How does market behave around the aggressive orders?

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Abstract

In the paper we study how aggressive orders, defined as those with exceptionally high volume, influence other dimensions of liquidity on the stock market. We conduct the intraday event-study around huge price movements. The sample consists of the most liquid stocks listed on the Warsaw Stock Exchange during three months of 2016. We consider market width defined as the cost of reverting position, market depth, that is the ability to absorb big orders, and resiliency, which is defined as the ability to recover after big shocks. We find differences between spreads that are related to the trading activity of particular stocks. The change in the spreads lasts only for a short time interval, and the market tend to recover very quickly.

1 Introduction

A vast majority of stock markets around the world are organized as a pure limit order market. In such a trading system unfilled orders are stored in the order book for a specified period or are removed. There are no market makers, and instead liquidity is provided by the limit order book. Depending on the offers on both sides of the book, investors will or will not be able to execute their orders in sufficiently short time and without significant changes in prices. According to Pastor and Stambaugh (2003) liquidity is defined as a possibility to trade non-incremental amount of shares, with little or no impact on the prices and at possibly low costs. For liquid markets, all these conditions should hold.

One of the crucial issues considered within limit order markets are the aggressive orders. They are defined in number of ways; the most general definition states that these orders provoke exceptional changes in the order book (Large, 2007). The aggressive orders are described usually as ones for which the ask (or the bid) price is relatively far from what is observed in the order book. The limit price set by trader reveal his or her aggressiveness in the sense, that it shows how much may he or she is able to sacrifice to execute the order. The bigger the distance between the present and recent orders is, the more aggressive is the order.

Also Biais et al. (1995) stress that "aggressiveness" is a relative term, which is not unequivocally defined. It is measured either as proportion of price changes in limit orders (Hall and Hautsch, 2007) or in the trading volume framework, where exceptionally high volume indicate aggressiveness (Large, 2007). With the respect to the first proposal, according to Beltran-Lopez et al. (2012) "aggressive" trades are these that are executed beyond the best bid and ask prices, and thus they "walk up" the book. Referring to the second one, Large (2007) propose to use quantiles to define the aggressive orders as a complimentary indicator.

Cenesizoglu and Grass (2018) show that liquidity on the bid-side and ask-side is different and that spreads express asymmetric features. This could also to be considered in the aspect of aggressive orders. Hall and Hautsch (2007) show that there is a periodicity in setting the aggressive orders: they tend to arrive after market opening and in the afternoon, but disappear at the end of the trading day. The aggressive orders tend to cause order imbalances. When market reveals such imbalances on the bid or the ask side, the pressure on trading activity of the buy or sell side is stronger.

Harris and Panchapagesan (2005) show that both pre-commited traders and value-motivated traders are willing to place aggressive orders. The former do this to increase the probability of trading, while the latter use these orders when they want to exploit the opportunity of the profitable trade. Generally these type of orders tend to create order imbalances in the order book and as such are informative about future price changes.

Havran and Váradi (2015) show that the aggressive order consumes all available offers on any side, and as a result the order book will change substantially. Their work is in the strand of the literature, that focuses on the resiliency of the market defined as the time, which is required to recover from the shock in the order book (Large, 2007). Degryse et al. (2005) show that some time is required for spreads to come back to the previous levels after an event. They show that aggressive orders tend to be informative and result in persistent price changes. Gomber et al. (2013) provide the excellent literature review in this area. Our work is similar to their in the sense that they are also focused on the the impact of large trades on liquidity. However, their research is more dedicated to the reaction to particular news that arrives on the market.

Our purpose of the study is to examine the reaction of spreads and trading activity measures to the aggressive orders defined as the ones executed with exceptionally high volume. We focus on the Warsaw Stock Exchange as one of the quickly growing emerging markets, that is organized as the limit order driven market. Our contribution to the literature is the following: first, we find that aggressive orders cause changes in spreads, but these changes are different for more and less actively traded stocks. Second, we find that trading activity measures are increasing at the time when the aggressive order is executed more in case of less actively traded stocks than the more actively traded ones. Third, we explore new dataset from the emerging European stock market and confirm the stylized facts already observed in more developed countries.

