Evaluating Trade Side Classification Algorithms Using Intraday Data from the Warsaw Stock Exchange

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Abstract According to the literature, to measure both market liquidity and dimensions of market liquidity based on intraday data, it is essential to recognize the side initiating a transaction. Although the Warsaw Stock Exchange (WSE) is an order-driven market with an electronic order book, information of the order book database is not publicly available. Trade side classification algorithms enable us to assign the side that initiates a transaction and to distinguish between the so-called buyer- and seller-initiated trades. The aim of this paper is to evaluate several trade side classification procedures using high frequency intraday data for the WSE. The whole sample covers the period from January 3, 2005 to December 30, 2016, and it includes the Global Financial Crisis. Selected trade side classification algorithms are implemented, tested and compared with each other. Moreover, the robustness analysis of empirical results is provided. The empirical experiments show that the Lee and Ready (1991) algorithm performs better than other procedures on the WSE.

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1 Introduction

High frequency financial data is important in studying a variety of issues related to trading processes and market microstructure. The main motivation for this study is growing interest in market liquidity, dimensions of liquidity, and commonality in liquidity that has emerged in the literature over the recent years. As the nature of liquidity is multidimensional, the interpretation of market liquidity causes some problems. A common approach consists in breaking up liquidity into three or four components. Some authors propose four dimensions of liquidity (e.g. Ranaldo, 2001; von Wyss, 2004):

1. *trading time*,
2. *market tightness*,
3. *market depth*, and
4. *market resiliency*,

but usually the following three dimensions are distinguished (e.g. Kyle, 1985; Olbryś and Mursztyn, 2017a):

1. *tightness*,
2. *depth*, and
3. *resiliency* as trading time is discounted into main three liquidity dimensions and thus it does not have to be separately examined.

However, various analyses of market liquidity dimensions require usage of high frequency data, especially including information about a trade direction.

Moreover, to calculate several liquidity/illiquidity proxies using intraday data, it is essential to recognize the side initiating the transaction and to distinguish between the so-called buyer- and seller-initiated trades. The literature provides many alternative measures of stock market liquidity/illiquidity based on intraday data (e.g. Chordia et al, 2002, 2005; Goyenko et al, 2009; Ranaldo, 2001; Stoll, 2000; von Wyss, 2004; Nowak, 2017; Olbryś and Mursztyn, 2017a).

The Warsaw Stock Exchange (WSE) is an order-driven market with an electronic order book, but information of the best bid and ask price is not made public. In fact, even the non-proprietary 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.

Therefore, the main goal of this paper is to implement and to compare four trade side classification algorithms: the *quote rule* (QR), the *tick rule* (TR), the *Lee and Ready* (LR), and the *Ellis, Michaely and O'Hara* (EMO) procedures using high frequency data for selected WSE-listed stocks. The following research questions have been formulated:

1. Is the usefulness of trade side classification procedures similar on the WSE?
2. Are empirical results robust to the choice of a sample?

To verify the robustness of the obtained results, the comparison of trade side classification rules is provided both in the whole sample from January 3, 2005 to December 30, 2016 (3005 trading days) and over three adjacent sub-periods, each of equal size (436 trading days; see Olbryś and Mursztyn, 2015):

1. The pre-crisis period from September 6, 2005 to May 31, 2007.
2. The crisis period from June 1, 2007 to February 27, 2009.
3. The post-crisis period from March 2, 2009 to November 19, 2010.

The crisis period on the WSE was formally set based on the paper of Olbryś and Majewska (2015), in which the method for direct statistical identification of market states was employed.

The remainder of the study is organized as follows: Section 2 contains a brief literature review concerning the motivation and applications of trade side classification algorithms, and specifies procedures employed in the research. In Section 3, we present and discuss the empirical results on the WSE. We implement and compare four algorithms using high frequency intraday data for selected WSE-listed companies. The last section recalls the main findings and concludes.

2 Trade side classification algorithms

The goal of the trade side classification is to determine the initiator of the transaction and to classify trades as being either buyer or seller motivated. However, a formal definition of a trade initiator is rarely stated in the literature. For example, the so-called "immediacy" definition describes initiators as traders who demand immediate execution (e.g. Lee and Radhakrishna, 2000). According to Odders-White (2000), the initiator of a transaction is the investor (buyer or seller) who placed his/her order last, chronologically (the so called "chronological" definition). These two definitions are equivalent in many cases. In both definitions, the initiator is the person who caused the transaction to occur.

