JEL codes: G14, C25, C58

Keywords: liquidity, jumps, intraday data, event study

How Jumps Affect Liquidity? The Evidence from Poland*

Barbara BĘDOWSKA-SÓJKA – Poznan University of Economics (Barbara.Bedowska-Sojka@ue.poznan.pl)

Abstract

We examine the changes in liquidity measures around the price jumps detected in intraday returns. The sample consists of 5-minute returns from the most liquid stocks quoted on the Warsaw Stock Exchange. Within an event-study we show that the appearance of the jumps has a two-fold impact on the market liquidity. On the one hand, jumps coincide with the increase in the transaction costs measured by the quoted spread, and on the other hand jumps are accompanied by the increase in the trading quantity measured by trading volume or the number of trades. The price jumps also coincide with the increase in the Amihud's illiquidity measure. All these effects are strong but short-lived, which constitutes the evidence for the market resiliency. Jumps are a result of the market inability to absorb huge orders without significant changes in the prices.

1. Introduction

Liquidity is one of the most important factors in finance both in the risk measurement and asset pricing (Amihud 2002). Although there is no general agreement in the literature regarding how liquidity should be defined and measured, four main dimensions are usually recognized: market width, market depth, the immediacy and the resiliency (Boudt and Petitjean 2014, Mazza 2015). The growing availability of microstructure data in the last years enables the analysis of the liquidity from this perspective. The goal of this paper is to assess the liquidity dynamics around jumps at the intraday level. We focus on the relationship between price discontinuities (jumps) and liquidity proxies prior to and after jumps. An event study is conducted to observe the behavior of the liquidity variables that describe the different dimensions of liquidity.

The literature considering the liquidity dynamics around price jumps in financial markets is expanding. The earlier works are devoted to the analysis of U.S. stock and bond market. Lee at al. (1993) examines the changes in liquidity proxies in intraday NYSE stock data around the time of the earnings announcements. They find considerable preannouncement drops in liquidity with spreads widening and depths falling before significant price changes. Brooks (1994) examines the components of

* I am grateful for helpful comments and suggestions from the anonymous reviewer. I also acknowledge the constructive feedback on the earlier versions of this paper from the participants at the 6th Annual Financial Market Liquidity Conference, Corvinus University of Budapest, 2015. Any remaining errors are the responsibility of the author alone.

spreads around earning announcements for NYSE and AMEX firms and shows that increase of spreads indicates the informative feature of these events. He finds that in case of such anticipated events as earnings announcements the trading volume as well as the spread components remain higher for at least an hour after the event. Joulin et al. (2008) claim that jumps in prices are more related to liquidity shocks than to news announcements.

Boudt and Petitjean (2014) provide an event study in which they examine liquidity dynamics around jumps for stocks included in the Dow Jones Industrial Average index. They study the reaction of different liquidity proxies around jumps detected with the Lee and Mykland (2008) test and show that jumps coincide with an increase in the trading costs. The greatest impact on the jump occurrence has the shocks in number of transactions and the effective spread. They find that the demand for the immediate execution of orders increases sharply around jumps, but extreme price changes are caused by a greater demand for liquidity rather than a weak supply of liquidity (Boudt and Petitjean 2014). Jiang et al. (2011) examine the effect of macroeconomic news announcements on liquidity dynamics around jumps, that are detected with Jiang and Oomen (2007) test on the U.S. treasury market. They show that information shocks, based on news announcement surprises, have a limited power in explaining jumps in bond prices. However, the shocks in the bid-ask spread and market depth display significant predictive power for jumps in bond prices.

Recently, studies conducted on the European markets data have appeared: Hanousek and Novotný (2012) compare jumps observed in high-frequency data in four stock indexes from Budapest, Frankfurt, Prague and Warsaw. They show that the distribution of jumps is related to different regulations on the markets and microstructure issues. Hanousek, Kočenda and Novotný (2014) examine the behavior of selected developed and emerging markets' stock indices during the period of January 2008 to June 2012. They show that individual stock markets exhibit differences in extreme price changes within the crisis and non-crisis periods. Mazza (2015) uses event study methodology in intraday data from Euronext exchanges and find that particular price patterns are associated with higher liquidity. Będowska-Sójka (2016) detects jumps in equally spaced 10-minute returns for most liquid stocks quoted on the Warsaw Stock Exchange within one-year sample period. She matches jumps with macroeconomic and firm specific news and finds that only the minority of jumps are associated with public information releases, whereas the majority of them are motivated by liquidity shocks observed in the quoted spreads, volume and the number of trades.

