The Budapest liquidity measure and the price impact function

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During the 2007/2008 global economic crisis, market liquidity became an important issue both on the field of theoretical finance and in practice. In theory market liquidity is usually being modeled with price impact functions. In this study we show how the price impact function can be estimated from order book data. Our estimation is based on the Budapest Liquidity Measure (BLM) which is a liquidity measure that captures the transaction cost nature of liquidity.

The main outcome of this paper is a method with which market participants can easily estimate price impact functions. This is of major importance, as the price impact function can be a useful tool during a dynamic portfolio optimization process. The price impact functions can help investors in their trading decisions.

Keywords: market liquidity, price impact function, liquidity measure

1. Introduction

In this paper we show how the virtual price impact function can be estimated from the BLM database. As the BLM captures the transaction cost nature of market liquidity, the estimation of the virtual price impact function from the time series data of the BLM is feasible. On illiquid markets, the market participants have to carry out dynamic portfolio optimization with respect to size, cost and time. In order to be able to solve this optimization, they should consider the underlying stochastic process, namely the process of the transaction costs; the costs which occur because of the lack of liquidity. Through the analysis of the virtual price impact function estimated from the BLM database, the market participants can gain insight into the evolution of transaction costs and into the evolution of market liquidity. Based on this information, market participants can carry out a dynamic portfolio optimization, which contains components like optimal execution strategies or order splitting.

This study is structured as follows: in the second section the Budapest Liquidity Measure is defined and calculated. In the next section we present the concept of virtual and empirical price impact, and we also define the price impact function. In this section we also show the relation between the virtual and empirical price impact functions, and we summarize those studies that analyze the shape of the price impact functions. In the fourth section a virtual price impact function is estimated from the BLM database. In the final section we summarize our results.

2. Budapest Liquidity Measure

In this section we provide a short explanation for the Budapest Liquidity Measure (BLM), the liquidity measure that underlies our research. In this section we introduce the concept, the calculation and the interpretation of the measure is presented. A more detailed description can be found in Kutas and Végh (2005).

BLM was created in 2005 by the Budapest Stock Exchange (BSE) using the measure of the German XLM as a prototype. The idea behind the BLM was to evaluate numerically one of the most important aspects of liquidity, namely the implicit costs of transacting.

There are basically two groups of transaction costs:

- explicit costs: these are the direct cost of trading (e.g. broker fees, taxes)
- implicit costs: these are the indirect cost of trading (e.g. spreads)

BLM covers the implicit costs. The total implicit costs of a transaction consist of two parts: the bid-ask spread and the adverse price movement. The latter is the effect of the total transaction not being executed at the best level, but at worse levels. In this case the average price the market participant pays is worse than the best price.

BLM measures the implicit costs in percentage of the total transaction value. Consequently, it can only be defined for given order sizes. The standard order sizes used by the BSE are (in thousand EUR): 20, 40, 100, 200, 500.

In the following we highlight the calculation of the BLM. Let a_i be the i^{th} best ask price, b_i the i^{th} best bid price and P_{mid} the mid-price. Then denote:

- $LP = \frac{a_1 - b_1}{2P_{mid}}$, the so-called liquidity premium, the half of the bid-ask spread,
- $b(n) = \frac{\sum b_i \cdot n_i}{n}$, where $\sum n_i = n$, the weighted average bid price at which the total of n shares can be sold,
- $a(n)$, the weighted average ask price, defined similarly as $b(n)$,
- $APM_{bid}(q) = \frac{b_1 - b(n)}{P_{mid}}$, where $P_{mid}\, n = q$ the size of the position in EUR, the adverse price movement for the bid side,
- $APM_{ask}(q) = \frac{a(n) - a_1}{P_{mid}}$, the adverse price movement for the ask side, defined similarly as APM_{bid}.

With the above notation BLM is calculated as follows:

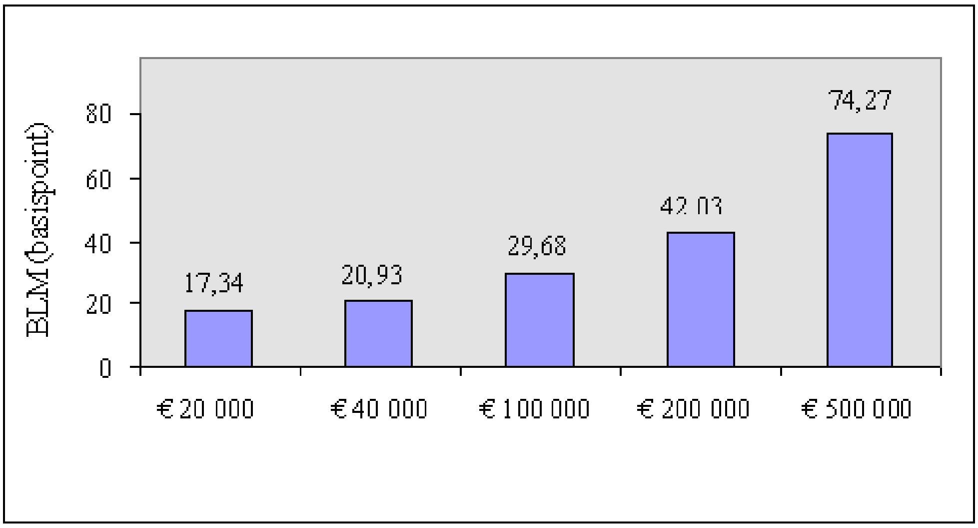
$$BLM(q) = \left(2 \cdot LP + APM_{bid}(q) + APM_{ask}(q)\right) \times 100 \qquad (1)$$