There are quite many trade side classification procedures proposed in the literature: the *quote rule*, the *at the quote rule*, the *revised quote rule*, the *tick rule*, the *reverse tick rule*, the *LR algorithm*, the *revised LR algorithm*, the *EMO algorithm*, and the *Bulk Volume Classification methodology* (BVC). We will describe the content of each classification rule as follows:

- The *quote rule* classifies a transaction as buyer initiated if the associated trade price is above the midpoint of the bid and ask. If the trade price is below the midpoint quote, then the trade is classified as seller initiated (e.g. Lee and Ready, 1991; Lu and Wei, 2009; see Table 1).
- The *at the quote rule* classifies a transaction as buyer initiated if the associated trade price is traded at the asking price. If the trade price is at the bidding price, then the trade is classified as seller initiated (Lu and Wei, 2009).
- The *revised quote rule* considers the problem of "no bid or no offer quote". The trade would be classified as buyer initiated if there is only the bid-side quote and it would be classified as seller initiated if there is the offer-side quote only (Lu and Wei, 2009).
- The *tick rule* is based on price movements relative to previous trades. If the transaction is above (below) the previous price, then it is buyer initiated (seller initiated). If there is no price change, but the previous tick change was up (down), then the trade is classified as buyer initiated (seller initiated; e.g. Lee and Ready, 1991; Lu and Wei, 2009; see Table 1).

- The *reverse tick rule* uses the next trade price to classify the current trade. If the next trade occurs on an up-tick or zero up-tick, the current trade is classified as seller initiated. If the next trade occurs on a down-tick or zero down-tick, the current trade is classified as buyer initiated (e.g. Lee and Ready, 1991; Lu and Wei, 2009).
- The *LR algorithm* (Lee and Ready, 1991) is a combination of the quote rule and the tick rule. In the first stage the trade is classified according to the quote rule. In the second stage the midpoint transaction is classified according to the tick rule (see Table 1).
- The revised *LR algorithm* (Lu and Wei, 2009) first adjusts the "no bid or no offer quote" problems, and then classifies a trade according to the quote rule and finally the tick rule.
- The methodology proposed by Chakrabarty et al (2007) is a hybrid of the tick and quote rules. It uses the quote rule when transaction prices are closer to the ask and bid, and the tick rule when transaction prices are closer to the midpoint.
- The *EMO algorithm* introduced by Ellis et al (2000) classifies the trades by means of the at the quote rule first, and then the tick rule (see Table 1).
- The *BVC procedure* (Easley et al, 2013) aggregates trades over short time intervals or volume intervals and then uses the standardized price change between the beginning and the end of the interval to approximate the percentage of buy and sell volume. Unlike traditional trade classification algorithms that assign trades to be either buys or sells, the BVC approach apportions trades into buy volume and sell volume.
- The trade classification procedure proposed by Andersen and Bondarenko (2015) combines real-time trade and order book information to classify the active buy and sell volume. It compares the trade price with the preceding bid and ask.

Table 1: The quote rule (QR), the tick rule (TR), the Lee-Ready (LR), and the Ellis-Michaely-O'Hara (EMO) trade side classification algorithms.

Rule	Conditions			
QR	$P_t > P_t^{mid}$	Trade is classified as buyer-initiated		
	$P_t < P_t^{mid}$	Trade is classified as seller-initiated		
	$P_t = P_t^{mid}$	Trade is not classified		
TR	$P_t > P_{t-1}$	Trade is classified as buyer-initiated		
	$P_t < P_{t-1}$	Trade is classified as seller-initiated		
	$P_t = P_{t-1}$	Trade is signed using the previous transaction price; if the sign of the last non-zero price change is positive (negative) then the trade is classified as a buy (a sell).		
LR	Stage I			
	$P_t > P_t^{mid}$	Trade is classified as buyer-initiated		
	$P_t < P_t^{mid}$	Trade is classified as seller-initiated		
	$P_t = P_t^{mid}$	Then:		
		Stage II		
		$P_t^{mid} > P_{t-1}$	Trade is classified as buyer-initiated	
		$P_t^{mid} < P_{t-1}$	Trade is classified as seller-initiated	
		$P_t = P_t^{mid}$	The decision is taken using the sign of the last non-zero price change P_{t-k}.	
			$P_t > P_{t-k}$	Trade is classified as buyer-initiated
			$P_t < P_{t-k}$	Trade is classified as seller-initiated
EMO	Stage I			
	$P_t = P_t(a) = P_t^L$	Trade is classified as buyer-initiated		
	$P_t = P_t(b) = P_t^H$	Trade is classified as seller-initiated		
	Stage II			
	Trades with prices different from best ask and bid prices are categorized by the tick rule. P_t is compared to P_{t-1}:			
	$P_t > P_{t-1}$	Trade is classified as buyer-initiated		
	$P_t < P_{t-1}$	Trade is classified as seller-initiated		