This article is the continuation and the extension of the previous studies. As the WSE is still perceived as an emerging market, we extend the state of art already developed in advanced markets to one of the Eastern European markets. First of all, we use the equally sampled 5-minute data from the Warsaw Stock Exchange (WSE). The primary data is from the extensive tick-by-tick database that allows us to calculate similar measures as in Boudt and Petitjean (2014), although we use the jump detection test proposed by Barndorff-Nielsen and Shephard (2004). Second, we focus on the analysis of the individual, most liquid stocks quoted on the WSE. There is a strong evidence to show that macro announcements are responsible for sizable changes in indices (Hanousek et al. 2013, Będowska-Sójka 2013). However, with the respect to individual stocks, the literature indicates that jumps are rarely directly associated with macro news and that the majority of jumps occur with unscheduled news (Lee and Mykland 2008, Lahaye et al. 2011). As for our sample macro news seem to cause less than 10% of the jumps, we do not distinguish the informational sources of the jumps.

Our contribution to the existing literature is as follows: Within the event-study approach we describe the behavior of the various liquidity proxies around the jumps. We find that the relationship between the liquidity variables and jumps is very strong. It means that liquidity contributes to price discovery on the WSE. On the one hand the jumps occur simultaneously with an increase in trading quantity measured by the trading volume and the number of trades, what suggests the market depth widens. On the other hand, jumps are accompanied by the increase in the transaction costs proxied by the quoted spread. It means that liquidity characterized by market width worsens at the time of the jumps. They also coincide with the increase in Amihud's (2002) illiquidity. Altogether it suggests that jumps result from an increased demand for liquidity and imbalances that occur in the market at the time when the orders are huge.

Moreover, we observe the overreaction in the returns within the time of the jumps occurrences; after a negative price jump the returns tend to be positive, whereas after a positive jump they tend to be negative. This indicates short-term market overreaction and constitutes the evidence for the market resiliency. In order to complement the non-parametric event study approach, we introduce the parametric models to assess the impact of the liquidity shocks on the jumps. We find that the effect of jumps on liquidity variables is also short-lived as liquidity variables revert to the pre-jumps level within five to ten minutes.

The rest of the paper is organized as follows: in the Section 2 we describe the sample data, the jump test used in the study and the liquidity proxies. Section 3 presents the empirical study and consists of two subsections: in the first we conduct the event study aimed to describe the behavior of different liquidity proxies at the time of the jumps. In the second we estimate logit models with liquidity proxies in order to assess the impact of an individual measure on the probability of the jump occurrence. In Section 4 we conclude.

2. Data and liquidity variables

In the empirical analysis, we focus on the most liquid stocks quoted on the Warsaw Stock Exchange (WSE). The raw database consists of *tick-by-tick* trading, bid and ask prices as well as trading, bid and ask volumes. Six stocks chosen on the basis of the highest liquidity according to WSE Yearbook 2012 are included in the sample. These are in alphabetical order: KGHM SA, PEKAO SA, PGE SA, PKN Orlen SA, PKOBP SA, and PZU (relevant ticker symbols are: KGH, PEO, PGE, PKN, PKO and PZU). The information considering industry, major shareholder and market capitalization are shown in Table 4 in the Appendix. Our sample period starts on 2012-10-01 and ends on 2013-10-01. The primary data comes from ftp://ftp2.cait.com.pl. The data have been carefully cleaned and aggregated into equal-sampled data. In order to obtain a balance between a sufficient power to detect jumps and bias coming from the microstructure noise, we follow much of the existing literature and use a 5-minute frequency data (Andersen et al. 2007, Kostrzewski 2012, Gurgul and Wójtowicz 2015). In Table 1 we provide the basic statistics for the returns of stocks considered in the study. The statistics show that mean returns are not significantly different from zero, but are characterized by significant negative asymmetries as well as very high excess kurtosis. The negative estimates of skewness indicate that in all cases the left tails are longer and supports the claim that these stocks are dominated by negative jumps. The high kurtosis indicates that the distributions are fat-tailed which again stay in line with the presence of the extreme price movements. Both skewness and kurtosis show that the distribution of the returns is not Gaussian, suggesting the presence of price jumps. In all cases but one the absolute values of the minimum returns are higher than the values of maximum returns.