The rest of the paper is the following: in Section 2 we present the structure of the market and our data. In Section 3 the methodology is described, the spreads and trading activity measures are presented as well as periodicity filtering method. Section 4 presents the results of empirical research, while Section 5 concludes and sets some further issues.

2 Market structure and data

The Warsaw Stock Exchange was recreated in 1991 following the model of the Paris Stock Exchange. This is the open limit order book market with continuous trading and no designated market makers. There exists a double auction mechanism; submitted orders are displayed in the order book and matched automatically. The floor opens at 9:00 a.m. with opening fixing and ends up on 4:50 with final fixing. From 9:00 a.m. to 4:50 p.m. the trading is continuous, where matching orders process is based on the price and time priority. In the paper a unique tick-by-tick database created from data obtained directly from the WSE is used.

Our empirical analysis is based on the data over three months for eight constituents of WIG20 index, the main Polish blue chip index, based on 20 biggest and most liquid stocks on the Warsaw Stock Exchange. There are substantial cross-sectional differences between the

Table 1: Basic characteristics of the stocks included in the sample.

No.	*Ticker*	*Price*	*MV (PLN)*	*Share (%)*	*Total quotes*	*Adj quotes*
1	PKO	27.33	23438017	14.40%	258351	97075
2	PKN	67.85	21033364	12.92%	238703	84217
3	PZU	34.02	19039973	11.69%	165031	55886
4	PEO	143.5	18794482	11.54%	383503	123089
5	PGE	12.79	9951630	6.11%	468715	171406
6	KGH	63.49	8660671	5.32%	190259	67964
7	BZW	284	8620252	5.29%	154283	70041
8	PGN	5.14	8369416	5.14%	95055	36898
9	LPP	5 555	7104909	4.36%	45221	19973
10	CPS	20.88	4475983	2.75%	80632	32790
11	ACP	56.8	4255286	2.61%	48239	21001
12	OPL	6.56	4246662	2.61%	98080	38643
13	MBK	314	4045890	2.49%	95149	31271
14	EUR	48.5	3788093	2.33%	69617	28110
15	ALR	66.5	3615007	2.22%	76935	32030
16	CCC	138.55	3510857	2.16%	136371	48975
17	TPE	2.88	3005539	1.85%	128690	51122
18	ENG	12.64	2537354	1.56%	105895	43234
19	ENA	11.3	2419081	1.49%	76372	31390
20	SNS	3.81	1892389	1.16%	59520	27523

Note: The table presents components of WIG20 index with index share. *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, *Total quotes* informs what is the number of quotes within the sample period and *Adj quotes* shows the number of quotations after filtering the data (mistakes, double recordings etc.). This table was already used in the previous paper of Będowska-Sójka (2019).

stocks in the index that are reflected in the index weights. There are four stocks with relatively higher capitalization and weights greater than 10%, while for another four weights are lower than 2%. We consider sample period from 1 January to 4 April 2016 (61 days). The same dataset was used in the previous study of Będowska-Sójka and Echaust (2019). The tick-by-tick data are cleared from all mistakes, omissions etc. according to the procedure described in Barndorff-Nielsen et al. (2009) and then aggregated into equally sampled 10-minute data.

Here we focus on the number of quotes in the index, and we treat this number as an indicator of trading intensity. That is why out of WIG20 constituents we choose four stocks with the highest number of listings within first three months in 2016. For the comparison we also consider four stocks out of this index with the lowest number of quotations. The list of the WIG20 stocks as of January 1, 2016 is provided in Table 1. The stocks with the highest number of quotes are in blue and for simplicity we call them further bib-big, while these with the lowest number of quotes are in red (and these would be called big-small). Not only the differences between weights in the index, but also in number of quotes are striking. Moreover, although the highest number of quotes falls on the stocks with the highest share (with PZU as an exception), stocks with the smallest number of quotes are not necessary these with the smallest weights in the index. As we are considering this particular period, we follow the number of quotes.

3 Methodology

In order to examine the liquidity measures behaviour around aggressive orders we follow Gomber et al. (2013) and focus on exceptionally high volumes. Thus applying intraday event study in the manner similar to Boudt and Petitjean (2014), Gomber et al. (2013) and Havran and Váradi (2015) we examine the behavior of different liquidity measures around the event, that is the appearance of trading volume that is higher than 99th percentile of the volumes within whole sample period.