BLM represents the implicit cost of turning around a position, that is, selling and buying certain amount of stocks at the same time. For example, $BLM(500) = 60$ bps means that the buying and selling of a position of EUR 500 thousand have an implicit cost of $500{,}000 \times 60$bps = EUR 3,000.

BLM clearly always depends on the actual state of the order book, thus the calculation can only be done at a given time point. On trading days the system of the Budapest Stock Exchange calculates the BLM for every second within the time interval of 9:02 am and 4:30 pm. The daily average BLM values are calculated as the time weighted averages of the intraday data.

Figure 1 shows the average BLM values for OTP for different order sizes for a three and a half year period:

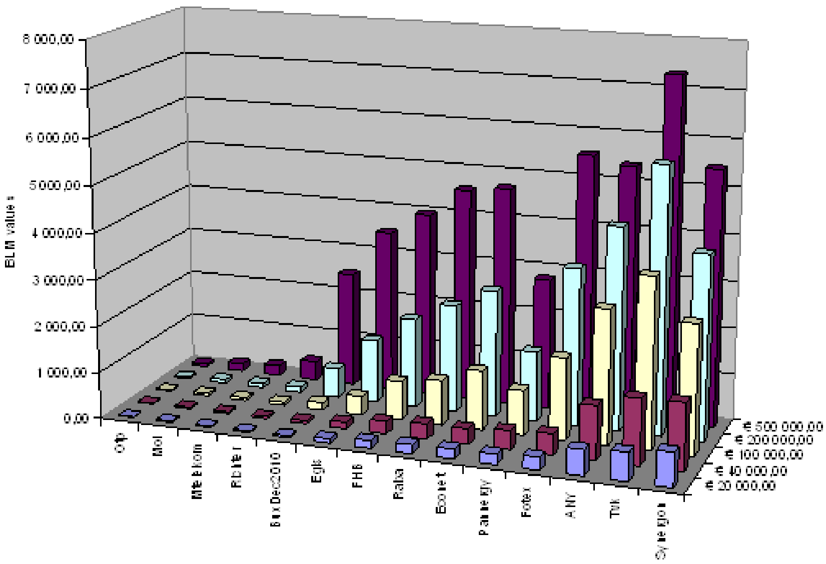
Figure 1: Average BLM values of OTP at the different order sizes (01.01.2007 – 16.07.2010)



Source: Gyarmati et al. (2010).

As the Figure 1 highlights, the larger the size of the order the larger the BLM figures are. From the perspective of the investors it is important to know which instrument has the lowest liquidity measure values, as the lower this figure is, the smaller the implicit cost incurred to the investors when they buy the stock. Figure 2 shows the average BLM figures of the shares in the BUX index and the futures BUX in 2010:

Figure 2: Average BLM values in basispoints – 2010



Source: Gyarmati et al. (2010).

Figure 2 clearly demonstrates that BLM values are monotonically increasing for each of the stocks, that is, BLM1 figures are the smallest ones, while BLM5 are the largest. Moreover, it is striking that the order of the shares based on the BLM1 values differs from the one based on other BLM levels. This phenomenon is attributed to the limit order book, namely that the shape of the limit order book can differ for each stock.

3. Virtual and Empirical Price Impact

After defining the BLM, the concept of price impact (or market impact) and price impact functions (or market impact functions) are defined. These terms might be considered as one of the most important concepts of market liquidity. The price impact can be interpreted in two different ways. On the one hand, marginal price impact shows by definition how a certain order changes the mid market price. On the other hand, the average price impact equals the difference between a certain order's average price and the mid price just before the transaction. This second definition provides crucial information for the market participants, as it measures the implicit cost of trading, that is, the transaction cost which they have to pay because of illiquid markets.

