THE DEFINITION OF STRESS SITUATIONS AND THEIR PREDICTION USING LIQUIDITY IN THE FRAMEWORK OF THE EMIR REGULATION

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ABSTRACT
The role of the central counterparties (CCP) in the financial sector is very important, since they bear the counterparty risk during the trading on stock exchanges. Because of the notable risk central counterparties have to face, the attention of the regulators has turned towards them lately, by defining several processes how the CCPs should measure and manage their risk. The definition of stress has a crucial role, however it is not specified clearly. Based on the regulation, we investigate a possible definition of stress, its consequences on the Hungarian stock market, and its relationship to and predictability from market liquidity.

INTRODUCTION
Trading with financial instruments takes place on stock exchanges or on over-the-counter (OTC) markets. One of the basic differences between the operation of the two markets is the presence of the central counterparty on the organised markets, that acts as the trading partner in each trade. The role of the CCP is to take over counterparty risk, namely the risk that one of the parties will not perform as promised (Brealey et al. 2011). Since the counterparty risk is a notable risk category, CCPs should measure and manage their risk efficiently, in order to maintain the market’s financial stability, as bankruptcy of a CCP would have a serious effect on the whole financial sector. It is also important to note, that in the future, regulators aim to extend the activity of the CCPs for the OTC markets as well, in order to decrease the risks on that market segment also.

As a regulatory answer for the financial crises, on 4th July, 2012 the European Parliament and the Council established a new regulation, called European Market Infrastructure Regulation (EMIR, Regulation (EU) No. 648/2012 on OTC derivatives, central counterparties and trade repositories). This regulation was supplemented by the European Commission on 19th December, 2012, with the Regulation (EU) No 153/2013, providing the technical standards of the EMIR regulation.

The above regulations aim to ensure the prudence of the risk management procedure of the central counterparties, however in some cases the EMIR is not specific enough, and doesn’t give an exact solution how to interpret some notions, like one of its key terms: the stress situation. The proper definition is important, since according to the regulation, the different applications of certain models are based on whether a financial stress is present on the market or not.

Although the role of the central counterparties and their regulation has an increasing literature recently, the problem of defining stress has arisen as a practical issue yet, so we do not know any academic study dealing with it.

In this paper we present a definition for the stress situation, based on the results of the backtest of the applied risk measurement model, and we show its effect on real market data of the Hungarian Stock Exchange, in the after crisis period, between 2010 and 2013. Furthermore, we analyse how the identified stress situation would have been predictable from the (il)liquidity of the market.

Our paper is built up as following: first, we introduce the regulations focusing on their elements that apply the notion of stress. Then we introduce the risk measure Value-at-Risk (VaR), as the risk management process and our analysis is based on it. The next section presents the measurement of market liquidity, since the liquidity of the market in stress is tested also. The following part contains our empirical research, the methodology, the market data and the analysis of the stress situation and its co-movement with liquidity. The last section summaries our results and conclusions.

THE REGULATIONS
The main risk, CCPs are facing, derives from the default of their clearing parties. For taking over this risk, CCPs apply a waterfall system of collateral elements, that decreases their losses if one of the parties does not fulfil its obligations. The first component ensuring the performance of the trading parties is an initial margin, a certain amount of cash or cash-equivalent that is required to be placed by both
parties - the seller and the buyer - of the trade. The concept of determining the level of this margin is regulated by EMIR and the 153/2013 regulation.

**Model of margin determination**

The regulation says, that ‘a CCP shall calculate the initial margins to cover the exposures arising from market movements for each financial instrument that is collateralised on a product basis’ (Regulation 153/2013/EU, Article 24). The regulators do not define the models the CCPs shall use. The only limitations they give are the following:

1. CCP has to use a 99% confidence interval in case of financial instruments other than OTC derivatives, and 99.5% for OTC derivatives (Regulation 153/2013/EU, Article 24).
2. For estimating the model CCPs shall use the data at least of the latest 12 months’ data (Regulation 153/2013/EU, Article 25).
3. CCPs shall take into account the time horizon for the liquidation period, which shall be two days for financial instruments other than OTC derivatives, and five days for OTC derivatives (Regulation 153/2013/EU, Article 26).