Table 1 Descriptive statistics of the returns series for stocks considered in the study

	Mean	*St.deviat.*	*Skewness*	*Excess kurtosis*	*Maximum*	*Minimum*	*Number of observations*
KGH	0.00	0.21	-2.20	107.40	4.71	-6.90	24298
PEO	0.00	0.17	-2.08	66.65	1.89	-4.81	24298
PGE	0.00	0.23	-0.15	26.91	4.05	-4.98	24298
PKN	0.00	0.21	-0.51	21.50	3.50	-3.24	24298
PKO	0.00	0.16	-1.39	54.30	2.36	-4.47	24298
PZU	0.00	0.17	-0.67	56.67	3.46	-5.20	24298

There is a plenty of jump detection tests. The extensive simulation study aimed to compare the relative performance of broad class of price jump indicators with respect to the Type I and Type II identification errors is given e.g. in Hanousek et al. (2012). In the paper to detect jumps in high frequency returns we conduct Barndorff-Nielsen and Shephard (2004) test, based on the comparison of realized daily volatility and realized bipower variation (Andersen et al. 2007). Combining those two measures allows to separate the two components of the quadratic variation process: the continuous process and the jump diffusion process. We adopt the test statistic based on the logarithm of the variation measures (Huang and Tauchen 2005). The test statistics are based on the realized tripower quarticity statistics presented in Andersen et al. (2007). We consider a significance level of $\alpha = 0.001$.

The Barndorff-Nielsen and Shephard (2004) test itself does not indicate the precise moment of the jump. Therefore, the sequential algorithm proposed by Andersen et al. (2008) and modified by Ané and Métais (2010) was used to indicate the precise moment when the jump occurs, as well as its size. This algorithm allows us to detect as many jumps as occurred within a day, but we considered only the biggest jump within a single day in the sample. It seems to be justifiable as Ané and Métais (2010) show that jumps are rare and represent isolated events; the majority of jump days (90%) exhibit only a single jump (Ané and Métais 2010).

In the event study, we consider only twelve 5-minute intervals before and after jumps, therefore those jumps that occurred within the first and the last hour of the trading day (from 9:00 to 10:00 and from 16:20 to 17:20) are not included in the sample. It allows us to obtain the whole event window within one day not disturbed by the beginning or the end of the session. As a by-product, by omitting these observations we do not have to adjust for the intraday patterns, that are usually recognized in intraday data at the beginning and at the end of the trading day.

Lee et al. (1993) show that liquidity changes are observed within half hour. Our event window in an event study is centered around a 5-minute interval in which a jump is detected and contains additionally twenty-four intervals. In the null hypothesis, we assume that jumps are not related to liquidity. The alternative is that liquidity around a price jump is abnormal.

From the broad spectrum of liquidity measures presented in the literature we choose a few that account for different aspects of liquidity. We observe three out of four dimensions of liquidity identified in the literature: the price impact, the market depth and the market width. *Price impact* shows how fast price reverts to the new equilibrium level (Kyle 1985). We use percentage logarithmic 5-minute returns within interval *i* (RET_i) and volatility proxied by absolute value of the returns, $VOLAT_i = |RET_i|$. *Market depth* described by the trading activity shows the ability to absorb relatively big orders without significant impact on prices (Kyle 1985). In the empirical study, we consider the following measures of market depth: trading volume, number of trades, and illiquidity measure (Amihud 2001). Trading volume is calculated as:

$$VOLUME_i = \sum_{k=1}^{NT_i} size_{i,k} \, , \tag{1}$$

where: *size* is a number of shares traded in interval *i*, and *k* stands for each transaction. The number of trades, NT_i, accounts for number of all transactions made within a single interval *i*. The Amihud's illiquidity is calculated as:

$$IILIQ_i = |RET_i| / \ln(VOLUME_i) \, . \tag{1}$$

Market width is described by the trading costs calculated as the costs of reverting the position within an interval *i*. In our study the trading cost are measured with quoted spread ($QSPRD_i$) that are size-weighted average of *k* transactions over interval *i* (Mazza 2015):

$$QSPRD_i = \sum_{k=1}^{Q_i} QS_{i,k}\left(Ask\ depth_{i,k} + Bid\ depth_{i,k}\right) \Big/ \sum_{k=1}^{Q_i}\left(Ask\ depth_{i,k} + Bid\ depth_{i,k}\right) \tag{2}$$

where Q_i describes the number of quotes within interval *i*, QS_{ik} is a relative quoted spread, standardized by the quote midpoint,

$$QS_{ik} = (Ask_{i,k} - Bid_{i,k}) \Big/ \left(\frac{Ask_{i,k} + Bid_{i,k}}{2}\right), \tag{3}$$

$Ask\ depth_{i,k}$ and $Bid\ depth_{i,k}$ are the number of shares displayed in interval i at the best offer or best buy price respectively.

As bid and ask prices and volumes differ substantially across stocks in our sample, we standardize the liquidity measures ($VOLUME_i$, NT_i, $ILLIQ_i$, $QSPRD_i$) for each stock in the sample. For standardization purposes we use medians and median absolute deviation (MAD) as the robust statistic measures of range and scale respectively. The following formula is used (Jajuga, Walesiak 2000):

$$z_{ij} = (x_{ij} - Me_j)/1.4826 * MAD_j \tag{5}$$

where x_{ij} is a random variable, Me_j is a median of observations and MAD_j is a median absolute deviation. The value of 1.4826 is a scale factor depending on the distribution (normal in this case).

3. Empirical results and discussion

Jump test results

First, we detected jumps and then calculated different liquidity measures in the event window. There are 130 jumps in the sample; in case of 73 of them the returns at the moment of the jump are negative, whereas in case of 57 returns are positive. The total number of jumps for each company, including number of positive and negative jumps as well as maximum and minimum jump return are presented in Table 2.

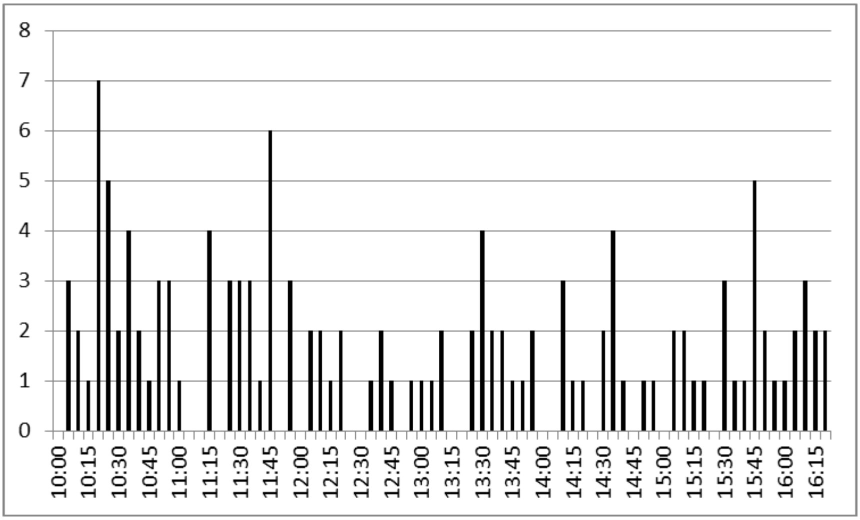
Table 2 The number of jumps detected within the sample

	Number of jumps	*Positive jumps*	*Negative jumps*	*Maximum jump return*	*Minimum jump return*
KGH	17	8	9	0.71	-0.69
PEO	27	12	15	0.78	-0.76
PGE	24	10	14	4.05	-0.92
PKN	28	12	16	1.16	-2.09
PKO	17	6	11	1.04	-1.28
PZU	17	9	8	0.97	-0.72

According to previous observations the number of negative jumps is higher than the number of positive ones. The maximum and minimum jump returns are clearly different from the maximum and minimum returns in the whole sample in all cases but one. This is a result of the methodology of the Barndorff-Nielsen and Shephard (2004) jump detection test which is based on the differences of realized variance and bipower variation within a day and not simply on the extreme values of the returns.