3.1 Liquidity measures: spreads and trading activity

We consider several spread measures as well as trading activity measures. These are:

- Proportional bid-ask spread (Będowska-Sójka, 2018):

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

  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 20000, $volume_k$ 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.

- Proportional quoted spread (Boudt and Petitjean, 2014):

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

  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.

- Proportional effective spread (Boudt and Petitjean, 2014)

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

  where

$$ES_k = \frac{2DIR_k(p_k - \frac{p_k^A + p_k^B}{2})}{\frac{p_k^A + p_k^B}{2}}$$

  and 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 (1991) algorithm to categorize buyer and seller-initiated trades.

These three spread measures reflect different liquidity aspects: PQS represents the ex-ante liquidity 'to be consumed', BAS shows ex-post liquidity 'already consumed' while PES 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.

We also consider three activity measures, which are: volume measured as the a 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 filtering

Quite well-known stylized fact is that intraday data display strong periodical pattern. In order to avoid the impact of that pattern on the results, before applying the event study methodology we filter the intraday series from the periodicity. There are many parametric and nonparametric methods to remove periodical pattern (Laurent, 2010). Here we use median absolute deviation MAD method, that belongs to nonparametric group and is said to be robust to outliers (Boudt et al., 2011).

Figure 1 shows the periodicity pattern of various spreads calculated for equally sampled 10-minute data. The pattern is calculated with MAD method for each stock separately. The common inverted-J shape pattern is recognizable in the series: all spreads tend to be higher at the beginning of the day and decrease gradually through the trading day, obtaining the average level after two hours from the start.

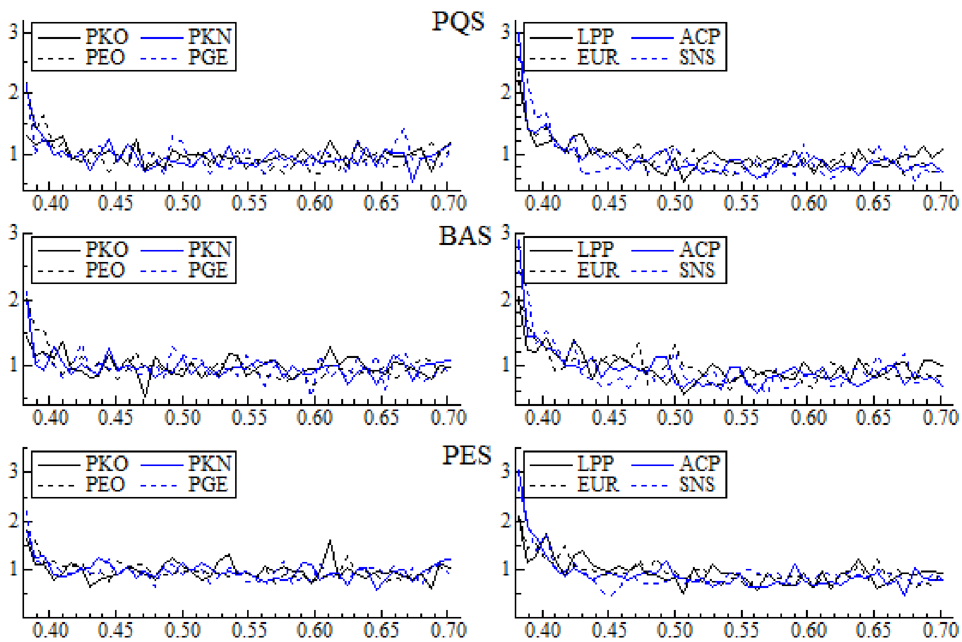

Figure 1: Periodicity filters for spreads

Note: PQS stands for proportional quoted spread, PES for proportional effective spread and BAS is bid-ask spread with last price. On the left side there are periodicity filters for four most traded stocks in WIG20, while on the right side there are four least traded stocks.

