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Commonality in Liquidity Measures. The evidence from the Polish Stock Market

Barbara BĘDOWSKA-SÓJKA

Poznań University of Economics and Business, Poznań, Poland
barbara.bedowska-sojka@ue.poznan.pl

Abstract. The purpose of the paper is to examine commonality in liquidity across stocks listed on the Warsaw Stock Exchange. Commonality refers to the common behavior of the liquidity measures across different stocks. We consider liquidity proxies based on widely available low-frequency data, as well as spreads calculated from the transaction data. Our sample consists of stocks listed constantly from 2006 through 2016. We find that commonality in liquidity is weak and robust to the choice of liquidity proxy. Large companies show more commonality than the smaller ones. Commonality is time-varying: it increases as liquidity dries up.

Keywords: High-low Range, Effective Spread, Illiquidity.

1 Introduction

Liquidity is one of the most important issues considered in the contemporary finance. The evolution of liquidity is of concern in many papers [1, 2, 16] as are the reasons for common movement in liquidity measures within a given market [3, 11, 14, 18] and among different stock markets [12, 13].

As liquidity itself is a latent variable, it is generally accepted in the literature that different proxies are used. Within the literature devoted to the stock markets, a vast number of papers is dedicated to the choice of the best liquidity measure [7, 8]. Another strand of the literature focuses on the issue to what extent are these, better or worse, measures correlated [15]. This is often called the commonality in liquidity and defined simply as the covariation between different liquidity measures. Thus commonality is the market-wide co-movement in various liquidity measures that determines the systematic liquidity risk. The seminal paper on the commonality is written by Chordia, Roll and Subrahmanyam in 2000 [4]. They point the important issue whether shocks in trading costs constitute a source of non-diversifiable priced risk. As the risk is connected with illiquidity (the lack of liquidity) we may put it in other words: is there an additional systemic risk that comes from the commonality in liquidity? Implications for commonality are twofold [4]: first, in the static approach it explains the differences in trading costs among stocks within a single time period, and second, the in dynamic one, it is connected with liquidity risk for the portfolio within the given period.

Several theories on the origin of commonality in liquidity have been proposed. Surveys such as that conducted by Coughenour and Saad [6] on U.S. market show that commonality in liquidity comes from the fact that stocks share common market makers. On the contrary Naik and Yadaw [17] indicate that within the decentralized trading market makers focus on the liquidity risk position of the assets in portfolios managed by them and not by other dealers. Such approaches, however, have failed to address the situation in the order-driven markets, that operate without market makers (and this is the system used by several major stock exchanges in Europe, including the Warsaw Stock Exchange). Moreover, on the U.S. market Chordia, Roll, and Subrahmanyam [4] find the evidence in favor of commonality in liquidity, but the level of market-wide movement is rather low. It could be caused by the chosen liquidity proxy as well as time-varying feature of commonality, that depends on the specific market conditions. Hameed, Kang, and Viswanathan [10] find evidence that commonality in liquidity increases during periods of market downturns causing a spiral effect.

This study aims to contribute to this growing area of research by exploring the commonality issue on the emerging order driven market and considering few liquidity proxies, both in the static and the dynamic approach. In short, we examine if there exists the commonality in liquidity measures. The extensive research has been carried out already by Karolyi et al. [12], with the data from 44 stock exchanges, but we focus on one market only and get into the issue more deeply. We consider a portfolio consisting of big stocks listed constantly on the Warsaw Stock Exchange within the period of 11 years. Liquidity measures are calculated on the basis of widely available daily data. The importance and originality of this study are that it explores not only the level of commonality, but also examines if there are differences between commonality for various liquidity measures. It takes into account the size of the firms and looks for the reasons of commonality changes. Our findings can be summarized as follows: the commonality in liquidity proxies is weaker than reported in the previous studies [12] and weaker than on the developed markets [5, 9]. Commonality on the Polish capital market is time-varying and increases during global market turbulences as the global financial crisis, the European sovereign debt crisis and the Chinese debt crisis. We further find significant differences in commonality with respect to the size of the company: big firms show higher level of commonality than small firms. This result is robust to the choice of the liquidity proxy.