P_t: the transaction price at time t (approximated by the closing price), $P_t(a) = P_t^L$: the best ask price (approximated by the lowest price at time t), $P_t(b) = P_t^H$: the best bid price (approximated by the highest price at time t), $P_t^{mid} = \frac{P_t(a)+P_t(b)}{2} = \frac{P_t^L+P_t^H}{2}$: the so-called "quoted midpoint" (at time t).

Notice here that trade side classification algorithms are utilized in a variety of empirical literature about international financial markets. There are some strands of market microstructure research concerning various applications of trade side classification procedures. The first and most important strand includes papers that assess various aspects of trading processes and market liquidity. Trade classification algorithms are commonly used to generate estimates of market liquidity measures. Among others, Chan and Fong (2000) examine the significance of the number of trades, size of trades, and order imbalance (buyer- versus seller-initiated trades) in explaining the volatility-volume relation for a sample of NYSE and NASDAQ stocks. They use the Lee and Ready algorithm to identify the side that initiated each transaction. Chordia et al (2000, 2002, 2005) also follow the Lee and Ready procedure to assign a trade direction. The authors investigate properties and determinants of order imbalances, examine common determinants of stock and bond liquidity, and detect the existence of commonality in liquidity on the NYSE. Goyenko et al (2009) try to define high quality liquidity measures based on data of different frequency. They utilize the Lee and Ready algorithm to support the calculations of some intraday liquidity proxies. Hameed et al (2010) document that liquidity responds asymmetrically to changes in asset market values. The authors show a drastic increase in commonality in liquidity after large negative market returns. They point out that illiquidity in one industry spills over to other industries that suggests contagion in illiquidity. Korajczyk and Sadka (2008) explore an issue of pricing the commonality across alternative measures of liquidity and they use the Lee-Ready algorithm to classify a trade direction. Easley et al (2012) present a new procedure to estimate flow toxicity based on volume imbalance and trade intensity. The procedure requires trades classified as buys or sells. Furthermore, Sarkar and Schwartz (2009) focus on identifying trade initiators and their objective is to disentangle evidence of trade initiation triggered by asymmetric information. They contribute to the literature by introducing a new liquidity proxy, the so-called sidedness measure, which enables us to better distinguish between alternative trading motivates. Boehmer et al (2007) use order data from the NYSE and find that inaccurate trade classification leads to downward bias in estimates of the probability of informed trading.

The second strand concerns various versions of bid-ask spread and other transaction costs. Among others, McInish and Van Ness (2002) decompose the bid-ask spread into order-processing and asymmetric information components using intraday data. They take advantage of the Lee and Ready procedure to determine trade classification. Peterson and Sirri (2003) use order data to assess the accuracy of execution cost estimating with trade and quote data. They emphasize that the problem of quotes recorded ahead of trades has always existed, but has increased substantially with the widespread use of electronic books by specialists. Piwowar and Wei (2006) find that effective spread estimates are sensitive to trade-quote matching algorithms. In particular, they show that the Lee and Ready procedure can overestimate effective spreads for active stocks. Ball and Chordia (2001) investigate various statistical models that capture features of the price setting process. They estimate the equilibrium prices and true spreads. The authors use a trade indicator for buyer/seller classification of trades.

