p_k^B}{2}}. \tag{4}$$

DIR_k stands for the direction of the *k-th* trade in interval i with $+1$ and -1 for buy and sell orders, respectively. As is common in the market microstructure literature we use the Lee and Ready Lee and Ready (1991) algorithm to categorize buyer and seller-initiated trades.

These three spread measures reflect different liquidity aspects: WQS represents the ex-ante liquidity 'to be consumed', BAS shows ex-post liquidity 'already consumed' while WES stays between these two as it takes into account not only the estimated trade direction, but also price and quantity of the offers in the order book.

The market depth (DEPTH) is measured as the quantity of shares available at the best bid and offer,

$$DEPTH_t = q_t^A + q_t^B, \tag{5}$$

where $q_t^A = \sum_{k=1}^{Q} q_k^A$ is a sum of the best ask (ADEPTH) and $q_t^B = \sum_{k=1}^{Q} q_k^B$ is a sum of the best bid offers in interval t (BDEPTH).

To estimate the trading speed, we apply depth imbalance, DI:

$$DI_t = \frac{q_t^A - q_t^B}{DEPTH_t}. \tag{6}$$

DI shows what is the difference between both side of the order book. We also consider order imbalance, OI, which accounts for the direction of the orders:

$$OI_t = \frac{sum_{k=1}^{N_i} DIR_k * (volume_k)}{(volume_t)}. \tag{7}$$

Additionally, a few trading activity measures are applied: volume measured as the product of prices and quantities in a given period of time (VOLUME), the average number of transactions traded within a given time interval (NT), and the average size of transaction within a given interval (ATS).

3.2 Periodicity and standardization

The literature shows that liquidity measures show strong periodical patterns in intraday data (e.g. Mazza 2015; Large 2007). As we found no studies considering the periodicity in liquidity proxies on the WSE, we examine this issue with the respect to our sample. Thus we plot the average spread measures across the time within a day. Figure 1 shows the periodicity patterns in liquidity measures for a single stock (PKO). The patterns are similar for the other stocks: at the beginning of the trading day the spreads are higher and the depths are lower than during the rest of the day. The same applies to volume and transaction number that are characterized by U-shape patterns. This is consistent with the previous studies from other markets (Kempf and Mayston 2008). In the case of the depth imbalance and the order imbalance the periodicity is less pronounced.

To enable the comparison of liquidity measures between different stocks and account for the periodicity simultaneously, we use the procedure described in Boudt and Petitjean (2014). We assumed that for the non-negative measures, intraday liquidity for each interval t in each day j, L_{tj}, is specified by multiplicative model in the following manner:

$$L_{tj} = \widetilde{L}_t \widetilde{L}_j \epsilon_{tj}, \tag{8}$$

where $\widetilde{L}_j$ represents the daily factor and is calculated as a median liquidity measure within a given day, $\widetilde{L}_j = median_j(L_{tj})$, $\widetilde{L}_t$ accounts for the periodicity in a given interval, whereas ϵ_{tj} is an IID error term with median 1. Our estimator of intraday periodicity is calculated as:

$$\widetilde{L}_t = median_t(L_{tj}/\widetilde{L}_j). \tag{9}$$

Then in the last step we analyze the percentage deviation of the deseasonalized liquidity proxies with the respect to their daily level:

$$\widetilde{L}_{tj} = L_{tj}/(\widetilde{L}_t \widetilde{L}_j) - 1. \tag{10}$$

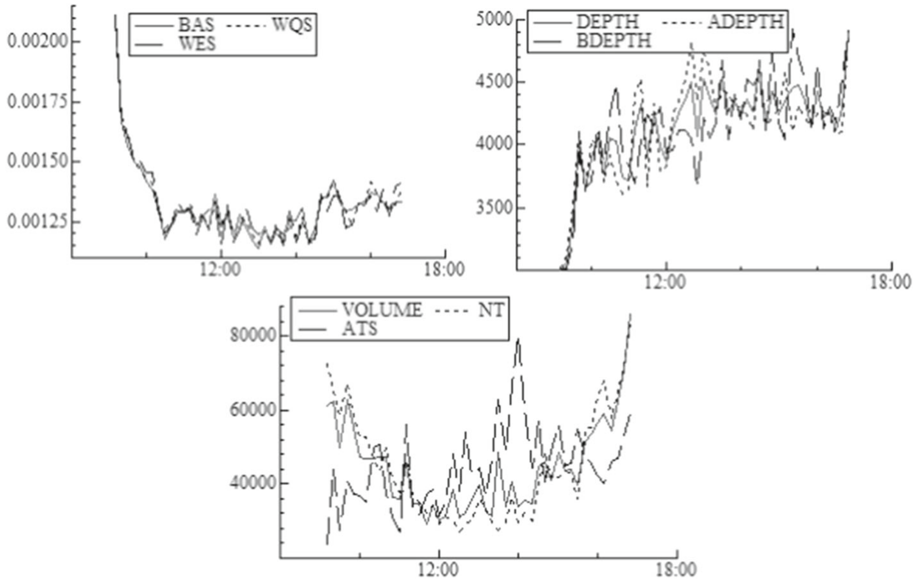

Fig. 1 Periodicity of liquidity measures - the case of PKO. Note: BAS is bid-ask spread with last price, WQS stands for weighted quoted spread and WES for weighted effective spread. DEPTH, ADEPTH and BDEPTH denote overall depth, depth on the ask side and on the bid side, respectively. DI stands for depth imbalance, OI stands for order imbalance. Volume is the trading volume, while NT stands for number of transactions

This approach allows the removal of the periodicity from the series with the MAD method commonly used in the intraday series (Laurent 2010). There is an evidence that this method is robust (see e.g. Boudt and Petitjean 2014; Boudt et al. 2011). For two liquidity measures that obtain both positive and negative values, DI and OI, we use additive approach in the following way:

$$L_{tj} = \widetilde{L}_t + \widetilde{L}_j + \eta_{tj}, \tag{11}$$

where η_{tj} is IID with median 0. Thus

$$\widetilde{L}_t = median_t(L_{tj} - \tilde{L}_j) \tag{12}$$

and

$$\widetilde{L}_{tj} = L_{tj} - \widetilde{L}_t - \widetilde{L}_j. \tag{13}$$

The periodicity removal allows us to focus on the unexpected liquidity rise and drops rather than the changes that are due to pure periodical pattern. Conducting simultaneous median standardization allows control over skewness in the liquidity proxies as well as to gather all price configurations for different stocks in one set. Again, we use the medians as an aggregation method.

3.3 An event study type of approach

In our study we investigate the behavior of the various liquidity measures around the predefined price configurations. We achieve this using event study approach in a similar spirit as Degryse et al. (2003), Mazza (2015) or Boudt and Petitjean (2014), and construct windows consisting of four time stamps before and four after the price configuration appears. Thus we create the windows comprising of nine observations from $t = -4$ to $t = +4$, where $t = 0$ denotes the time interval in which a price configuration is found. The values of a liquidity measure are calculated for each stock during every 10-min interval time stamp. Then these values are aggregated across different stocks for each time stamp. This is considered reasonable since all measures are previously standardized. We look at the evolution of averaged liquidity measures within the whole window and examine, whether there are any regular patterns in their behavior. More specifically we look directly into the levels of the liquidity measures and examine if there are significant changes between liquidity measures in time $t = 0$ and remaining time stamps.