Figure 1 shows the repartition of jumps within the session time.

Figure 1 Jump repartition by time interval



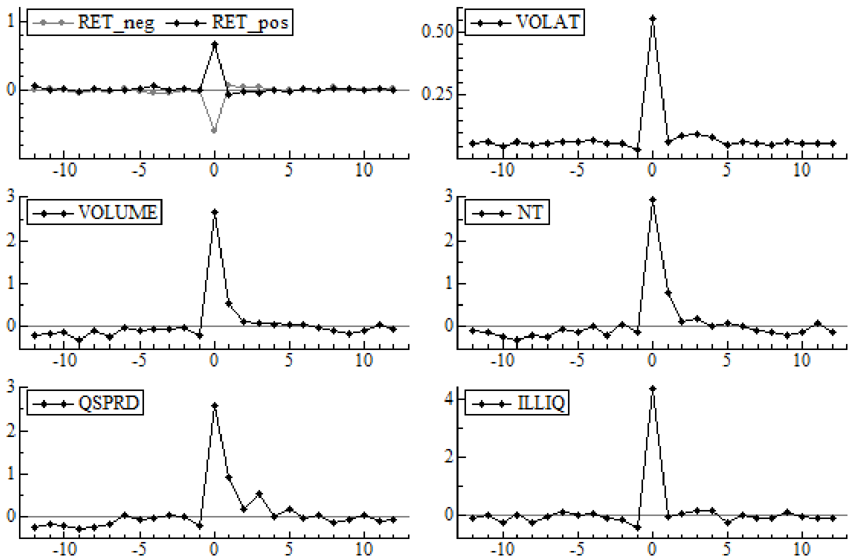
Notes: on X axis is time (CET), whereas on Y axis is number of jumps.

The number of jumps detected within each 5-minute interval over the day are presented. They are rather randomly distributed – on the one hand for some intervals there are no jumps within the whole sample, on the other seven jumps are detected on 10:20 CET. In most cases, at least one jump is observed.

Event study

In the next step, we calculate different liquidity measures in the window consisting of twelve 5-minutes interval before and after a jump occurred. These measures are obtained for each stock individually and then standardized. The descriptive statistics of standardized liquidity variables are presented in Table 5 in Appendix.

Figure 2 Returns, volatility, volume, number of transactions, quoted spread around the jumps and illiquidity



Notes: RET, VOLAT, VOLUME, NT, QSPRD, ILLIQ denote medians for returns, volatility and standardized: volume, number of trades, quoted spread and illiquidity for all stocks across the sample in the event window. In case of returns "pos" and "neg" describe the medians calculated for the positive (black) and negative (grey) jumps divided on the basis of the sign of the return at the moment of the jump. The event window consists of twelve five minute intervals before and twelve five minute intervals after jump centered at 0.

Figure 2 shows the dynamics of the medians of the standardized variables for the whole sample. In the case of returns (*RET*) we consider the positive and negative jumps separately, which are conditioned on the sign of the return at the moment of the jump. At $t = 0$ the median of returns for positive jumps increases, whereas for negative jumps decreases. There is a symmetry of the reaction to good and bad news, represented by positive and negative jumps: the median returns associated with negative jumps are almost the same as the median returns associated with positive jumps. Moreover, the median return for intervals $t = +1$, $t = +2$ and $t = +3$ after a positive jump tends to be negative, whereas after a negative jump it tends to be positive. The Mann-Whitney test rejects the null hypothesis asserting that the medians of the positive and negative jumps in these three intervals are identical. This indicates the short-term 15 minutes' market overreaction, although it is small in size.