The rest of the paper has been divided into four parts. Section 2 presents the data, Section 3 introduces methodology and explains the liquidity proxies calculations as well as the commonality regressions structure. Section 4 is devoted to the empirical results, while last Section concludes.

2 Data

We use the data on 44 stocks that have belonged to WIG20 or WIG30 blue chip index listed on the Warsaw Stock Exchange (Poland). This exchange operates as an open limit order book market without market maker. The trades are made within a continuous double auction mechanism where orders are matched with the price and time priority. Our stocks have been listed constantly from 2006 till 2016 and are considered as big stocks with capitalization over 250mln euro at the end of 2016. The sample period consists of 2754 days observed in 132 months. The data are from www.stooq.pl database and includes four prices and volumes. We apply the usual filtering methods within the dataset [19]. We also use spreads calculated on the basis of high-frequency tick-by-tick data. This dataset comes directly from the WSE.

For each stock in the sample we calculate the average turnover as a product of daily close price and volume traded. Then we form a portfolio from stocks and calculate on a daily basis the weights of each stock as a proportion of stock turnover to the turnover of the whole portfolio (index weights). Although all these stocks were considered by the exchange as big ones at the end of 2016, there are substantial differences between the stocks included in this study, both in the aspect of their free float and turnover. We have five stocks with relatively high weights over 8% and twenty-one small stocks with weights lower than 0.5%. Thus the stocks represent the very diverse set.

3 Methodology

In absence of a commonly accepted liquidity index we propose two measures of market liquidity. We form two portfolios including stocks from our sample: first encompasses stocks with equal weights, and second uses the dynamic weights changing every day on the basis of the daily turnover of index constituents. Then we run commonality regressions for each stock and each market liquidity index.

We set few hypotheses: first, there is the commonality between single stock liquidity and the market liquidity (liquidity index), although it is weaker than shown in the previous studies [12]. Second, we expect there should be no significant differences between commonality coefficients for different liquidity proxies. Each proxy expresses different liquidity features, but in general there should be a consensus on the issue if market move together or not. Third hypothesis is that commonality is not stable over time. The last states that commonality differ between big and small stocks.

3.1 Liquidity Measures Used in the Study

We calculate several liquidity measures for each stock in our sample. The common feature of these measures is that all are based on the daily data (four prices and volumes) and are calculated in daily frequency. Thus we consider illiquidity measure of Amihud (2002):

$$ILLIQ_t = |r_t|/[\log(volume_t)] \tag{1}$$

where r_t is a percentage logarithmic return, and $volume_t$ is a product of the number of stocks traded within the day and the closing prices, $volume_t = vol_t * C_t$. We consider logs of volumes to reduce the impact of outlier observations. Next measure is Volatility over Volume, VoV_t:

$$VoV_t = \frac{\log\left(\frac{H_t}{L_t}\right)^{0.6}}{volume_{it}^{0.25}} \qquad (2)$$

where H_t is the highest, and L_t is the lowest price observed within a given day t, while $volume_t$ is rescaled in order to smooth the series [7]. Next measure is based on the range, that is the difference between the high and the low prices, and is scaled by mid-price:

$$HLR_t = \frac{H_t - L_t}{0.5(H_t + L_t)} \qquad (3)$$

We also use the high-low spread estimator of Corwin and Schultz (2012):

$$S_t = \frac{2(e^{\alpha} - 1)}{1 + e^{\alpha}}, \qquad (4)$$

where $\alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}}, \beta = \left[\ln\left(\frac{H_t}{L_t}\right)\right]^2 + \left[\ln\left(\frac{H_{t+1}}{L_{t+1}}\right)\right]^2,$

and $\gamma = [\ln((\max\{H_t, H_{t+1}\})/(\min\{L_t, L_{t+1}\})]$.