It means that additional to the actual event observation one obtains four pre- and four post-event observations, that is four 10-min intervals before and after the event. In order to avoid the effect of the opening or closing of the market (that is the effect of overlapping of days), we exclude from the sample the first and the last four 10-min observations within a trading day. Also the overlapping events are excluded from the sample. The overlapping events are those, that occur too close to the previous event (as we need a window starting from $t - 4$ and ending at $t + 4$ there should be a space of 9 intervals between the next event). This reduces the overall number of events from 6975 to 822 for CC configuration, from 3475 to 698 for CCH configuration, and from 3227 to 702 for CCL. It also causes some price configurations of type CC to be deleted from the sample, while CCH and CCL that are reported at the same time (as zero-returns with extra condition) are retained. This reduction differs between certain stocks: the largest (and more liquid) stocks having lower reduction rates than the smaller stocks. This results from the fact that the zero-returns appearance is less frequent for large and more liquid stocks and hence the clusters of price configurations are observed less often. Finally, as the liquidity measures of stocks are standardized, we aggregate them in the event windows by calculating the median values at each time interval for each liquidity proxy separately.

As far as the timing of the configurations is considered, these differ within the daily period. Figure 2 shows the number of price configurations type CC within a trading day for all stocks. Due to avoiding overlapping days the first four (from 9:10 to 9:40) and the last four intervals (from 16:20 to 16:50) are omitted. More price configurations occur at the beginning and the end of the day than in the lunch time (a kind of U-shape pattern is observed).

4 Empirical results

The main hypothesis in this paper is that the zero-returns have no effect on liquidity. We test this hypothesis by examining the behavior of different liquidity measures within the periods of zero-return (price configuration CC) occurrence. We also control special cases of zero-return, where the close price is equal to the maximum price (CCH) and the minimum price (CCL) within the specified interval.

Figure 3 shows the behavior of spreads around the event. Generally for all measures, WOS, WES and BAS, the spreads are decreasing at the time of the event (when the price configuration CC appears). The lowest spread is observed during the first 10 min interval after the price configuration (at $t = +1$). On average a 5% drop in the spreads is observed. However, when the specific configurations, CCH and CCL, are considered, for BAS and WQS the lowest spreads seem to occur at $t = 0$. This should be noted that differences between spreads in $t = 0$ and $t = +1$ are not statistically significant.

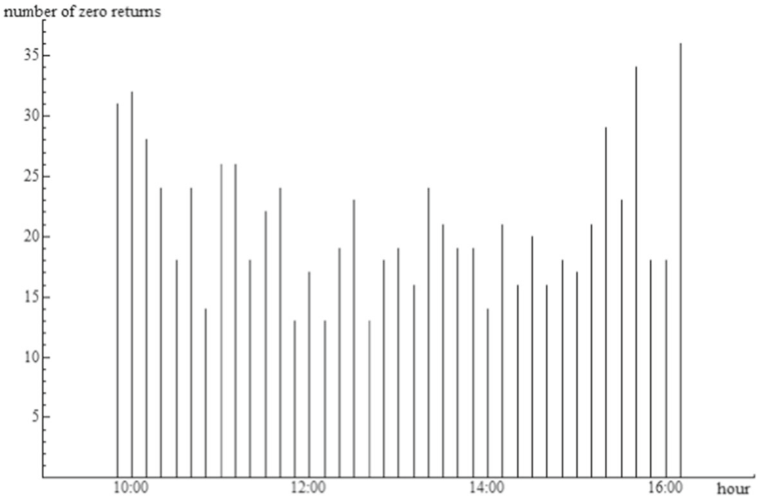

Fig. 2 The frequency of zero-returns (CC) price configurations in each 10-min interval within a trading day