3.1. Implicit Cost

In the literature only a few studies analyze the value of the price impact of transactions, that is, the additional costs which are not paid as an explicit cost of trading. One prominent study of the field is prepared by Torre and Ferrari (1999). The authors estimated the total transaction costs of trading with the stocks of the S&P 500 index. The authors have estimated the transaction cost to be 25 cents by assuming buying and selling of 10,000 pieces of stocks with a median mid price of 400 dollars. Torre and Ferrari (1999) estimated that the composition of this 25 cent is built up as follows: execution costs equal 5 cents, while the remaining 20 cents equal the price impact. From this 20 cents, 7 cents cover the half of the bid-ask spread, while the adverse price movement is responsible for 13 cents. It is remarkable, that the adverse price movement equals the half of the total transaction cost. According to the data of ITG Global Trading Cost Review, in the last five years the average transaction cost of trading with the shares of American corporations with high capitalization was 23 basispoints (bps). From this amount 9 bps were the fees, while 12 bps were the straightforward consequence of the price impact (Ferraris, 2008).

The above examples show that the largest part of the transaction costs is caused by the price impact. The examples explicitly highlight that the price impact is indeed important and that market participant should be aware of this fact. Had they taken the price impact into account during trading, they could save notable amounts of money.

3.2. Price Impact Functions

There are two different price impact functions, the virtual and the empirical price impact functions. The virtual price impact function (vPIF) shows the relative difference of the executed price of the last contract in the order and the mid price in the function of the transaction size, that is, it gives the marginal price impact in the function of the order size (Bouchaud et al., 2008, Bouchaud, 2010a; Gabaix et al., 2003). The vPIF can also be interpreted from another aspect. In this case the vPIF shows the average price impact of a transaction. In none of the cases reflects the vPIF the real value of the price impact. Instead, it provides the experts a hypothetical value as it measures the marginal or the average price impact of an intended transaction. The name virtual price impact stems from this fact. If a market player assumes on the basis of the virtual price impact function, that the planned transaction would change the market price notably, than most probably he does not add the transaction to the order book. Instead, he splits the order into pieces and inputs the order when he considers the price impact to be smaller. Accordingly, the virtual price impact only occurs, if the market player places the market order immediately. In contrast, the empirical price impact function (ePIF) shows the actual price impact, that can be measured from real transaction data.

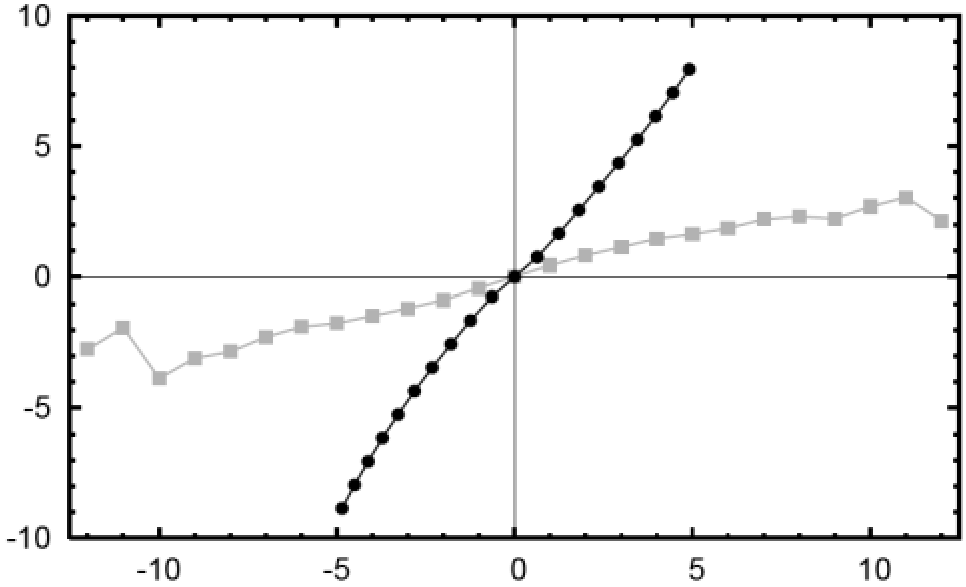
The relationship between the virtual and empirical price impact function is shown in Equation 2. The left side of the equation is the empirical price impact function ($E(r|q)$), while the right side of the equation shows the virtual price impact ($E(r)$) multiplied by the probability of the price impact ($P\ (+|q)$).

$$E(r|q) = P(+|q)E(r) \qquad (2)$$

where „r” is the change of the mid price, „q” is the total value of the order, „E” stands for the expected value, while „P” stands for probability.

Figure 3 demonstrated how the virtual and empirical price impact functions are related. On the basis of figure the vPIF can be approximated by an almost straight line, while the ePIF’s shape can be approximated by a concave curve. In the empirical literature researchers have identified various shapes for the PIF-s and highlighted some reasons for the diverse shapes. This empirical research is summarized in Subsection 3.3.

Figure 3: The virtual (circle) and the empirical (square) price impact functions



Source: Weber and Rosenow (2005, pp. 360). The impact functions are calculated for the ten largest stocks of Iceland measured by turnover. (The figure is based on aggregated volume data of every 5 minutes.)