Figure 2 shows the periodicity filters for volume, number of transactions and average transaction size. First two trading activity measures tend to decrease in the beginning of the day, and this is mostly pronounced for big-big stocks, and increase at the end of the day, thus constituting U-shape pattern. The average transaction size does not provide any specific pattern during the trading day.

Next we consider the averages for the filtered series of spread and trading activity measures across our stocks. Table 2 shows the averages for each measure and stock separately. First four stocks in the Table are big-big, while last four stocks are big-small. The spreads measured with PQS and BAS in big-big group are lower than in the bis-small group with the exception of LPP stock. For PES similar exception is observed for SNS. If $VOLUME$ is considered, the higher values are due to big-small stocks, the same is observed for NT (with exception of EUR), and ATS (with exception of LPP). In the literature higher volumes are usually related

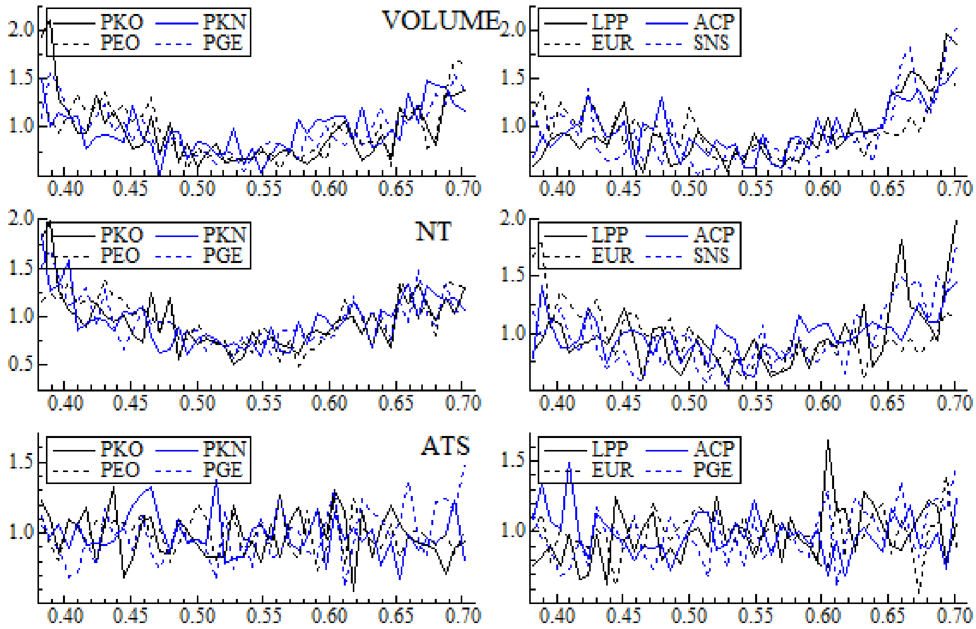

Figure 2: Periodicity filters for volume

Note: First row presents filters for $VOLUME$, second for number of transactions NT, and third for the average size of transaction ATS. On the left side there are periodicity filters for four most traded stocks in WIG20, while on the right side there are four least traded stocks.

to higher liquidity, while higher spreads mean that the transaction costs are higher. So the results are ambiguous: the costs are higher for smaller stocks as the trading activity is.

3.3 Intraday event-study approach

We aim to examine what is the dynamic around aggressive orders, represented by exceptionally high volume. This leads us to search for the evidence of volume higher than 99th percentile during whole sample period. We con consider two cases: the first one where we take into account 99th percentile of the original series, and the second one, where we adjust for the presence of periodical pattern. In the latter case we consider an order to be aggressive, if it is characterized not only by the exceptional high volume in the original series, but also in the filtered one. The first case is called original volume, while the second is called filtered volume.

We take into account four most frequently traded stocks from WIG20 and four least traded. All stocks are considered in 10 minute sampling frequency. In order to avoid overlapping of the events we restrict the aggressive orders to these that occur individually. This means that we do not observe any other aggressive order either 40 minutes before, nor 40 minutes after. Altogether we obtain 132 top volume events.

4 Empirical results

The empirical part is divided into two sections: the first is devoted to the analysis of reaction to high volume events in 10-minute frequency, while the second shows the same analysis in 5- and 20-minute sampling frequency.