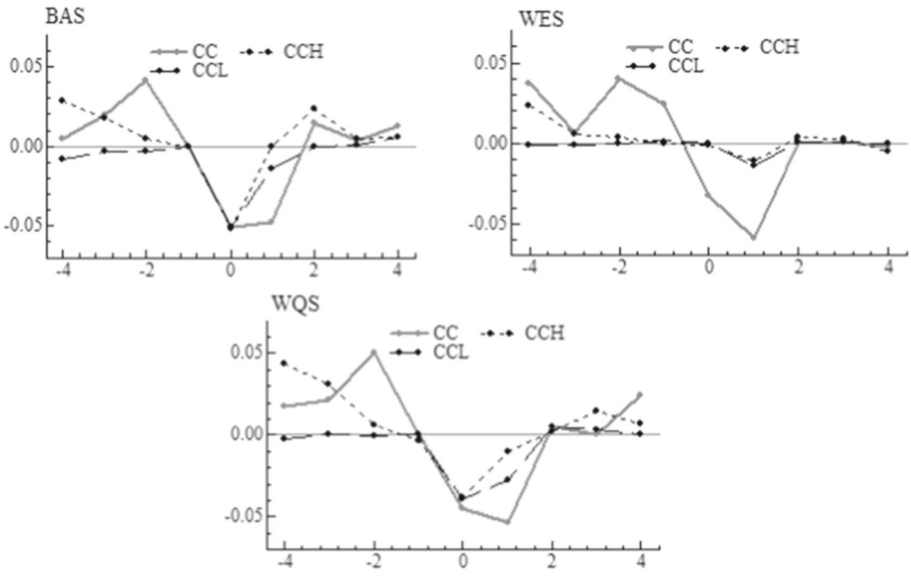

Fig. 3 Spreads around zero-returns. Note: WQS stands for weighted quoted spread, WES for weighted effective spread and BAS is bid-ask spread with last price. CC denotes price configuration, in which price in interval t is the same as price in interval $t-1$. CCH and CCL denote additional conditions, that the highest price or the lowest price in the interval is the same as the close price, respectively. On the axis of ordinates there are the intervals t around the events under study $t \in \{-4, -3, \ldots, 0, \ldots, 3, 4\}$, that is from 40 min before the event to 40 min after it

More specifically, we use the Mann-Whitney test to detect if the medians in particular intervals from $t = -4$ to $t = +4$ are different from each other. Specifically we focus on the comparison between $t = 0$ and remaining time intervals under the null hypothesis that the medians of two samples are the same. Table 2 presents the results. For BAS medians

Table 2 The comparison of aggregated value in different time intervals: Mann-Whitney U test results

t	BAS Z-Score	t = 0 *p-value*	WQS Z-Score	t = 0 *p-value*	WES Z-Score	t = 0 *p-value*	WES Z-Score	t = +1 *p-value*
− 4	3.91	*0.00*	3.96	*0.00*	− 2.90	*0.00*	3.54	*0.00*
− 3	3.05	*0.00*	3.36	*0.00*	− 1.82	*0.07*	2.42	*0.02*
− 2	3.56	*0.00*	3.78	*0.00*	− 2.73	*0.01*	− 3.38	*0.00*
− 1	1.43	*0.15*	1.71	*0.09*	1.82	*0.07*	2.41	*0.02*
0	–	–	–	–	–	–	0.48	*0.63*
1	− 0.52	*0.60*	− 0.06	*0.96*	0.48	*0.63*	–	–
2	− 3.54	*0.00*	3.27	*0.00*	1.90	*0.06*	2.50	*0.01*
3	2.99	*0.00*	2.37	*0.02*	1.37	*0.18*	1.93	*0.05*
4	2.97	*0.00*	3.73	*0.00*	− 1.07	*0.28*	− 1.62	*0.11*

BAS is bid-ask spread with last price, WQS stands for weighted quoted spread, and WES for weighted effective spread. The null hypothesis is that the medians in two different time intervals are the same. Table presents the empirical statistics of Mann-Whitney U test together with p values for the medians of spreads in $t = 0$ or $t = +1$ and other t

at $t = 0$ are not statistically different from medians at $t = -1$ and $t = +1$. In other time intervals medians for BAS are statistically different from these observed for $t = 0$. For WQS the results are similar. When we analyze WES the picture is different: there are only two intervals, $t = -4$ and $t = -2$ for which we reject the null hypothesis. Thus we examine also the equality of medians with respect to $t = +1$. In this case medians of spreads in $t = -4$ to $t = -1$ are statistically significantly different from $t = +1$.