The next strand of the literature regards short sales. For example, Asquith et al (2010) analyse short sale transactions for stocks on the NYSE and NASDAQ and they conclude that short sales are often misclassified by the Lee and Ready procedure. The authors argue conceptually that short sales should be predominantly seller-initiated, while the Lee-Ready procedure identifies most of them as buyer-initiated. To discuss these results, Chakrabarty et al (2012) use order data to identify true trade initiator and they document that short sales are predominantly buyer-initiated and that the Lee and Ready algorithm correctly classifies most of them.

Moreover, some researchers compare various trade side classification procedures. The authors test usefulness and the accuracy of algorithms to infer the direction of trade using intraday datasets on international stock markets (e.g. Aitken and Frino, 1996; Boehmer et al, 2007; Chakrabarty et al, 2007, 2015; Ellis et al, 2000; Easley et al, 2013; Finucane, 2000; Lee and Radhakrishna, 2000; Lu and Wei, 2009; Odders-White, 2000; Olbryś and Mursztyn, 2015, 2017b; Theissen, 2001).

On the contrary to research conducted on international stock markets, studies that utilize trade side classification algorithms on the Polish stock market are rather scarce. Nowak (2017) analyses the problem of asset pricing on the basis of high frequency data on the WSE. She uses the quote rule to classify the side that initiates a transaction. Olbryś (2017) presents the study of interaction between market depth and market tightness on the WSE and she uses the Lee-Ready algorithm to infer trade sides. Olbryś and Mursztyn (2017a) investigate dimensions of Polish stock market liquidity and they also utilize the Lee and Ready procedure.

3 Empirical results on the Warsaw Stock Exchange

In this section, we present results of empirical experiments on the WSE. In order to find answers to the research questions, we investigate the performance of four trade side classification procedures for selected WSE-traded companies.

3.1 Sample and data description

In the study, high frequency data rounded to the nearest second from the Warsaw Stock Exchange (available at `www.bossa.pl`) is utilized. The data set contains the opening, high, low, and closing prices, and volume for a security over one unit of time in the whole sample period from January 2, 2005 to December 30, 2016 (3005 trading days). As the intraday data set is large, special programs have been implemented to reduce the time required for calculations. The implementation of four trade side classification algorithms is presented in detail in the paper (Olbryś and Mursztyn, 2015).

When forming the database, we included only the securities that existed on the WSE for the whole sample period since December 31, 2004, and were not suspended. 139 WSE-listed companies met these basic conditions, and they were initially selected. Next, we decided to provide an adequate representation of stocks according to their liquidity/illiquidity, as Nowak and Olbryś (2016) documented that a large number of the WSE-traded companies reveal a substantial non-trading problem, i.e. the lack of transactions over a particular period when the WSE is open for trading. Therefore, to mitigate the non-trading problem, we excluded the stocks that exhibited extraordinarily many non-traded days during the whole sample period, precisely, above 300 zeros in daily volume, which constituted about 10 % of all 3005 trading days. Finally, 105 WSE-listed companies were entered into the database.

3.2 Results of empirical research

Within the trading days during the whole sample period from January 3, 2005 to December 30, 2016, the total number of transactions in the database is large and it is equal to 35 307 993 transactions. Every transaction for each stock is assigned using the QR, TR, LR, and EMO trade side classification algorithms (see Table 1). The first opening trade is treated as unclassified in the TR, LR, and EMO procedures because it cannot be compared to the previous one (see Table 1). Of course, there is inevitably some assignment error (Chordia et al, 2002). However, the proposed algorithms are accurate enough as not to pose serious problems in our large sample study (e.g. Chakrabarty et al, 2012; Ellis et al, 2000; Finucane, 2000; Lee and Radhakrishna, 2000; Odders-White, 2000).

Attempting to find answers to both research questions, we investigate the performance of the QR, TR, LR, and EMO trade side classification procedures in the case of three selected big (KGHM Polska Miedz S.A. (KGH)), medium (AMICA S.A. (AMC)), and small (ENAP Energoaparatura S.A. (ENP)) companies, during the whole sample period and three adjacent sub-periods, respectively (see Tables 2–4).

Table 2: Performance of the quote rule (QR).