3.3. The Shape of the Price Impact Functions

The price impact of transactions depends on the order size and on the time horizon of the analysis. In Table 1 we have summarized the most important findings on limit order markets. The majority of the studies analyze the price impact by different level of aggregation. The aggregation is either carried out along time (e. g., aggregating transactions for every 5 minute), or along transactions (e.g., summing up ten consecutive transactions).

In the initial studies, the researchers plot the price impact functions without defining its functional form. The results of these studies are summarized in the first few rows of Table 1. Most of the researchers identify the price impact functions with positive slope and with a concave form. However, the studies contradict with relation to the changing of the function’s slope. Part B of Table 1 shows the most important results of those studies that examine the price impact function on the level of single transactions. All the authors make efforts to define the functional form of vPIF. The majority of the studies identify a concave function. However, on different markets the price impact function can be formalized differently.[1] In Part C part of the table results with relation to aggregated transactions are summarized. Finally, in Part D of the table the literature on the virtual price impact function is reviewed briefly.

Table 1: Empirical facts for the shape of the price impact functions

Authors	Examined stock exchange	Shape of the PIF
A) Initial studies: no formalization of the PIF		
Hasbrouck (1999)	NYSE, AMEX and regional exchanges, 62 days from 1989	Positive slope, concave function.
Hausman, Lo & MacKinlay (1992)	10 randomly chosen American stocks from 1988	Positive slope, concave function with decreasing growth.
Biais, Hillion & Spatt (1995)	Stocks of the Paris Bourse CAC 40 index	Almost a straight line, slightly concave function, which has the greatest slope on the best price levels.
Niemeyer & Sandas (1995)	30 stocks of the Stockholm Stock Exchange's OMX index	Nonlinear function, the slope of the curve at the best price levels is low.
Kempf & Korn (1999)	DAX futures, between 17 September 1993 and 15 September 1994, aggregated in every 5 minutes	Concave function that flattens on the sides: the large orders have relatively smaller price impact than the small orders.
Evans & Lyons (2002)	DM/USD & Yen/USD, daily aggregation	Strong positive relation: the net order flow explains a notable portion of the exchange rates' volatility.
B) Price impact of single trades – the PIF is being formalized		
Lillo, Farmer & Mantegna (2003)	1000 stocks of the New York Stock Exchange from the period of 1995-1998	Concave function. The slope of the function changes in the function of the order size.
Bouchaud & Potters (2002)	Stocks of the Paris Stock Exchange and from the London Stock Exchange (LSE)	Logarithmic relation.
Farmer & Lillo (2004)	Three stocks of the LSE	The price impact function can be estimated by a power-law function.
Lim & Coggins (2005)	300 stockss of the Australian Stock Exchange from the period of 2001-2004	The price impact function can be estimated by a power-law function.
Hopman (2007)	Stocks of the Paris Bourse CAC40 index; period of 4 January 1995 and 22 October 1999.	The price impact function can be estimated by a concave power-law function.

[1] The power law function is concave/convex if the exponent is smaller/greater than 1. If the exponent equals 1, than the power law function is a straight line.

Zhou (2011)	23 stocks of the Shenzen Stock Exchange in 2003	The fulfilled order's PIF can be estimated by a power-law function. With the exception of large values the partially fulfilled orders' PIF is constant.
Cont, Kukanov & Stoikov (2011)	TAQ database (NYSE, AMEX, NASDAQ), 50 randomly selected stocks	The price impact in the function of the imbalance of the bid-ask side is linear.
C) Price impact of aggregated transactions – the PIF is being formalized		
Plerou et al. (2002)	116 most traded stocks of NYSE, between 1994-1995, aggregated for 5 to 195 minutes intervals.	Authors define the price impact in the function of the number imbalance and in the function of order imbalance. In both cases the function is a concave, tangent function.
Almgren et al. (2005)	30 thousand transaction of Citigroup US, between December 2001 and June 2003.	The permanent price impact is linear. The temporary price impact is a concave power-law function.
Gabaix et al. (2003, 2006)	1000 largest stocks of the TAQ database, between 1994-1995, aggregation for 15 minutes intervals	The price impact function can be estimated by a concave, power-law function.
Hopman (2007)	Stocks of the Paris Bourse CAC40 index, 7 different aggregation level	The authors estimate the ePIF by linear regression. The daily aggregation provided the best result with R2=43,5%.
Margitai (2009)	Budapest Stock Exchange: MOL, aggregation of 5 and 20 transactions	Estimation with square-root function. With the increase of the level of aggregation, the function flattens.
Bouchaud, Farmer, Lillo & des Meurisiers (2008)	Stocks of the NYSE and LSE, Aggregation of transactions: N=1, 8, 64, 512.	As the aggregation level increases, the price impact function flattens and becomes less slope.
D) Virtual price impact		
Challet & Stinchcombe (2001)	4 stocks, 15 best bid and ask price level on Island ECN (NASDAQ)	The virtual PIF can be estimated by a convex power-law function.
Maslov & Mills (2001)	NASDAQ Level II	The virtual PIF is a convex power-law function.
Weber & Rosenow (2005)	10 most frequently traded stocks on Island ECN (NASDAQ), data from 2002	In case of the limit orders, the vPIF is a convex function.