The most widespread risk measure used also by the Basel rules – regulating financial institutions – is the Value-at-Risk (VaR), and because of its popularity and applicability for the purposes of the EMIR, it was applied by most of the CCPs, too. The features, shortcomings and alternatives of VaR are introduced in details in the next section.

**Time horizon for historical volatility**

The regulation requires a period of at least 12 months to be used to estimate the historical volatility. Besides that the regulation requires further specification in order to be prepared for even extreme market circumstances, by prescribing a ‘full range of market conditions, including periods of stress’ (Regulation 153/2013/EU, Article 25).

This means, that the definition of stress has an effect on the observation period the CCP shall use to calculate the model, and also on the calculated volatility and margin level.

**Procyclicality**

The financial crisis shed light on the possible procyclical effect of the risk management regulations in the financial sector. The models using more rigorous capital requirements in case of market turbulences, contributed to the financial difficulties of the institutions and deepened even the crisis. Consequently the latest direction of the macroprudencial regulations aims to minimise that effect by applying anticyclical provisions.

That was formulated in Regulation 153/2013/EU: ‘A CCP shall ensure that its policy for selecting and revising the confidence interval, the liquidation period and the lookback period deliver forward looking, stable and prudent margin requirements that limit procyclicality to the extent that the soundness and financial security of the CCP is not negatively affected’ (Regulation 153/2013/EU, Article 28). To achieve this goal, the regulator requires the CCPs to use a margin buffer at least equal to 25%, when calculating margin in normal market conditions. On the other hand, in case of changing market conditions, which would cause an essential rise in the margin requirements, the CCP can disregard the margin buffer. This procedure is to be used in stress situation that is depending on the definition of stress, also.

**Definition of stress**

The present practice of most CCPs relies on the decision of the risk management committee when deciding about the existence of stress. Although we agree to maintain this kind of flexibility, it is suggested to define some objective criteria that give a signal that the market may be regarded in stress.

As the risk measurement models are reviewed and tested on a daily basis, we suggest to use the results of these backtests as a warning signal about stress. If the real market change exceeds the maximal movement based on the applied risk measure (VaR) for one or more main products, the situation is to be analysed further as stress situation is assumable.

**RISK MEASURING MODELS**

A risk measure is defined as a function that assigns a scalar to a random variable quantifying a certain loss. In the models of the capital market, standard deviation is used to quantify risk, but for risk management purposes measures focusing on the downside outcomes are more appropriate.

Value-at-Risk (VaR) was defined by JP Morgan in the mid 90’s, as the maximum loss of the portfolio over a predefined time horizon \((T)\) at a given significance level \((\alpha)\) under normal circumstances. VaR can be expressed either in absolute value or as a percentage of the portfolio value (Jorion, 2007). Because of its simplicity VaR was adopted by the whole financial sector, even though the regulation of the financial institutions – Basel Rules – uses it in the risk management systems, since it is easy to use and to understand.

In order to calculate VaR, the probability distribution of the position in the certain security/portfolio at time \(T\) is to be modelled.

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1 We thank for the idea Edina Berlinger, who lead the risk management validation project of the Hungarian CCP.
The \((1-\alpha)\)th percentile of this distribution shows the threshold value \((K)\) the portfolio underperforms with a probability of \((1-\alpha)\) at time \(T\) (Jorion, 2007), as it is shown in Equation (1).

\[
P(V<K)= 1-\alpha
\]  
(1)

where the value of the position is \(V\) at time \(t\).

Value-at-Risk is given as the difference of the actual value and the threshold.