In fact these three measures show illiquidity, so the higher are the values of proxies, the lower liquidity is provided on a given day. We also include one proxy, LIX_t measure, with opposite approach [7]:

$$LIX_t = \log_{10} \frac{volume_t}{H_t - L_t}. \qquad (5)$$

We also include liquidity proxy that is calculated as the spread based on the tick-by-tick data with following the formula:

$$BAS_t = \frac{\sum_{k=1}^{N_k} vol_k (p_k^A - p_k^B)/p_k * c}{vol_t} \qquad (6)$$

where p_k^A is an ask price of a given trade k,, p_k^B is a bid price, and p_k is a price of transaction k, c is a constant equal to 2000, vol_k is a number of shares traded with a given price p_k, N_k is a number of all transactions within a day t and vol_t is the overall volume within given day.

We calculate all liquidity proxies for every stock included in the sample. Table 1 presents summary of cross-sectional statistics for the time series of these liquidity measures. There is right skewness in the cross-section of average liquidity measures, namely $ILLIQ$, HLR, CS, VoV and BAS, as the sample means exceed sample medians. LIX behaves in the opposite way due to its reverse approach (the higher the value, the more liquidity is observed). The differences between single liquidity measures are not surprising as they take into account different features of liquidity.

On the basis of the stocks proxies, the market liquidity indices are calculated. Figure 1 presents the dynamics of liquidity indices – for more transparent presentation they are aggregated into monthly values. They are some similarities between them: $ILLIQ, VoV, HLR$ and CS show the strong decrease in liquidity during financial crisis in 2008 and sovereign debt crisis in 2011. LIX shows a strong increase in liquidity in 2006, while spreads calculated on intraday data (BAS) increase strongly in the beginning of 2006 and then decrease gradually showing similar variations as the first four measures.

Table 1. Descriptive statistics for the liquidity measures

Proxy:	mean	sd	25%	50%	75%
ILLIQ	0.1148	0.1267	0.0297	0.0794	0.1579
HLR	0.0292	0.0216	0.0155	0.0246	0.0374
CS	0.0069	0.0099	0.0000	0.0025	0.0110
VoV	0.0404	0.0332	0.0193	0.0306	0.0518
LIX	5.9314	1.6254	5.0458	6.1226	7.0753
BAS	0.0038	0.0042	0.0012	0.0024	0.0049

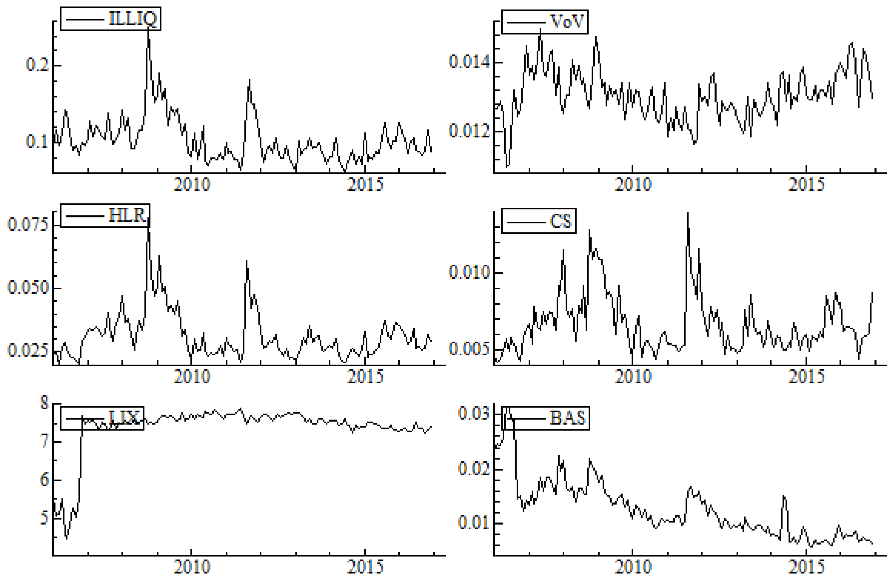

Fig. 1. The dynamics of aggregated liquidity indices.