Next we consider depth measures. Figure 4 shows the behavior of overall depth as well as the depth on the bid and the ask side. The depth increases at the time of the CC price configuration's appearance. However, the rise is more pronounced in the cases of CCH and CCL configurations. The depth stays on the same level after two 10-min intervals. In the case of zero-return price configuration there is a significant increase of 2% from interval $t = 0$ to $t = +1$. For the depth on the bid and the ask side (BDEPTH and ADEPTH), the situation is different: for the ask side there is a significant increase specifically for the CCH configuration, while for the bid side the increase is due to CCL configurations (and is two times smaller).

We also provide the analysis of trading activity measures. Figure 5 presents the volume (VOLUME), number of transactions (NT), and average size of transactions (ATS) within the event window. It is surprising that although spreads are lower on the market, the volume and number of transactions is definitely lower at the time of all price configuration occurrence.

Mann-Whitney tests shown in Table 3 for the medians indicate that for VOLUME, NT and ATS there is a significant difference between the value of proxies in $t = 0$ and other time intervals. This effect is short-term as at the next interval the liquidity measures revert to the normal levels indicating the high resiliency of the market. This drop in volume and the number of transactions as well as the average transactions size constitutes the evidence for a lack of noise traders activity. The decrease in volume is the most severe in the case of CCL configuration (40%), followed by CCH (30%). In the case of CC configurations we observe 10% decrease both in volume and in the average number of transactions, NT. The average size of transactions, ATS, shows a less spectacular decrease at time $t = 0$ of 2.5%

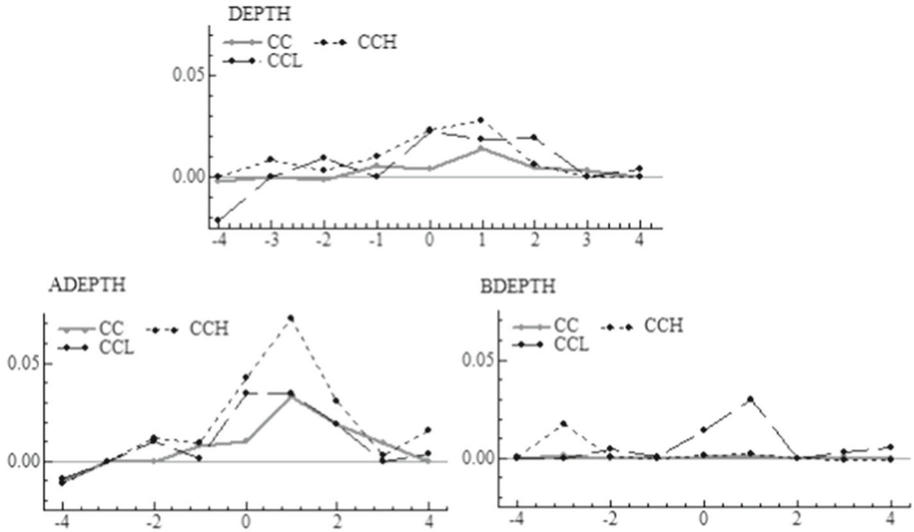

Fig. 4 Depth measures around zero-returns. Note: DEPTH, ADEPTH and BDEPTH denote overall depth, depth on the ask side and on the bid side, respectively. CC denotes price configuration, in which price in interval t is the same as price in interval $t-1$. CCH and CCL denote additional conditions, that the highest price or the lowest price in the interval is the same as the close price, respectively. On the axis of ordinates there are the intervals t around the events under study $t \in \{-4, -3, \ldots, 0, \ldots, 3, 4\}$, that is from 40 min before the event to 40 min after it