QR	Stock	Total number of trades	Buyer-initiated trades [%]	Seller-initiated trades [%]	Unclassified trades [%]
Whole sample	KGH	4579991	5.57	5.89	88.54
	AMC	148147	6.32	7.21	86.47
	ENP	83919	6.19	6.90	86.91
Pre-crisis	KGH	390256	2.03	2.52	95.45
	AMC	22279	5.73	6.76	87.51
	ENP	37901	6.15	7.00	86.85
Crisis	KGH	502403	5.50	5.37	89.13
	AMC	15754	5.50	8.52	85.98
	ENP	18961	7.45	7.99	84.56
Post-crisis	KGH	635691	5.45	5.66	88.89
	AMC	36703	7.41	8.06	84.53
	ENP	8039	5.65	5.44	88.91

Whole sample: 3.01.2005 – 30.12.2016
Pre-crisis: 6.09.2005 – 31.05.2007
Crisis: 1.06.2007 – 27.02.2009
Post-crisis: 2.03.2009 – 19.11.2010

Table 3: Performance of the tick rule (TR) and the Lee-Ready (LR) algorithm.

TR	**Stock**	**Total number of trades**	**Buyer-initiated trades [%]**	**Seller-initiated trades [%]**	**Unclassified trades [%]**
Whole sample	KGH	4579991	51.23	48.57	0.20
	AMC	148147	49.63	46.57	3.80
	ENP	83919	49.37	44.13	6.50
Pre-crisis	KGH	390256	50.86	48.36	0.78
	AMC	22279	48.79	46.83	4.38
	ENP	37901	51.94	45.41	2.65
Crisis	KGH	502403	51.11	48.63	0.26
	AMC	15754	45.92	49.27	4.81
	ENP	18961	50.07	45.70	4.23
Post-crisis	KGH	635691	52.04	47.78	0.18
	AMC	36703	52.25	45.54	2.21
	ENP	8039	47.43	42.95	9.62
LR	**Stock**	**Total number of trades**	**Buyer-initiated trades [%]**	**Seller-initiated trades [%]**	**Unclassified trades [%]**
Whole sample	KGH	4579991	51.25	48.55	0.20
	AMC	148147	49.64	46.65	3.71
	ENP	83919	49.49	44.11	6.40
Pre-crisis	KGH	390256	50.86	48.37	0.77
	AMC	22279	48.69	46.95	4.36
	ENP	37901	51.92	45.45	2.63
Crisis	KGH	502403	51.17	48.58	0.25
	AMC	15754	46.01	49.24	4.75
	ENP	18961	50.34	45.53	4.13
Post-crisis	KGH	635691	52.06	47.76	0.18
	AMC	36703	52.19	45.64	2.17
	ENP	8039	47.78	42.78	9.44

See Table 2 for explanations concerning the sampling periods.

Table 4: Performance of the EMO algorithm.

EMO	Stock	Total number of trades	Buyer-initiated trades [%]	Seller-initiated trades [%]	Unclassified trades [%]
Whole sample	KGH	4579991	5.89	5.59	88.52
	AMC	148147	7.20	6.32	86.48
	ENP	83919	6.90	6.19	86.91
Pre-crisis	KGH	390256	2.52	2.03	95.45
	AMC	22279	6.76	5.73	87.51
	ENP	37901	7.00	6.15	86.85
Crisis	KGH	502403	5.37	5.50	89.13
	AMC	15754	8.52	5.50	85.98
	ENP	18961	8.00	7.46	84.54
Post-crisis	KGH	635691	5.65	5.45	88.90
	AMC	36703	8.06	7.41	84.53
	ENP	8039	5.45	5.66	88.89

See Table 2 for explanations concerning the sampling periods.

The empirical findings indicate that the usefulness of various trade side classification methods on the WSE is not qualitatively the same, whereas the results turn out to be robust to the choice of the period. Specifically, the tick rule and the Lee-Ready algorithm are more appropriate compared to the quote rule and the EMO procedure. In the case of the TR and LR methods, the percentage of unclassified transactions is relatively low and similar, which is consistent with the literature. For example, Theissen (2001) points out that the Lee-Ready method classifies transactions quite correctly, but the simpler tick test performs almost equally well. In the case of the LR and TR algorithms, the percentage of identically classified trades for the group of 105 WSE-listed companies during the whole sample period is very high and it is equal to 97.02 % (unclassified trades are excluded). The amount of buyer- and seller-initiated trades is almost equal, with a little predominance of buyer-initiated in all investigated periods. This evidence is consistent with the literature, as it is demonstrated in some papers that short sales are sometimes misclassified as buyer-initiated by trade side classification algorithms (e.g. Asquith et al, 2010). Furthermore, it is worth to note that the percentage of unclassified trades in the case of the LR and TR algorithms for KGH is extraordinarily small because KGH is the most liquid WSE-traded company.