Table 2: **The average spreads and trading activity measures**

ticker	PQS	PES	BAS	VOLUME	NT	ATS	NumbEv
PGE	0.04	0.08	0.06	0.37	0.15	0.16	18/23
PEO	0.05	0.07	0.06	0.48	0.19	0.25	22/26
PKO	0.03	0.05	0.03	0.27	0.19	0.08	7/16
PKN	0.06	0.08	0.06	0.24	0.16	0.14	15/24
LPP	0.05	0.10	0.04	0.66	0.34	0.18	16/23
ACP	0.13	0.19	0.13	0.84	0.28	0.67	23/23
EUR	0.08	0.10	0.09	0.51	0.17	0.36	19/20
SNS	0.10	0.04	0.12	1.12	0.38	0.47	12/14

Note: The table presents the averages of filtered series for various measures of spreads and trading activity of the components of WIG20 index. PQS stands for proportional quoted spread, PES for proportional effective spread and BAS is bid-ask spread. $VOLUME$ stands for trading volume, NT shows the number of transactions, and ATS is the average size of transaction. $NumbEv$ is number of events, the aggresive orders, detected within the sample period for a given stock.

4.1 Original volume series

Figure 3 shows the behavior of three spread measures around the aggressive orders with the distinction between four mostly traded stocks in WIG20 index (big-big, bb) and four least traded (big-small, bs). We find that for PQS and BAS spreads in big-small stocks are increasing about 20% at the interval in which the aggressive order is executed. This is not the case in the big-big stocks. When in the next interval after the aggressive order the spreads are declining and the dynamics in both big-big and big-small stocks are similar: PQS and BAS are declining. For PES there is no change in the less actively traded stocks, but spreads in the interval when the aggressive order is executed are declining by about 10%.

For trading activity measures around the execution of the aggressive orders we find that trading volume, number of transactions and average transaction size are increasing at the time of the event. This is not surprising due to the fact that we are focused on high volume transactions. However this increase is much higher in case of big-small stocks than for big-big ones. This might be caused by smaller supply side for the big-small stocks, that result in higher spread increases.

4.2 Filtered volume series

We apply the same procedure for detecting aggressive orders in filtered volume series as for original ones. This time we have obtained 169 events, with the condition of no overlapping orders. Figure 5 shows the behavior of spreads around aggressive order event detected in the filtered volume series. When we compare it with the behaviour for spreads for original series on Figure 3 there are no significant differences, although the number of events is different and some of them are not overlapping. For PES we observe decrease in spreads of big-big stocks, while for PQS and BAS there is a decrease of 20% in spreads of big-small stocks.

Finally, Figure 6 shows that independently on the approach, which is undertaken, there is the difference in the big-big and big-small stocks in trading activity measures. In case of each variable, volume, number of transactions within the interval and average size of transactions, for big-small stock they are higher than for big-big ones.