There are 3 main concepts to calculate VaR: historical calculation, analytical method and Structured Monte Carlo Simulation (Jorion, 2007). In the framework of the historical method, the events of a chosen reference period are supposed to describe the potential future outcomes, so the whole distribution is given by them. The analytical method assumes the knowledge of the distribution, and as it is provided in most of the cases to be normal, this method is also called delta-normal method.

The third possibility to determine the distribution is simulation that can rely either on historical data or on the knowledge of the value generating process. Although VaR is not a coherent risk measure, as it was presented by Artzner et al. (1999), and a coherent alternative was suggested by Acerbi and Tasche (2002), it is still the most commonly used risk measure in the financial sector. Even if EMIR does not restrict the circle of the applied risk measures to VaR, most CCPs use VaR for risk management, to measure their risk and to calculate margin requirements.

**MEASUREMENT OF LIQUIDITY**

The predictability of financial difficulties or even crisis would be very important for both micro- and macroeconomic perspectives. As financial stress is often attended by liquidity shortages, the question arises, whether liquidity can be used as an indicator of the forthcoming stress.

The notion of liquidity has several interpretations, like the liquidity of a company, the liquidity of the whole financial system, or the liquidity of the market. In each different interpretation liquidity is to be measured differently and so the management of illiquidity risk differs too, that is why it is always very important to clarify which liquidity notion we are using. In our paper we focus on the concept of market liquidity. The Bank for International Settlements (BIS) gave a generally accepted definition for market liquidity: ‘Liquid markets are defined as markets where participants can rapidly execute large-volume transactions with little impact on prices.’ (BIS, 1999)

The definition of liquidity suggests that its concept is very complex. There does not even exist a single best way to measure its value. A broad overview of liquidity indicators is provided by von Wyss (2004). The liquidity indicators can be grouped into three main categories (Csávás and Erhart, 2005): (1) indicators of transaction costs, (2) indicators of volumes, (3) indicators of prices.

In our analysis we will focus on a liquidity indicator, that is based on transactions cost, the so called Budapest Liquidity Measure (BLM). Since the notion of BLM is quite new in the literature of Finance, we introduce it in the next sub-section.

**Budapest Liquidity Measure**

The Budapest Liquidity Measure (BLM) belongs to the class of liquidity measures. The first liquidity measure of this type was the Xetra Liquidity Measure (XLM) created by the Deutsche Börse Group in 2002, by Gomber and Schweikert (2002). The same measure was introduced on the Budapest Stock Exchange (BSE) under the name of Budapest Liquidity Measure (BLM) in 2005 (Kutas and Végh, 2005, Gyarmati et al. 2010). These liquidity measures are weighted spread measures that represent the implicit costs of trading, which arise from the fact that actual trading is not executed at the mid-price. The simpler version of the liquidity measures is the relative spread measure, which can be computed according to Equation (2):

\[
RSpread_i = \frac{p^\text{Ask}_i - p^\text{Bid}_i}{\frac{1}{2}(p^\text{Ask}_i + p^\text{Bid}_i)}.
\]  
(2)

where \(p^\text{Ask}_i\) denotes the best ask and \(p^\text{Bid}_i\) the best bid price in the order book at time \(t\). This measure displays the loss realized when buying and then immediately selling the same asset, relative to the mid-price (average of the best bid and ask price in the order book).

Basically, the BLM is a version of the relative spread measure. The difference is, that in case of the relative spread, only the best ask and bid price appear in the calculation, while in case of BLM we take into account that an order is not necessarily fulfilled on the best price levels. The calculation of BLM is shown in Equation (3):

\[
\text{BLM}_i = \frac{\sum_{j} p^\text{Ask}_{i,j} q^\text{Ask}_{i,j} - \sum_{j} p^\text{Bid}_{i,j} q^\text{Bid}_{i,j}}{p^\text{Mid}_i q_i}.
\]  
(3)

where \(p^\text{Ask(Bid)}_{i,j}\) shows the \(j\)th best price on the ask(bid) side at time \(t\), whereas \(q^\text{Ask(Bid)}_{i,j}\) denotes the depth of (the overall quantity submitted to) that same price level. \(p^\text{Mid}_i\) is the mid-price at time \(t\).
An interpretation of the calculation of BLM is shown on Figure (1).