Source: Gyarmati et al. (2012).

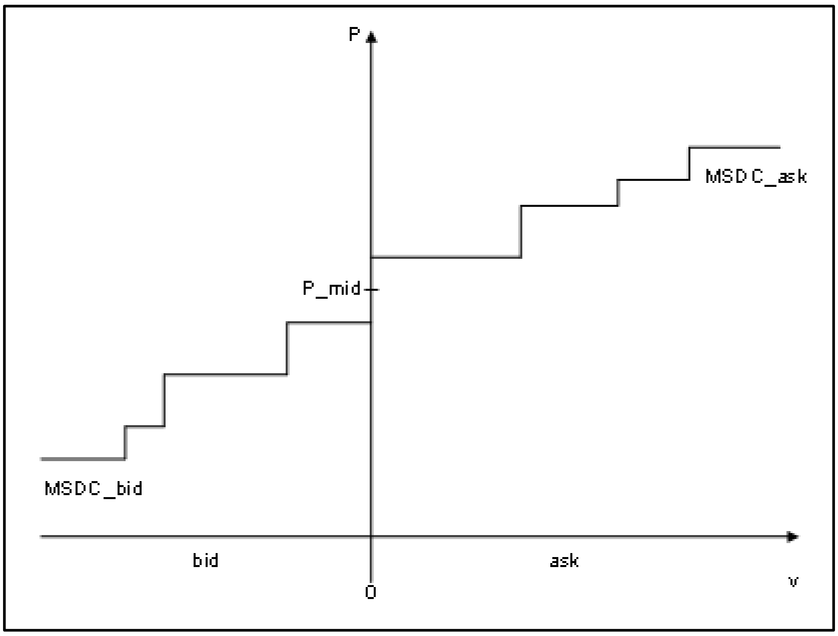
In sum, the findings of the researchers vary, both the ePIF and the vPIF have been formalized in several ways. Bouchaud et al. (2008) argue that these differences might be explained by the difference in markets, assets, time, and aggregation level. Bouchaud (2010a) summarizes the most important characteristics of the price impact function. By reviewing the previous literature the author concludes that the price impact function is nonlinear, concave and can be estimated by a power law distribution that has an exponent smaller than 1. This exponent is increasing with the increase of the aggregation level. On the level of single transactions the exponent is between 0.1 and 0.3. If the aggregation exceeds 1,000 transactions, then the exponent will be around 1. In the literature it is widely accepted, that the number of transactions has a more important role in the price impact then the order size (Bouchaud, 2010a, b). Besides, it is also a widespread view that the price impact is proportional to the bid-ask spread and to the volatility per trade (Bouchaud, 2010b).

The literature provides two explanations for the concave shape of the empirical price impact function (Bouchaud et al. 2008). The first explanation was given by Barclay and Warner (1993): the authors argue that the concave shape might be explained by the information content of the transactions. That is, if small transactions have the same information content than the large transactions, than the price impact of large transactions is not higher than that of the small transactions. The second explanation was provided by Farmer et al. (2004). The authors explain the concave shape with the concept of selective liquidity. Selective liquidity refers to the phenomenon that market participants' decision of placing an order or withholding it depends on the market liquidity. If market participants consider the liquidity to be sufficient on the market, they input a large transaction. In the opposite case they only try to execute small orders. Thus, the market participants are keen to place an order that can be fulfilled on the best price level and try to avoid deleting several levels of the limit order book.

4. Estimating the Virtual Price Impact Function on the basis of Liquidity Measures

The estimation of the virtual price impact function should rely on the determination of the Marginal Supply Demand Curve (MSDC). In this case the virtual price impact function is estimated for a given second; the measure is not based on average values of a certain time period. The MSDC shows the order book's actual status, that is, the price levels and the volume of orders on each price level. According to this the MSDC shows the price on which a transaction's last order was fulfilled, where the value of the transaction is „v" (volume) (Acerbi, 2010). The MSDC is shown in Figure 4:

Figure 4: The MSDC function



Source: Gyarmati et al. (2012).