Figure 2 shows that both returns (*RET*) and volatility (*VOLAT*) change sharply at the time of the jumps. However, we also observe an increase in the volume (*VOLUME*) as well as in the number of trades (*NT*). The illiquidity variable (*ILLIQ*) shows that relative increase in returns is higher than one observed in the volume, and as a result the illiquidity increases (the liquidity decreases) substantially at the moment of the jump. Moreover, the trading costs represented here by the quoted spread (*QSPRD*) are also affected by the occurrence of jumps. These findings are in agreement with the view presented in the literature by Lee et al. (1993), Brooks (1994) or Boudt and Petitjean (2014) who show that jumps coincide with higher volatility, larger spreads, larger volumes and higher trading costs.

The increase in the trading quantity measures, which are measured here by the volume and number of trades, which is usually matched to the increase in liquidity, whereas the increase in transaction costs, proxied here by the quoted spreads, as well as the increase in Amihud's illiquidity itself indicates the decrease in liquidity. This result is apparently contradictory and might cause a confusion. The reasonable explanation is that the price jumps occur at the time of growing imbalances that occur in the market as a result of the big orders and cause an increasing demand for liquidity. Jumps are owing to the market inability to absorb those orders without significant change in the price. Here the discontinuities in the prices are accompanied by significant changes in liquidity measures, but this effect is short-lived since all liquidity proxies are back to the pre-jump level in a very short time.

Logit regressions

To complement the non-parametric event study approach, we subsequently carry out a parametric analysis to assess the interdependence of liquidity shocks and price jumps. We use logit models in order to examine how shocks in the variables are correlated with the probability of the jump occurrence. In estimation, we use the standardized liquidity variables from the event window. As the variables used in the study are highly correlated, all models include only one independent variable in lags from $\tau = t-2$ to $\tau = t+2$.

The estimates in Table 3 confirm the earlier observations that jumps coincide with the changes in the liquidity variables. Considering the models without lags ($\tau = t$), the higher the value of these variables used in the study, namely volatility, volume, illiquidity, number of trades and quoted spread, the higher probability of the occurrence of the jumps.

We also examine the interdependence of liquidity shocks and jumps at different time lags. The case for $\tau = t-1$ shows the occurrence of jumps is preceded by a decrease in volatility as well as in illiquidity. The explanatory power of the illiquidity variable remains strong even at the 10-minute time lag ($\tau = t-2$). When considering variables at $\tau = t+1$, volume, number of trades and quoted spread remain at the higher level, whereas volatility and liquidity already revert to the pre-jumps level. Within the 10-minute period after a jump all considered variables are back at the pre-jump level. It confirms the previous observations from the event-study that all liquidity variables increase strongly at the time of the jump, but this effect is very short-lived.

Table 3 The estimates of LOGIT models

$$P(jump_t = 1|\mathbf{X}) = G(\beta_0 + \beta_i X_{i,\tau})$$

variable	$\tau = t-2$	$\tau = t-1$	$\tau = t$	$\tau = t+1$	$\tau = t+2$
VOLAT	-1.03 (0.66)	**-3.73**** (0.99)	**10.99**** (0.66)	-0.40 (0.58)	-0.62 (0.60)
VOLUME	-0.03 (0.03)	-0.03 (0.03)	**0.15**** (0.02)	**0.05**** (0.02)	-0.03 (0.03)
ILLIQ	**-0.15*** (0.07)	**-3.02**** (0.09)	**0.88**** (0.05)	-0.09 (0.06)	-0.02 (0.05)
NT	-0.02 (0.05)	-0.12 (0.07)	**0.53**** (0.04)	**0.12**** (0.04)	0.01 (0.04)
QSPRD	-0.03 (0.03)	-0.03 (0.03)	**0.12**** (0.01)	**0.03*** (0.01)	-0.01 (0.02)

Notes: The numbers in the Table 3 represents estimated coefficients and their standard deviations (in brackets) from the 25 logit regressions. The regressions are run for aggregated sample of six stocks over the period from 1st of October 2012 to 1st of October 2013 at the 5-minute frequency level. The liquidity variables are calculated as the medians of the standardized liquidity measures. Numbers in bold indicate the statistical significance, * at the α=0.05 and ** at the α=0.01. $P(jump_t = 1|\mathbf{X})$ is the probability that a jump occurs given one of the explanatory variables *X*, that is volatility (*VOLAT*), volume (*VOLUME*), illiquidity (*ILLIQ*), number of trade (*NT*) and quoted spread (*QSPRD*). All explanatory variables are included with a time lag τ . *G* is the CDF of the logistic distribution.