![Figure 1: The Calculation of the Liquidity Measure Source: Gomber and Schweikert (2002), p. 3.](image)

In sum, the smaller these measures, the higher the liquidity of the asset. The Budapest Stock Exchange calculates this measure every time there is a change in the order book, and also on a daily basis. The daily BLM value is the average of the intraday BLM data. The BSE publishes these daily data at the end of every month in order to provide information for the market.

**EMPIRICAL TEST OF STRESS**

In this research, first we test our stress-definition on real market data of the Budapest Stock Exchange. We calculate risk measure (VaR) for every day and investigate the potential stress signals in the analysed period.

For the analysis we used the daily closing prices of the bluechip stocks of the Budapest Stock Exchange, namely, the OTP, MOL, Richter, MTelekom of the last 4 years, between January 2010 and December 2013. In Finance the daily (log)return of financial assets are regarded to be a stationer random variable whose realisations derive from independent, identical distribution. Despite of some stylised facts (e.g. fat tail phenomena), daily logreturn is assumed to be normally distributed in most of the models. Following the literature, we calculate the daily logreturn ($y_i$) of the stocks, according to the Equation (4):

$$y_i = \ln\left(\frac{S_i}{S_{i-1}}\right)$$  \hspace{1cm} (4)

where $S$ denotes the stock price and the indices stand for the time. The Value-at-Risk for each day is calculated according to the delta-normal method, the parameters of the return generating process are calculated as the average ($\mu$) and standard deviation ($\sigma$) of the logreturns in the previous 250 days, as it is shown in Equation (5):

$$VaR = \mu + \Phi^{-1}(1-\alpha) \cdot \sigma$$  \hspace{1cm} (5)

where $\Phi^{-1}$ denotes the inverse of the cumulated distribution function of the standard normal distribution.

After having the logreturn and the VaR for every day, those days are to be investigated further, where the real price fall exceeds the VaR of the previous day, that should happen in $1-\alpha$ percent of the cases, as a consequence of the VaR-definition. We used a significance level ($\alpha$) of 99%, as it is prescribed by EMIR. Figure (2) illustrates the calculation in case of MOL, the Hungarian Oil company, representing almost one third of the Hungarian stock market.

The points below the red line show the days, when the negative price movement exceeded the maximal loss predicted by VaR with a probability of 99%. These days are to be examined further in order to decide about stress, according to our suggestion.

![Figure 2: The daily logreturns and VaR of MOL between 2010 and 2013. Source: own calculation based on the data of BSE.](image)

As the outlying points can be caused by company specific reasons, we searched for the outlying days for all 4 stocks, in order to find those periods, when more assets give a warning signal. According to the VaR model the number of the outlying days should sum up to 1 percent, so 10 days out of the 1000 working days during the period. We found 8-15 outliers for each of the tested group of stocks – the least, 8 in case of MTelekom, and the most, 15 in case of OTP. This result supports the applicability of the VaR model, as even in case of MOL, the difference is insignificant.
The potential stress days are depicted on Figure (3).

Figure 3: Stress signals of 4 Bluechips between 2010 and 2013.

Source: own calculation based on the data of BSE.

The only date when all the 4 tested papers signalled was the 6th of May 2010, when a sudden fall on the New York Stock Exchange due to technical problems caused worldwide market turbulences. Even then the market calmed down rapidly, so it is not reasonable to speak about a stress period.