Table 3 The comparison of median values of proxies in different time intervals: Mann-Whitney U test results for DEPTH, VOLUME, number of transactions NT and average size of transactions ATS

t	DEPTH		VOLUME		NT		ATS	
	Z-Score	*p-value*	Z-Score	*p-value*	Z-Score	*p-value*	Z-Score	*p-value*
− 4	2.27	*0.02*	5.29	*0.00*	5.80	*0.00*	− 1.27	*0.20*
− 3	0.82	*0.41*	4.40	*0.00*	4.71	*0.00*	− 1.70	*0.09*
− 2	0.87	*0.38*	5.15	*0.00*	5.17	*0.00*	− 2.43	*0.02*
− 1	0.66	*0.52*	4.66	*0.00*	− 4.42	*0.00*	2.72	*0.01*
0								
1	0.26	*0.80*	5.88	*0.00*	− 5.68	*0.00*	3.08	*0.00*
2	− 0.53	*0.60*	4.56	*0.00*	4.33	*0.00*	− 3.17	*0.00*
3	− 0.04	*0.97*	4.76	*0.00*	4.86	*0.00*	2.24	*0.03*
4	− 0.18	*0.86*	5.19	*0.00*	− 5.05	*0.00*	2.68	*0.01*

DEPTH stands for depth in the market, VOLUME is the average trading volume, NT is average number of transactions and ATS is the average size of transactions. The null hypothesis is that the medians in two different time intervals are the same. Table presents the empirical statistics of Mann-Whitney U test together with p values for the medians of spreads in $t = 0$ and other t

on average for CC configuration. This measure tends to overreact the decrease at $t = 0$ in interval $t = +1$, but after it all measures revert back to previous levels.

Finally, we consider depth and order imbalances. Figure 6 presents the behavior of these variables around an event window. There is no clear pattern in behavior of these measures. When DI is considered, the reaction to price configurations is differentiated. For OI the

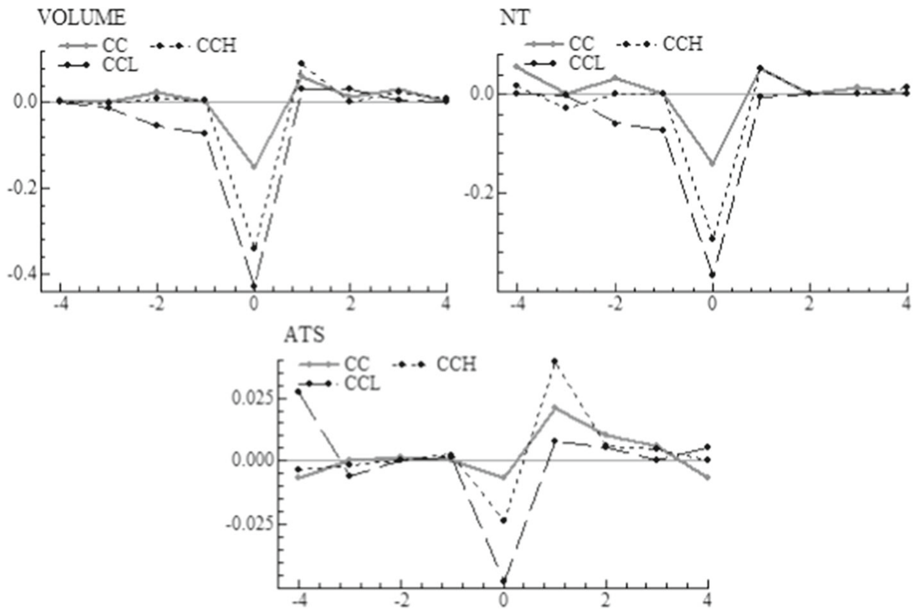

Fig. 5 Volume, number of transaction and average size of transaction around zero-returns. Note: VOLUME is the average trading volume, NT stands for the average number of transactions, while ATS stands for the average transaction size. CC denotes price configuration, in which price in interval t is the same as price in interval $t-1$. CCH and CCL denote additional conditions, that the highest price or the lowest price in the interval is the same as the close price, respectively. On the axis of ordinates there are the intervals t around the events under study $t \in \{-4, -3, \ldots, 0, \ldots, 3, 4\}$, that is from 40 min before the event to 40 min after it

dynamics observed for different configurations are also not coherent, but average standardized order imbalance is close to zero both at the time of the event and the two following intervals. Because the behavior of these two liquidity proxies varies, the overall conclusions are weakened. Mann-Whitney's test' results show no difference in medians in $t = 0$ or other time intervals (these results are available upon request).