3.2 Commonality regressions

Following Hameed, Kang, and Viswanathan [10] and Karolyi et al. [12] we use determination coefficient, R^2, of the regression of an individual stock on the market liquidity index. In our study we run regressions for each liquidity measure for every stock and our two liquidity indices. As the liquidity measures and the indices are non-stationary, we apply the regressions for the first differences of the series. These differentiated series are featured by strong autocorrelation of order 1, so we use filtering regressions both for differences in liquidity measures and for differences in market index in a following form:

$$\Delta LiqVar_{it} = \varphi_0 + \varphi_1 \Delta LiqVar_{i(t-1)} + \varepsilon_{it} \tag{7}$$

where $LiqVar_{it}$ is a liquidity variable for a stock or an index on day t, φ_0 is a constant, φ_1 is a coefficient and ε_{it} is assumed to be distributed normally IID. We also considered the filtering out of day-of-the week effect, but no such an effect existed. Finally in the commonality regressions we use the innovations ε_{it} from AR(1) models. As in Karolyi et al. [12] for the commonality regressions for each stock j we separately calculate market liquidity index out of innovations ε_{it} and exclude this stock in index computation. This exclusion is important specifically in case of stocks with relatively high weights in the portfolio. Finally, we estimate the commonality regression in the following form:

$$\varepsilon_{it} = \beta_0 + \beta_1 * \varepsilon_{Mt} + \vartheta_{it} \qquad (8)$$

where ε_{it} is the innovation for each stock (Eq.1), ε_{Mt} is obtained as a simple average or the market-value weighted-average of the innovations for the liquidity index and ϑ_{it} is assumed to be normally distributed IID.

4 Empirical results

The empirical part consists of three sections: the first one is devoted to the daily regressions for stocks, the second examines coherence of the aggregated measures, while the last one studies monthly dynamics of R^2 coefficients.

4.1 Daily regressions for stocks

In this section we use two parallel approaches: in the first one we obtain R^2 for each stock and the simple average of the stocks included in the sample (for the sake of brevity we will call it $INDEX_{eq}$). In the second approach, the market liquidity index is obtained as a weighted average of the liquidity measures of stocks, where weights are time-varying on a daily basis dependently of the turnover in a given day ($INDEX_w$).
Table 2 presents the results. The average value of the R^2 coefficients from commonality regressions are very low, ranging from 1% (BAS) to 8% (CS) for equally weighted index and from 3% (LIX) to 6% (HLR) for market-value weighted index.

Table 2. Descriptive statistics of R^2 coefficients from the commonality regressions

	$INDEX_{eq}$					$INDEX_w$				
	mean	st.dev.	0.25	0.5	0.75	mean	st.dev.	0.25	0.5	0.75
R^2_{ILLIQ}	0.06	0.05	0.02	0.05	0.08	0.04	0.05	0.01	0.02	0.05
R^2_{HLR}	0.02	0.02	0.01	0.01	0.03	0.03	0.04	0.00	0.01	0.03
R^2_{CS}	0.07	0.05	0.04	0.06	0.09	0.06	0.06	0.01	0.03	0.07
R^2_{VoV}	0.08	0.07	0.03	0.06	0.10	0.05	0.05	0.02	0.03	0.06
R^2_{LIX}	0.03	0.02	0.01	0.02	0.04	0.02	0.03	0.00	0.01	0.03
R^2_{BAS}	0.01	0.01	0.01	0.02	0.05	0.02	0.04	0.01	0.01	0.03

Note: The values in the table are the mean, standard deviations (st.dev.) and 25th, 50th and 75th percentile of the distribution of R^2 from commonality regressions estimated on daily data within the whole sample period for liquidity proxies. $INDEX_{eq}$ stands for the liquidity index with equal weights, while $INDEX_w$ stands for the market-value weighted liquidity index.

We have ordered stocks with respect to their average capitalization within the sample period measured by the daily turnover for each stock with respect to whole portfolio of 44 stocks. Figure 2 shows the average weight in the portfolio of a given stock within the whole sample period, the average R^2 from commonality regressions with $INDEX_{eq}$ as the independent variable, and average R^2 from commonality regressions with $INDEX_w$. The results are presented for each stock in the form of two bars; stocks are presented in descending order of the market value at the end of 2016. The first two bars are the determination coefficients R^2 from commonality regressions for the biggest stock, the last two are for the smallest one in the sample.