In this study we interpret MSDC as the limit order book in a given second. Note that some of the previous papers interpret MSDC as the average of the values highlighted in the limit order book during a given time period. Having the MSDC function at our disposal, the total transaction cost (mid price plus implicit costs) can be determined as follows:

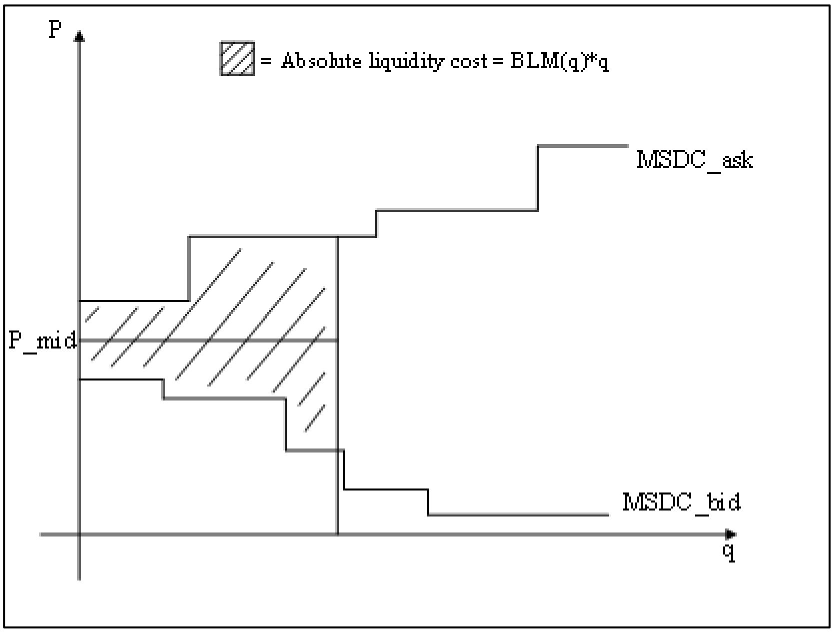
$$TotalCost(v) = \int_0^v MSDC(x)\,dx \qquad (3)$$

The majority of the market players do not have information on the entire limit order book. As a consequence, they do not have adequate information neither on the market liquidity nor can they define the MSDC function. The only information they have is what they can extract from the first few lines of the limit order book, such as the bid-ask spread, or the volume of the orders on the best price level. However, a price impact function can be estimated not only from the limit order book, but also from liquidity measures. Note that the liquidity measures are also calculated from the limit order book. In this study the Budapest Liquidity Measure (BLM) is used for calculation purposes.

The $BLM(q)$ in itself is not a price impact function, as the BLM does not inform the trader about the new mid price realized after the transaction. Instead, the BLM measures the implicit cost of trading (in basispoints) stemming from the illiquidity of the markets.

The relation between the price impact function and the $BLM(q)$ function is explained in the following paragraphs.

Figure 5: The relationship between the MSDC and the liquidity measure



Source: Gyarmati et al. (2012).

In accordance with Figure 5, the BLM can be calculated on the basis of Equation 4. In Ecuation 4 „q" stands for the total value of the transaction in euros, as the BLM shows the implicit cost in the function of the value, not the volume.

$$BLM(q) = \frac{\int_0^q MSDC\_ask(X)dx - \int_0^q MSDC\_bid(x)dx}{q} \qquad (4)$$

In order to be able to estimate the virtual price impact function with the help of the MSDC, we should estimate the SDC function first. For estimation purposes the BLM database is used.

If we assume that the daily $BLM(q)$ function can be approximated by a linear regression,[2] then the $BLM(q)$ function is as follows:

$$BLM(q) = a * q + b \tag{5}$$

The $BLM(q)$ function is estimated separately for the bid and the ask side of the limit order book. In the following equations BLM^b stands for the buy side, while BLM^a for the sell side.

$$BLM = 2 * LP + APM_{bid} + APM_{ask} \tag{6}$$

$$BLM^a = LP + APM_{ask} \tag{7}$$

$$BLM^b = LP + APM_{bid} \tag{8}$$

The linear regressions are defined as follows:

$$BLM^a(q) = a_{ask} * q + b_{ask} \tag{9}$$

$$BLM^b(q) = a_{bid} * q + b_{bid} \tag{10}$$

The estimation of the MSDC by means of the $BLM(q)$ function requires the following steps on the ask side:

$$BLM^a(q) = \frac{\int_0^q MSDC\_ask(x)dx - q * P_{mid}}{q} \rightarrow$$

$$BLM^a(q) * q = \int_0^q MSDC\_ask(x)\, dx - q * P_{mid} \rightarrow$$

$$dBLM^a(q) * q + BLM^a(q) = MSDC\_ask(q) - P_{mid} \rightarrow \tag{11}$$

$$a_{ask} * q + a_{ask} * q + b_{ask} + P_{mid} = MSDC\_ask(q) \rightarrow$$

$$\mathbf{2 * a_{ask} * q + b_{ask} + P_{mid} = MSDC\_ask(q)}$$

The estimation of the MSDC by means of the BLM(q) function requires the following steps on the bid side:

$$BLM^b(q) = \frac{q * P_{mid} - \int_0^q MSDC\_bid(x)dx}{q} \rightarrow$$

$$BLM^b(q) * q = q * P_{mid} - \int_0^q MSDC\_bid(x)\, dx \rightarrow$$

$$dBLM^b(q) * q + BLM^b(q) = P_{mid} - MSDC\_bid(q) \rightarrow \tag{12}$$

$$P_{mid} - (a_{bid} * q + a_{bid} * q + b_{bid}) = MSDC\_bid(q) \rightarrow$$

$$\mathbf{P_{mid} - (2 * a_{bid} * q + b_{bid}) = MDSC\_bid(q)}$$

[2] We have assumed the daily $BLM(q)$ function to be linear based on a movie e prepared in Matlab. The movie convinced us that $BLM(q)$ function is almost linear. We have also tested the linearity while estimating the linear regressions. We found that the value of the R^2 were always above 0.9, which means that the linear approximation is appropiate.

Finally, the virtual price impact function can be expressed in the function of $MSDC(q)$:

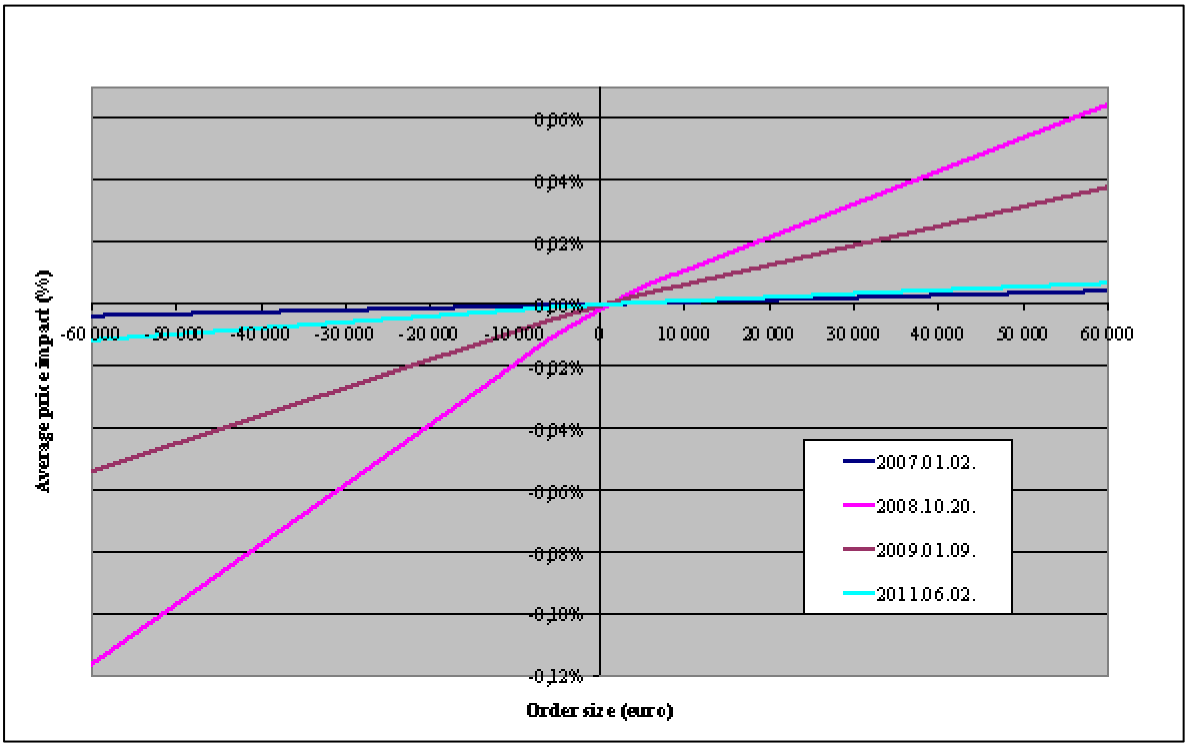
$$VPIF(q) = \frac{MSDC(q)}{P_{mid}} - 1 \quad (13)$$

On the basis of the vPIF the empirical price impact function cannot be estimated, as the BLM database does not provide information on the probability of the occurrence of the price impacts. The ePIF can be estimated, for example, from the TAQ (*trades and quotes*) database (Margitai, 2009). Estimating the ePIF from the TAQ database is a time- and calculation consuming task. In our study our main goal was to provide the market participants a method that enables them to estimate the price impact function easily. The market participants might build their trading strategies on the price impact function estimated by the above method. As the estimation procedure is based on the BLM, it can be carried out fast and easily.