Two other dates are worth investigating in the period, because 3 of the 4 stocks (except for MTelekom) signalled. The market fall of 8-9th of August 2011 was a consequence of global markets’ events. In September 2011 the possibility to pay back foreign denominated mortgage loan at out-of market exchange rate forced to the Hungarian banking sector caused the extreme price movement, but these days were also followed by some correction, that offset the losses of the previous market collapse.

The further warning dates are triggered by single stocks, so they are not to be interpreted as stress period in the market.

Based on the above, we can state, that the examined period of the last 4 years was characterised by quiet market movements and free of stress.

THE TEST OF LIQUIDITY IN STRESS

Even if we have not found evidence of a real stress, it is worth to analyse the market liquidity in the periods of the signalling days.

For the purpose to quantify liquidity we used the daily value of the Budapest Liquidity Measure, for the same stocks and for the same time period as in the case of the daily logreturn calculation. The time series are given by the Budapest Stock Exchange. BLM refers to the cost of trading a certain amount, expressed in basis points, in the calculations we used the 20,000 euro BLM figures, referring to the cost of trading in that volume. The time series of BLM need to be differentiated also in order to get stationer data, consequently we calculated the daily change of BLM.

As the liquidity shortage is indicated by growing BLM figures, similarly to the stress calculation, we looked for those days, when the daily change exceeded the 99% maximum of the previous 1 year period. We had access to BLM figures from 2010, so the analysed time-series shortened to 3 years because of the reference period.

For the purpose to quantify liquidity we used the daily value of the Budapest Liquidity Measure, for the same stocks and for the same time period as in the case of the daily logreturn calculation. The time series derive from the Budapest Stock Exchange.

The delta normal method cannot be applied, since the daily differences of BLM are not to be regarded normal, as shown on the example of MOL on Figure (4). The rejection of normality was confirmed by the Kolmogorov-Smirnov test also (with a p-value of 0.000).

Figure 4: Distribution of the daily BLM differences of MOL between 2010-2013.

Source: own calculation based on the data of BSE.

Therefore, we applied the historical method to calculate Value-at-Risk characteristic risk measure for BLM, too. We took the 99% percentile of the data, and warning signal was defined as those days, when the daily change of BLM exceeded the 99% percentile of the previous 250 days.

First, we examined the signals of the liquidity measure in the two periods – August and September 2011 - identified by stock returns.

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<thead>
<tr>
<th>OTP</th>
<th>MOL</th>
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<td>Stock_return</td>
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Table 1: Signalling dates of MOL and RICHTER between 2011-2013.

Source: own calculation based on the data of BSE.
The BLM of RICHTER gave no signals at all, and MTELEKOM had no extreme price fall in the period, so only the stress dates of MOL and OTP are shown in Table 1. We can see, that merely about the half of the warning dates were accompanied by a liquidity signal, and even in these cases the liquidity measure signs followed the market fall, instead of predicting it. It seems as if market participants withdraw their orders after the price fall of the market and not the reduction of the order book causes the fall of the prices.

The other warning signals of BLM in the period appeared independently from the extreme market movements.

The reason of our results could be, that there were no real stress in the last 4 years that explains the independence of the highest changes in price and liquidity.

CONCLUSION

Based on the recent direction of the regulation of financial markets and institutions, in this paper an objective reference for defining stress situation was suggested. As our empirical analysis showed, this basis has also some subjective elements, and further investigation of the market is needed in order to decide whether stress exists. We have found 3 dates in the reference period, when at least 3 of the 4 analysed stocks alarmed for stress simultaneously.

The paper analysed furthermore the connection between the above defined stress signal and market liquidity. We have found no strict connection of the price and liquidity movement. In contrast to our expectations the liquidity shortage rather followed the extreme price changes, than predicted it.

The market movements of the tested period – between 2010 and 2013 – proved to be very quiet that can explain our results. The analysis is to be extended for a longer period containing the years of the financial crisis as well.

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Regulations:


AUTHOR BIOGRAPHIES

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