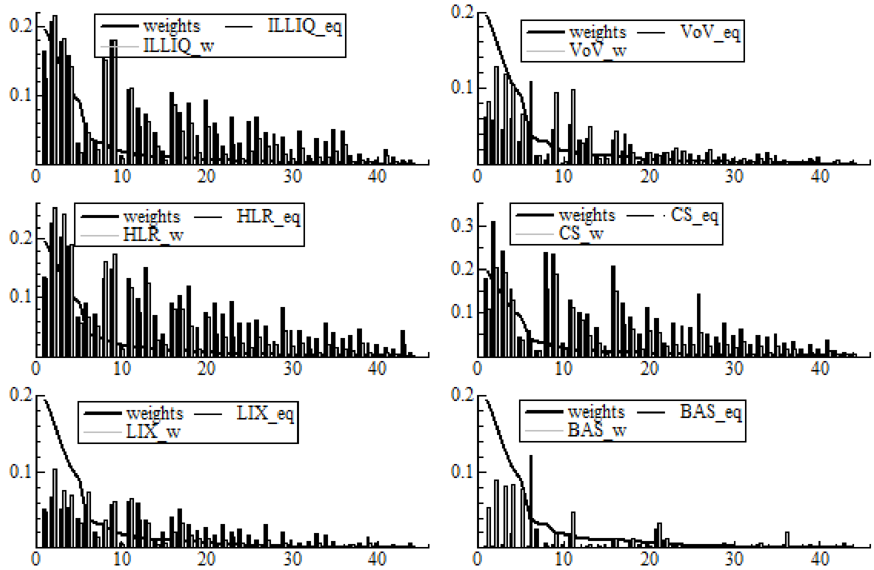

Fig. 2. The average R2 of commonality regressions for different liquidity proxies and the average stocks weights in the portfolio.

Note: The blue line shows the weights in the portfolio for each of the 44 stocks. Each stock gets two bars: the black bar is for the R^2 from commonality regression for a given stock and equally weighted index $INDEX_{eq}$, while the grey bar is representing R^2 from regressions with market-value weighted index $INDEX_w$.

We present the results ranking firms from the largest to the smallest ones – this ranking is based on the average capitalization within the sample period. Figure 2 shows that generally R^2 from commonality regressions for different liquidity measures are low; in majority of cases they do not exceed 0.2. The highest values of R^2 are observed for CS, while the lowest are found in case of BAS. There are visible differences between R^2 from both types of commonality regressions, but no single pattern is noticeable. When size is taken into account we find that for the big firms commonality measured by the R^2 coefficient is larger than for the smaller firms. This conclusion is robust to the method of the index calculation: liquidity measures of the small firms are less correlated with both liquidity indices than liquidity measures of the big firms. With minor exceptions, this rule applies to all measures employed in the study. It is the mostly recognized in the case of BAS measure, where for the majority of the stocks R^2 is close to 0.

4.2 Coherence of the Aggregate Measures

We also examine the commonality of the particular liquidity measures across the sample using the Spearman rang correlations. Thus we take into account the differences of liquidity proxies and calculate the correlations for each proxy separately for all stocks in the sample. Table 4 presents the cross-section sample descriptive statistics (the means, the standard deviations, 25^{th}, 50^{th} and 75^{th} percentiles) of Spearman rang correlations. The correlations on average are positive, but low, below 10%. In many particular cases (not shown in the Table 3) they are not significantly different from zero.

In order to differentiate between big and small companies we consider separately the four biggest (10%) and four smallest (10%) companies in the sample. Last three columns of the Table show medians for these two groups as well as the Mann-Whitney test for medians' differences. The results show that for each proxy in case of big companies the median Spearman rang correlations are statistically higher than for the small firms. This is a rather remarkable result and confirm the findings from Section 4.1: commonality is stronger for the big companies than for the small ones.