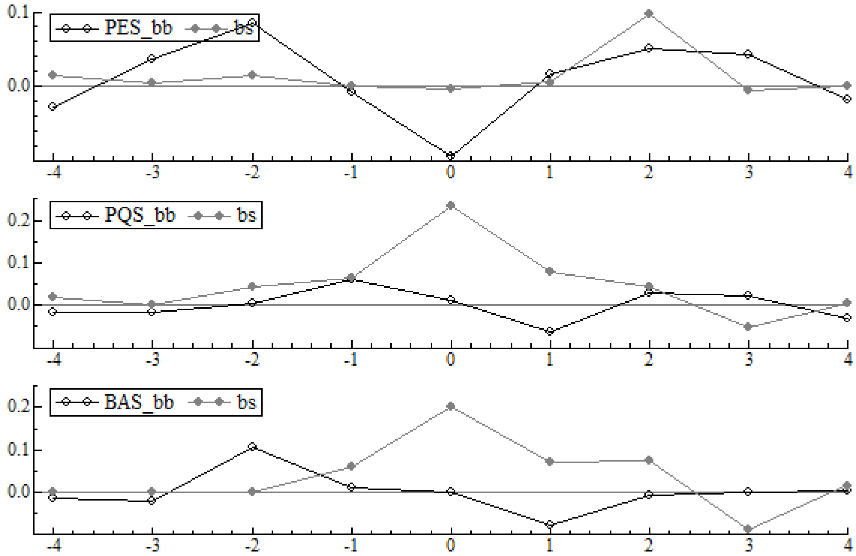

Figure 3: Spreads around aggressive order

Note: PES stands for the proportional effective spread, PQS for the proportional quoted spread, and BAS is bid-ask spread. On the axis of ordinates there are the intervals t around the event, that is the execution of the aggressive order, $t \in \{-4, -3, ...0, ..., 3, 4\}$, where each unit is equal to 10 minutes (from 40 minutes before the event to 40 minutes after it). *bb* (big-big) displays four most actively traded stocks, and *bs* (big-small) are the four least actively stocks in index WIG20 within sample period.

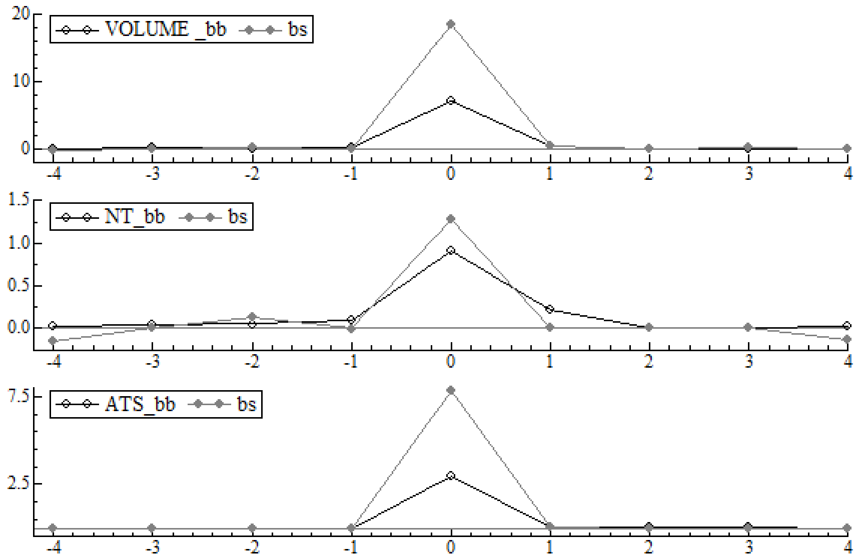

Figure 4: Trading activity measures around aggressive order

Note: $VOLUME$ stands for trading volume, NT shows the number of transactions, and ATS is the average size of transaction. On the axis of ordinates there are the intervals t around the event, that is the execution of the aggressive order, $t \in \{-4, -3, ...0, ..., 3, 4\}$, where each unit is equal to 10 minutes (from 40 minutes before the event to 40 minutes after it). *bb* (big-big) displays four most actively traded stocks, and *bs* (big-small) are the four least actively stocks in index WIG20 within sample period.