4. Conclusion

This study examines the behavior of liquidity measures around significant price changes on the Warsaw Stock Exchange, the emerging order driven market. We find that on the one hand the price jumps coincide with abnormally high increases in the trading volume and the number of transactions, that are the usual market depth measures. On the other hand, jumps are accompanied by an increase in the transaction costs and Amihud’s illiquidity measure. Although market depth is closely related to liquidity and volume, it does not mean that every stock which shows a high volume of trade has good market depth. There are the imbalances of orders large enough to create high volatility even in cases of high volumes. Altogether it suggests that jumps results from increased demand for liquidity and imbalances that occur in the market at the time of big orders. The rapid increase of these variables shows that extreme price changes coexist with a greater demand for immediate execution of orders. These effects are short-lived as the returns and liquidity variables are back to pre-jump levels from five to ten minutes after the jumps. It provides strong evidence of the market resiliency.

The results of this study indicate that occurrence of the jumps and liquidity changes are strongly tied. The growing trading quantity is accompanied by the increase in transaction costs measured by quoted spread. Although the shocks in liquidity have a very short-lived effect, market participants could benefit from temporary changes by executing their trades within the short period after a jump occurs.

APPENDIX

Table 4 The description of stocks included in the study

Ticker	*Name*	*Macrosector/Sector*	*Major shareholders (% of shares)*	*Market capitalization (in mln PLN)*
KGH	KGHM Polska Miedź SA	Industry/Raw Materials	31,79% (State)	38 000,00
PKN	Polski Koncern Naftowy ORLEN SA	Industry/Fuel	27,52% (State) 5,08% (AVIVA OFE)	21 171,60
PEO	Bank PEKAO SA	Finance/Banking	50,1% (UNICREDIT S.p.A)	43 963,03
PGE	Polska Grupa Energetyczna SA	Industry/Energy	57,39% (State)	34 048,34
PKO	Bank PKOBP SA	Finance/Banking	33,39% (State) 10,25% (BGK)	46 125,00
PZU	PZU SA	Finance/Insurance	35,1875% (State) 5,0446% (ING OFE)	37 735,96

Source: The Warsaw Stock Exchange Annual Report 2012 and individual web sites of companies from the end of 2012.

Notes: Only two major shareholders with their stakes are presented, assuming that each has more than 5% of shares. Otherwise only first major shareholder is presented.

Table 5 The descriptive statistics of standardized liquidity variables

	Mean	*St.deviation*	*Maximum*	*Minimum*	*Number of observations*
RET	0.00	0.21	4.05	-2.09	3250
VOLAT	0.12	0.18	4.05	0.00	3250
VOLUME	1.05	3.34	59.78	-0.95	3250
NT	0.50	1.81	41.82	-1.11	3250
QS	1.29	4.93	63.05	-0.90	3250
ILLIQ	0.52	1.76	28.30	-1.06	3250

REFERENCES

Amihud Y (2002): Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets*, 5 (1): 31–56.

Ané T, Métais C (2010): Jump Distribution Characteristics: Evidence from European Stock Markets. *International Journal of Business and Economics*, 9 (1): 1-22.

Andersen TG, Bollerslev T, Diebold FX (2007): Roughing it up: Including Jump Components in the Measurement, Modelling and Forecasting of Return Volatility. *The Review of Economics and Statistics*, 89 (4): 701-720.

Barndorff-Nielsen O, Shephard N (2004): Power and Bipower Variation with Stochastic Volatility and Jumps. *Journal of Financial Econometrics*, 2(1): 1–48.