Table 3. The descriptive statistics of cross section of Spearman rang correlations

Liquidity proxy	mean	st.dev.	25%	50%	75%	Median for 4 big stocks	Median for 4 small stocks	Z-score
ILLIQ	0.07	0.15	0.02	0.04	0.07	0.05	0.01	12.04
VoV	0.09	0.15	0.03	0.05	0.09	0.10	0.03	12.74
HLR	0.07	0.15	0.03	0.05	0.07	0.07	0.02	11.00
CS	0.06	0.15	0.01	0.03	0.05	0.05	0.01	10.36
LIX	0.06	0.15	0.02	0.04	0.06	0.03	0.01	7.27
BAS	0.05	0.16	0.00	0.02	0.04	0.03	0.01	7.27

Note: The values are descriptive statistics of the cross section of Spearman rang correlations between given liquidity proxies obtained for each stock in the sample. Z-score are the values of the Mann-Whitney statistics for the big and small stocks medians differences.

4.3 Monthly Dynamic R Squares: is Commonality Higher in Low Liquidity Periods?

In this section we consider coefficients from commonality regressions estimated in monthly windows and thus are able to examine the stability of R^2 in changing market conditions. Within our sample period there occurred few serious market downturns on the global market. We test the hypothesis that the commonality in the liquidity measures is stronger in the time of the market downturns than in the calm periods. Thus we employ the commonality regressions to the daily innovations in liquidity proxies for individual stocks and innovations for the market liquidity (Eq.2) for each month separately and calculate the averages across the sample.

Table 4 presents the descriptive statistics for the monthly R^2 from commonality regressions. The average values in the dynamic approach are higher than in the static one (see Table 2), but still low, and range from 4% for BAS spreads to 11% for Amihud illiquidity, $ILLIQ$. Some asymmetry in the distribution is observed for $ILLIQ, HLR$ and CS as the medians are lower than the means.

Table 4. The descriptive statistics of cross section of Spearman rang correlations.

	mean	st.dev.	25%	50%	75%
R^2_{ILLIQ}	0.11	0.12	0.07	0.09	0.13
R^2_{HLR}	0.07	0.12	0.04	0.05	0.08
R^2_{CS}	0.09	0.13	0.04	0.06	0.10
R^2_{VoV}	0.05	0.10	0.03	0.05	0.06
R^2_{LIX}	0.05	0.10	0.04	0.05	0.06
R^2_{BAS}	0.04	0.09	0.02	0.03	0.05

This is in contradiction with the results of Karolyi et al. [12], who focus on commonality in Amihud liquidity and for the Polish stocks find the R^2 coefficients' mean as high as 22% with standard deviation of 4.91% [12].

The next section of the study is devoted to the examination if the changes of the monthly indices built upon the various proxies are interrelated to the changes in R^2 coefficients from the respective commonality regressions. Thus we are able to check if the increase in commonality is observed at the time of the increase in illiquidity. In this part we consider sample medians of the R^2 from the commonality regressions with equally weighted indices as an independent variable. Figure 3 shows the dynamics of the cross-sectional average of R^2 for innovations from $ILLIQ$ proxy (Eq. 2) and the $ILLIQ$ liquidity index. The values of R^2 are changing from one month to another. They also comove with the index values.

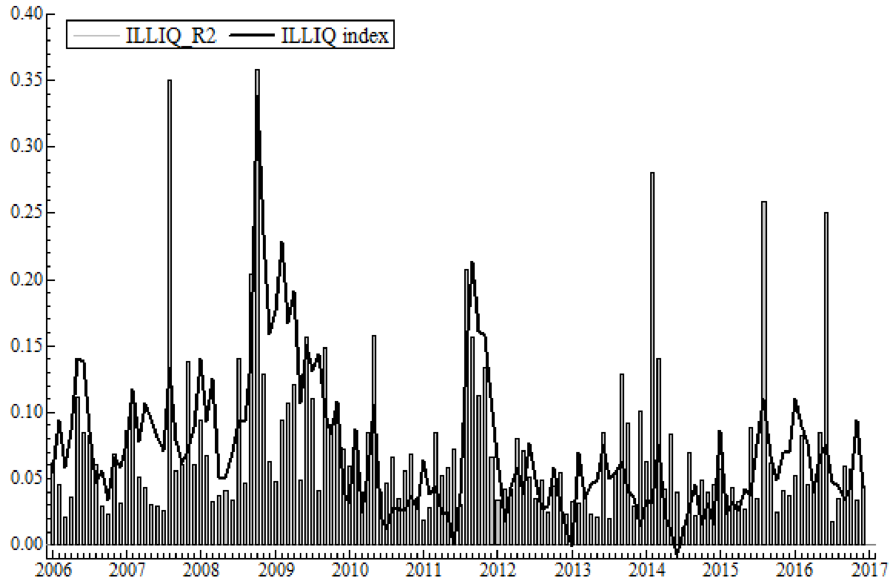

Fig. 3. The dynamics of commonality (Amihud illiquidity) and illiquidity index.