As a robustness check, we also examine the liquidity measures of the four biggest stocks in our sample. This is due to the presence of substantial cross-sectional differences between the stocks in the index, reflected in the index weights. There are 247 type CC price configuration in this group, which account for 30% of events for all stocks. Figure 7 presents medians of two spreads, BAS and WQS, for all and four biggest stocks separately, as well as VOLUME and average transaction size, ATS.

We found that there are no significant differences in the dynamics of the spreads. They decrease in time $t = 0$ and $t = +1$ in the case of four stocks as it has been observed for all 20 stocks. Also two activity measures, VOLUME and ATS, behave in a similar manner, but for the latter we observe that the decrease in four big stocks during time $t = 0$ is even more pronounced than for all 20 stocks. The results of Mann-Whitney U test for medians show that for BAS, WQS, VOLUME and ATS there is a significant difference between the value of proxies during both $t = 0$ and other time intervals (those results are available upon request). Tests for depth measures as well as order imbalances show the differences between medians in $t = 0$ and various time intervals remain insignificant. Thus, they do not bring any new light into previous results.

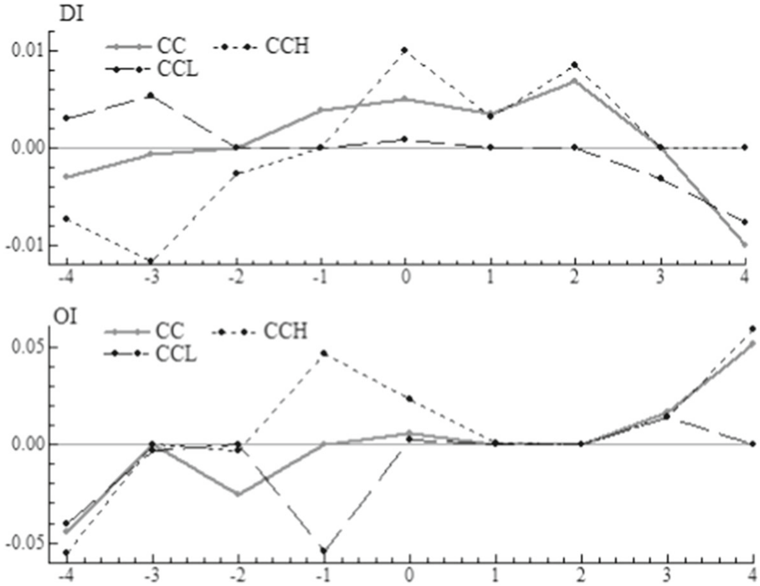

Fig. 6 Depth imbalance and order imbalance around zero-returns. Note: DI stands for depth imbalance, OI stands for order imbalance. CC denotes price configuration, in which price in interval t is the same as price in interval $t-1$. CCH and CCL denote additional conditions, that the highest price or the lowest price in the interval is the same as the close price, respectively. On the axis of ordinates there are the intervals t around the events under study $t \in \{-4, -3, \ldots, 0, \ldots, 3, 4\}$, that is from 40 min before the event to 40 min after it

5 Conclusions

Our paper is aimed to examine the behavior of various liquidity measures around distinct price configurations. We examined if zero-returns impact on liquidity in different dimensions. The study sample consisted of blue chip stocks listed on the Warsaw Stock Exchange and included in the WIG20 index. The differences between the biggest and the smallest stocks within the sample were found to be significant. By using a relatively recent dataset and applying different liquidity measures we provided a joint analysis of the liquidity measures, which incorporated spreads, width and depth of the market, as well as immediacy of reaction to changes. We controlled the periodicity of intraday liquidity measures and standardized these measures making them comparable across the sample.