The virtual price impact function is important for the market participants from several aspects. Most importantly, they might solve a dynamic portfolio optimization exercise more professionally on the basis of the time series of the vPIF. As a result, the transactions will be executed on the market in the function of the vPIF

Figure 6 shows the estimated virtual price impact functions for OTP for both the bid and the ask side for a few trading days. The trading days have been chosen with the intention to show how the price impact behaves in calm period (1st January 2007 and 2nd June 2011) and during crisis (20th October 2008 and 9th January 2009). Figure 6 demonstrate that during a crisis the price impact function is sloper, that refers to the fact, that the transaction cost of trading is higher: Obviously, during crisis the markets are more illiquid, then during normal times.

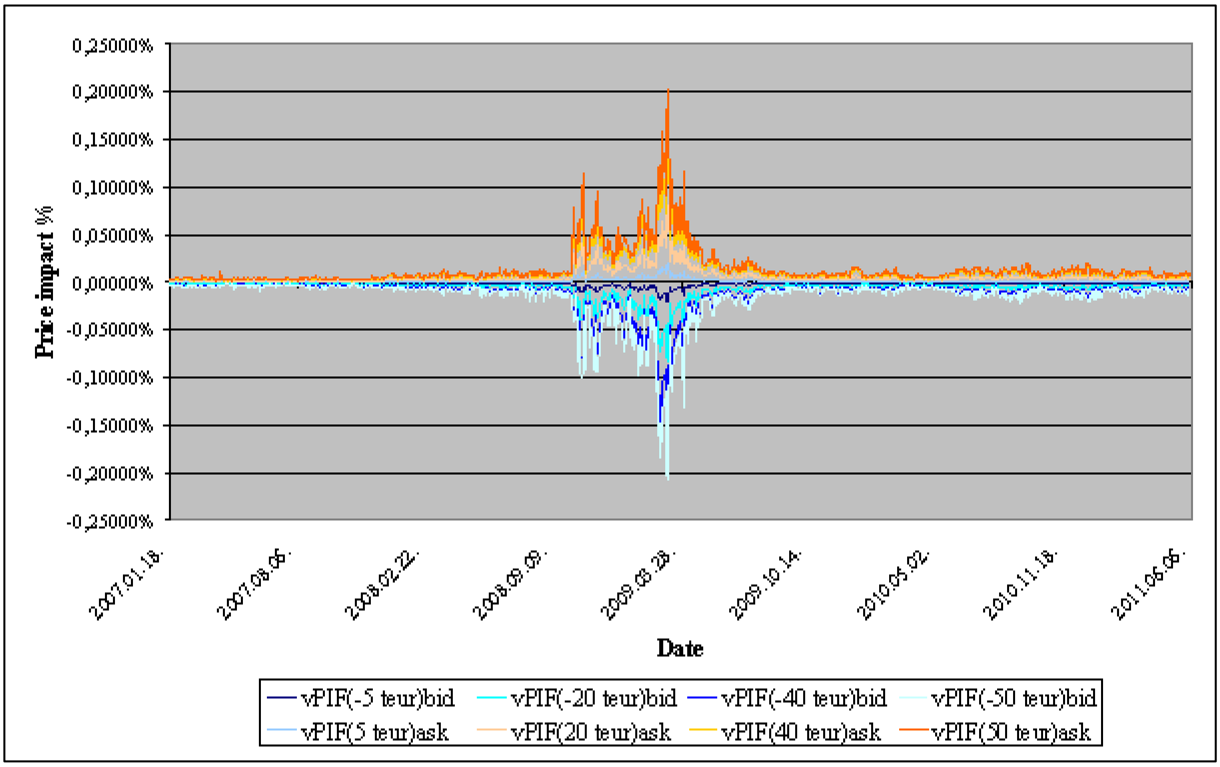
Figure 6: Virtual price impact function



Source: Gyarmati et al. (2012).

Besides having an idea of the virtual price impact function for certain trading days, it is worth plotting the time series of the vPIF values for a few order sizes. The time series are shown on Figure 7 for the time period of 1 January 2007 and 2 June 2011. Similarly to Figure 6, Figure 7 also demonstrates that the crisis of 2008 was coupled with higher price impacts, thus, with lower market liquidity.

Figure 7: The time series of the virtual price impact function



Source: Gyarmati et al. (2012).

5. Conclusion

In this study we have developed a method for estimating a virtual price impact function from the Budapest Liquidity Measure database. This is of major importance, as market participants might build their trading strategies on this estimation.

Further research might include the estimation of the virtual price impact function on the basis of intraday data. In this case the $BLM(q)$ function cannot be approximated by a linear regression, as the function in either concave or convex. In addition, the slope of the intraday $BLM(q)$ is changing from second to second.

In the future it would also worth to analyze the relationship between the virtual and the empirical price impact function. Besides comparing their time series data, we might get an idea whether it is essential to analyze the empirical price impact function or the analysis of the virtual price impact function in itself is also sufficient.

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