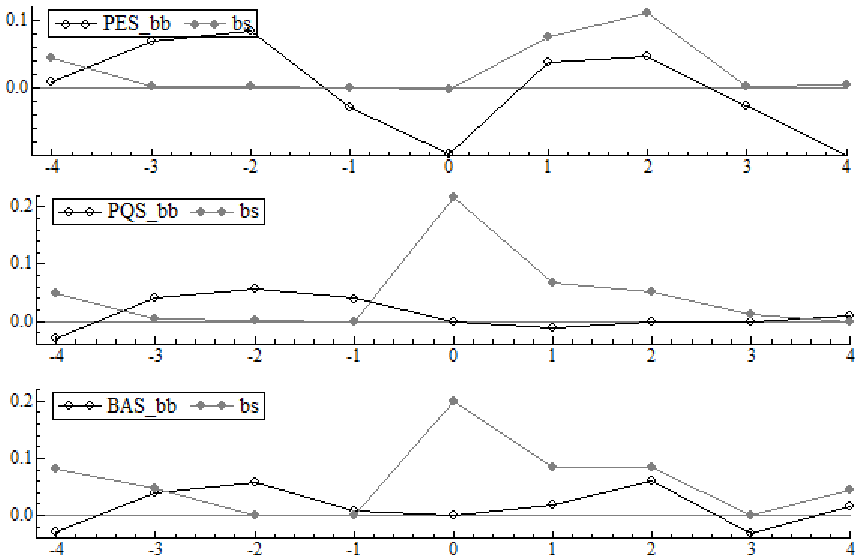

Figure 5: Spreads around aggressive order in filtered volume series

Note: PES stands for the proportional effective spread, PQS for the proportional quoted spread, and BAS is bid-ask spread. On the axis of ordinates there are the intervals t around the event, that is the execution of the aggressive order, $t \in \{-4, -3, ...0, ..., 3, 4\}$, where each unit is equal to 10 minutes (from 40 minutes before the event to 40 minutes after it). *bb* (big-big) displays four most actively traded stocks, and *bs* (big-small) are the four least actively stocks in index WIG20 within sample period.

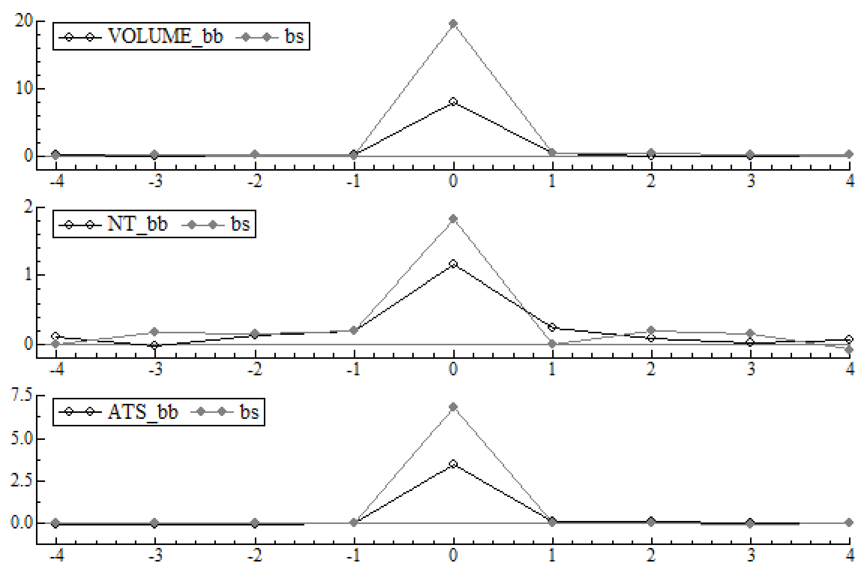

Figure 6: Trading activity measures around aggressive order in filtered volume series

Note: $VOLUME$ stands for trading volume, NT shows the number of transactions, and ATS is the average size of transaction. On the axis of ordinates there are the intervals t around the event, that is the execution of the aggressive order, $t \in \{-4, -3, ...0, ..., 3, 4\}$, where each unit is equal to 10 minutes (from 40 minutes before the event to 40 minutes after it). *bb* (big-big) displays four most actively traded stocks, and *bs* (big-small) are the four least actively stocks in index WIG20 within sample period.

5 Conclusions and further work

This study is devoted to examining the behavior of several spread measures as well as trading activity variables around aggressive orders. These orders are defined as the exceptionally high volumes observed within the three months sample of stocks listed on the Warsaw Stock Exchange. This is the order-driven market, for which liquidity is supplied within the order book. We take into account four most traded stocks, that constitute WIG20 index, and four least traded stocks that are also WIG20 components.

We show that independently on what series is considered, the original volume series or volume filtered from periodical pattern spreads are behaving in the same way around the exceptionally high volume event. For proportional effective spread we observe decrease in transaction costs only for the most traded stocks, while for proportional quoted spread and bid-ask spread we observe increase in spreads, but only for the least traded stocks in WIG20 index. Additionally, trading activity measures are increasing stronger for least traded stocks than for the most liquid ones.

Further work should be focused on different sampling frequencies. Specifically, for the most actively traded stocks higher frequency might help in explaining the differences between particular spreads, while for least actively traded stocks lower frequency might be proper. Also different definition of the aggressive order should bring some new light into the examined issue.

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