We found that trading costs measured by spreads, volume, average number and size of transactions within given interval are all affected by the occurrence of the zero-returns. We found this impact to be short-term as the variables revert to the previous levels quickly, and this confirms the high resiliency of the market.

Our study extended previous findings of Lesmond et al. (1999), which argued that zero-returns are observed only when the value of information is not sufficient to exceed the cost of trading; in other words, zero-returns appear when the transaction cost threshold is not exceeded. The examination of high-frequency data shows that zero-returns are in fact accompanied by better liquidity in terms of lower spreads and thus lower transaction costs. However, this potential improvement to liquidity is seldom exploited as all trading activity measures decrease at the time of price configuration's occurrence. Ultimately during zero-returns intervals liquidity measures from different dimensions seem to behave in incoherent

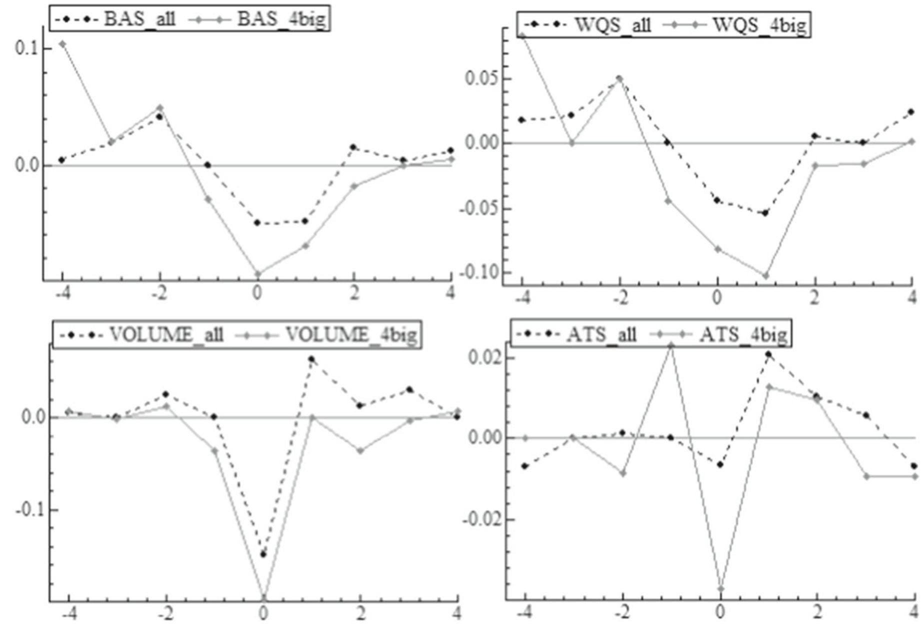

Fig. 7 Spreads and volume around zero-returns: four biggest stocks versus all remaining stocks.Note: BAS is bid-ask spread with last price, and WQS stands for weighted quoted spread. VOLUME is the average trading volume, while ATS stands for the average transaction size. "all" refers to medians for all stocks in the sample, while "4big" refers to medians of the biggest four companies. On the axis of ordinates there are the intervals t around the events under study $t \in \{-4, -3, \ldots, 0, \ldots, 3, 4\}$, that is from 40 min before the event to 40 min after it

manner. The lack of price changes, which creates the zero-returns, does not have to be a signal of illiquidity itself. Zero-returns might be caused by lack of information. Hence, informed investors refrain from trading, while noise traders prefer to await for the next move on the market. The zero-return is a kind of "take a breath" for a little while before next trigger.

Although the differences within the blue chip constituents with respect to capitalization are substantial, we have found no discrepancies in the results for spreads, depths and trading activity measures between the biggest stocks and all index constituents. The dynamics of various liquidity measures around zero-returns remain similar, although for the biggest stocks the changes in liquidity measures are much more pronounced.

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