To better illustrate this potential co-movement between commonality and indices, we calculate the Spearman rang correlations between the series of average monthly R^2 and each liquidity index. The results presented in Table 5 are ambiguous: for three liquidity proxies, $ILLIQ, HLR$ and CS, the correlations are positive and statistically significant, while the remaining proxies the correlations between indices and R^2 from the regressions for the respective proxies are not statistically significantly different from zero.

Table 5. The descriptive statistics of cross section of Spearman rang correlations.

Liquidity Index:	I_{ILLIQ}	I_{VoV}	I_{HLR}	I_{CS}	I_{LIX}	I_{BAS}
Spearman rang correlation	0.4475	-0.0958	0.2956	0.3467	0.1771	0.0214
p-value	*0.0000*	*0.2742*	*0.0006*	*0.0001*	*0.8716*	*0.8069*

In order to deepen the analysis we look for the coexistence of the extreme values of commonality. Thus we search for the months in which for at least two proxies the values of R^2 coefficients where among the five highest. Table 6 summarizes the results showing that there are five such months. The coefficients obtain the highest values in the crisis periods, e.g. August 2007 (BNP Paribas suspended three funds), October 2008 (downturn on the WSE resulting from the Lehman Brother collapse in September 2008), May 2010 (first bailout in Greece) or June 2016 (China debt crisis). The latter is the winner of the game with four cases where the coefficients belong to the five highest values in the whole sample. These results confirm that commonality of liquidity increases in hectic periods and decrease in the calm periods.

Table 6. The months in which commonality obtains the extreme values.

date	R^2_{ILLIQ}	R^2_{VoV}	R^2_{HLR}	R^2_{CS}	R^2_{LIX}	R^2_{BAS}
2007-08	0.32		0.24	0.47		
2007-12		0.16			0.11	
2008-10	0.31		0.28	0.36		
2010-05		0.13			0.13	
2016-06	0.28		0.43	0.54		0.14

Note: The values in the Table are the highest R^2 that occurred at the same time in at least two series. First column shows in which month this event appeared.

5 Conclusions

This paper is devoted to the examination of the commonality in liquidity observed in the emerging European order-driven market. In this study we examine the market-wide movements of liquidity measures calculated for stocks quoted on the Warsaw Stock Exchange within 2006-2016 period. Six liquidity proxies are considered and two liquidity indices are constructed, a simple aggregate and turnover weighted aggregate.

We show that commonality in liquidity measures is rather weak as the determination coefficients in commonality regressions are low (usually lower than 10%). The average commonality for different proxies differ, the highest values are observed for high-low range and Amihud illiquidity, and the lowest for spread calculated on the basis of intraday data. This evidence suggests that commonality in liquidity measures is less pronounced than it was shown by the previous studies and is much weaker than on the developed markets.

This could lead to the conclusion that on the Polish capital market liquidity risk is more idiosyncratic than systemic. But, we find that commonality depends on the firm size: the biggest firms in our sample show much more commonality than the smaller firms. Additionally, our results indicate that commonality is time-varying, specifically it increases in the periods in which liquidity dries up. These two results together might offer an interesting explanation of the commonality behavior: stocks of big firms are bought by financial intermediaries more often than stocks of small ones. In market downturns the intermediaries withdraw funds from the market, and this effects mainly these big firms in which they invested. This withdraw of the funds causes a decrease in liquidity. The less liquidity is supplied, the higher is the commonality, but it concerns mostly the big firms. Thus the liquidity risk for a big firms' segment of the market seems to be systemic.

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