Table 5: Average percentage values of classified and unclassified trades for the whole group of 105 WSE-listed companies (the LR, TR, QR, and EMO procedures).

Rule	Period	Total number of trades	Mean value of buyer-initiated trades [%]	Mean value of seller-initiated trades [%]	Mean value of unclassified trades [%]
LR	Whole sample	35307993	48.06	45.58	**6.36**
	Pre-crisis	5210359	49.08	45.41	**5.51**
	Crisis	5267234	46.47	47.03	**6.50**
	Post-crisis	5743223	47.77	44.85	**7.38**
TR	Whole sample	35307993	47.95	45.60	6.45
	Pre-crisis	5210359	49.07	45.35	5.58
	Crisis	5267234	46.28	47.11	6.61
	Post-crisis	5743223	47.64	44.86	7.50
QR	Whole sample	35307993	5.88	6.35	87.77
	Pre-crisis	5210359	5.95	6.44	87.61
	Crisis	5267234	5.85	6.73	87.42
	Post-crisis	5743223	5.69	5.89	88.42
EMO	Whole sample	35307993	6.35	5.88	87.77
	Pre-crisis	5210359	6.44	5.95	87.61
	Crisis	5267234	6.73	5.85	87.42
	Post-crisis	5743223	5.89	5.69	88.42

See Table 2 for explanations concerning the sampling periods. The best results for the LR algorithm are marked in bold.

On the contrary, the applicability and accuracy of the QR and EMO procedures is rather low, with a high percentage of unclassified trades for all companies, regardless of firm size and the choice of the period. Both the QR and EMO procedures work poorly on the WSE. The percentage of both unclassified trades is equal to 88.84 %. The percentage of the opposite or mixed classification is rather high and it is equal to 11.12 %. On the other hand, the percentage of both identically classified trades for the group of 105 companies during the whole sample period is very low and it is equal to 0.04 % (unclassified trades are excluded). In our opinion, the explanation of this phenomenon on the WSE is the problem of relatively many trades for which high and low prices are equal over one unit of time. Moreover, it is pertinent to note that the EMO method was proposed for the NASDAQ, which is a hybrid market, while the WSE is classified as an order-driven market. Hence, the empirical findings for the U.S. stock markets are not directly comparable to the Polish stock market. Besides the differences between markets' structure, the availability of data is crucial. As was mentioned in Subsection 3.1, in this research high frequency data rounded to the nearest second is used, while transaction data sets that are utilized in other studies contain more useful information (e.g. Aitken and Frino, 1996; Lu and Wei, 2009). Therefore, one probable explanation of discrepancies in trade side classification results between markets is that stock market structure and trading mechanisms may affect the accuracy of classification procedures. Moreover, the problem with transaction data availability is vast for the WSE and other emerging markets in the world.

Table 5 presents the average percentage values of classified and unclassified trades in the case of all trade side classification methods, for the whole group of 105 WSE-listed companies. The results confirm that the Lee and Ready (1991) algorithm performs better then other procedures on the WSE.

4 Conclusion

The validity of many market microstructure studies depends on the ability to accurately classify transactions as buyer- or seller-initiated. Despite the importance of trade classification to economic research, the available data generally does not contain this information and the trade direction is not made public. Hence, the aim of this paper is to evaluate selected trade side classification methods using high frequency data on the WSE. The empirical experiments show that the Lee and Ready algorithm performs better then other procedures on the WSE (see Table 5), which is consistent with the literature. Moreover, the robustness analysis reveals that the empirical findings turn out to be robust to the choice of the sample and rather do not depend on firm size. Although for the simple tick rule the percentage of unclassified trades is also relatively low, the main advantage of the Lee-Ready algorithm is that it combines the quote and tick rules. Therefore, the main conclusion of the conducted study is the statement that the Lee-Ready algorithm is recommended for inferring trade direction on the Warsaw Stock Exchange in further research.

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