Będowska-Sójka B (2016): Liquidity dynamics around jumps. The evidence from the Warsaw Stock Exchange. *Emerging Market Finance and Trade*, 52(12): 2740-2755.

Będowska-Sójka B (2013): Macroeconomic news effects on the stock markets in intraday data, *Central European Journal of Economic Modelling and Econometrics*, 5 (4): 249-269.

Boudt K, Petitjean M (2014): Intraday liquidity dynamics and news release around price jumps: Evidence from the DJIA stocks. *Journal of Financial Markets*, 17 (C): 121–149.

Brooks RM (1994): Bid-ask Spread Components Around Anticipated Announcements. *Journal of Financial Research*, 17 (3): 375–386.

Huang X, Tauchen G (2005): The Relative Contribution of Jumps to Total Price Variance. *Journal of Financial Econometrics*, 3 (4): 456-499.

Gurgul H, Wójtowicz T (2015): The Response of Intraday ATX Returns to U.S. Macroeconomic News. *Finance a úvěr - Czech Journal of Economics and Finance*, 65 (3): 230-253.

Hanousek, J, Kočenda E, Novotný J (2013): Price Jump Behavior during Financial Distress: Intuition, Analysis and a Regulatory Perspective. In: Arouri M, Boubaker S, Nguyen D (eds): *Emerging Markets and the Global Economy: A Handbook*, Academic Press, Elsevier, New York: 483-507.

Hanousek, J, Kočenda E, Novotný J (2012): Identification of Price Jumps. *Monte Carlo Methods and Applications* 18 (1): 53 – 77.

Hanousek, J, Kočenda E, Novotný J (2014): Price Jumps on European Stock Markets. *Borsa Istanbul Review*, 14 (1): 10-22.

Hanousek, J, Novotný J (2012): Price jumps in Visegrad-country stock markets: An empirical analysis. *Emerging Markets Review*, 13(2): 184-201.

Jajuga K, Walesiak M (2000): Standardization of Data Set Under Different Measurement Scales. In: Decker R, Gaul W (eds): *Classification and Information Processing at the Tum of the Millennium*, Springer-Verlag, Berlin, Heidelberg, 105-112.

Jiang GJ, Lo I, Verdelhan A (2011): Information shocks, jumps, and price discovery: Evidence from the U.S. treasury market. *Journal of Financial and Quantitative Analysis*, 46 (2): 527–551.

Jiang GJ, Oomen RCA (2008): Testing for Jumps When Asset Prices are Observed with Noise – a Swap Variance Approach. *Journal of Econometrics*. 144 (2): 352-370.

Joulin A, Lefevre A, Grunberg D, Bouchaud JP (2008): Stock Price Jumps: News and Volume Play a Minor Role. *IDEAS Working Paper Series from RePEc*, Federal Reserve Bank of St Louis, St. Louis, http://ideas.repec.org/p/arx/papers/0803.1769.html.

Kostrzewski M (2012): On the Existence of Jumps in Financial Time Series. *Acta Physica Polonica B*, 43(10): 2001-2019.

Kyle A (1985): Continuous Auctions and Insider Trading. *Econometrica*, 53 (6): 1315-1335.

Lahaye, J, Laurent S, Neely C (2011): Jumps, cojumps and macro announcements. *Journal of Applied Econometrics*, 26 (6): 893–921.

Lee CM, Mucklow B, Ready MJ (1993): Spreads, Depths, and the Impact of Earnings Information: An Intraday Analysis. *Review of Financial Studies*, 6(2): 345–374.

Lee S, Mykland PA (2008): Jumps in Financial Markets: A New Nonparametric Test and Jump Dynamics. *Review of Financial Studies*, 21 (6): 2535-2563.

Mann HB, Whitney DR (1947): On a Test of Whether one of Two Random Variables is Stochastically Larger than the Other. *Annals of Mathematical Statistics*, 18 (1): 50–60.

Mazza P (2015): Price dynamics and market liquidity: An intraday event study on Euronext. *The Quarterly Review of Economics and Finance*. (56): 139–153.