8. ESTIMATING THE PRICE IMPACT OF MARKET ORDERS ON THE BUCHAREST STOCK EXCHANGE

Mircea BAHNA[1]
Cosmin-Octavian CEPOI[2]
Bogdan Andrei DUMITRESCU[3]
Virgil DAMIAN[4]

Abstract

In this paper, we study the price response when high dimension buy or sell market orders for equities with different levels of liquidity are introduced into a limit order book system. Using high frequency data from five blue-chips listed on the Bucharest Stock Exchange, we capture the interactions between these types of orders and prices by the estimated impulse response functions in a VECM framework. The results reveal that the impact is high and persistent in time for the less liquid equities and is smaller when dealing with liquid ones. Thus, the corresponding prices of less liquid stocks can be easily manipulated by a trader willing to buy or sell significant volumes. This is a very common imbalance in the capital markets of the emerging countries and should be adjusted very quickly by the regulators.

Keywords: market impact, market orders, limit orders, cointegration
JEL Classification: C22, C53, D53, G10, G14

1. Introduction

Trading in capital markets has expanded significantly over the past 30 years, driven mainly by advances in information technology, financial innovation and favoured by globalization and deregulation. Technological progress also has led to a change in the framework within which the transactions are taking place and currently most financial markets worldwide are using an order-driven system based on an electronic limit order book, *i.e.,* a record of all orders, with their corresponding prices and amounts at a given moment in time. The system collects and automatically finds an equivalent for a certain order, depending on its size and

---

[1] *The Bucharest University of Economic Studies, Finance Department.*
E-mail: mirceabahna@yahoo.com.
[2] *The Bucharest University of Economic Studies, Money and Banking Department, CEFIMO.*
E-mail: cosmin.cepoi@fin.ase.ro.
[3] *The Bucharest University of Economic Studies, Money and Banking Department, CEFIMO.*
E-mail: bogdan.dumitrescu@fin.ase.ro.
[4] *The Bucharest University of Economic Studies, Money and Banking Department, CARFIB*
E-mail: virgil.damian@fin.ase.ro.

price. In this way, traders benefit from low transaction costs, low latency, high liquidity and, last but not least, an increased transparency of transactions as all market participants have access to all input orders.

Currently, a large body of literature is devoted to investigate the limit order book (LOB) markets. Hasbrouck (1991), Jang and Venkatesh (1991), Dufour and Engle (2000) or Cont *et al.* (2014) have conducted relevant studies with the objective of capturing the impact of orders as main elements in price formation. Based on high frequency data, they investigated how some microstructure characteristics like the bid-ask spread, the order flows and volumes contributed to price dynamics. Some theoretical analysis on order submission strategies performed by Foucault (1999), Goettler *et al.* (2005), Foucault *et al.* (2005) or Roşu (2009) capture the movements in a limit order market by means of the game theory. Other papers, such as Parlour and Seppi (2008), report that limit orders have a visible impact on prices, despite the fact that such orders are not executed immediately or are cancelled. Their theoretical results are supported by the empirical findings of Eisler *et al.* (2012), Cont *et al.* (2010) or Hautsch and Huang (2012), who reveal a series of stylized facts for limit order book markets, namely: *i)* price changes are induced by the order flow imbalance, *ii)* incoming limit orders have a significant effect on ask and bid quotes on both short- and long-run, *iii)* order book events that appear on the same side are long-range correlated, and *iv)* most of the limit orders are cancelled.

Another direction of research in market microstructure theory is devoted to the market impact of large or aggressive orders. For example, Wuyts (2012) uses a VAR approach to estimate the market impact of some aggressive limit orders, by incorporating in the model different levels of liquidity. In the same line, Escribano and Pascual (2006) show that unanticipated buy limit orders with considerable volumes have, on average, a larger impact on ask quotes, than an unexpected high-dimensional sell order on the bid quotes. Other important contributions to the field are attributable to Ranaldo (2004) and Griffiths *et al.* (2000), who studied the probability of occurence for different types of orders. According to them, the likelihood for buy limit order is higher when the book on the sell side is deep and lower down when the buy side is also deep.

Although there are many studies examining limit order book markets worldwide, *i.e.*, Cont *et al.* (2014) and Eisler *et al.* (2012) for NASDAQ, Riordan and Storkenmaier (2012) for Deutsche Boerse, Naes and Skjeltorp (2006) for Oslo Stock Exchange or Biais *et al.* (1995) for Paris Bourse, one less investigated topic is the market microstructure of the Bucharest Stock Exchange. Even though some empirical papers were devoted to study a series of important issues, such as realized volatility and asymmetric volatilities (Damian and Cepoi, 2016; Albu *et al*., 2015), probability of informed trading (Cepoi and Toma, 2016), price discovery (Cepoi, 2014a) or trading costs (Cepoi, 2014b; Radu and Cepoi 2015), no investigation was made in order to estimate the impact of market orders in a limit order book environment.

This paper aims to fill the existing gap in the literature by investigating for the first time the price impact of market orders on the Bucharest Stock Exchange. Based on intra-day data from five blue-chips (SIF 1, SIF 2, SIF 3, SIF 4 and SIF 5), we apply the previous work of Hautsch and Huang (2012) by employing a vector error correction model in order to capture the impact on prices implied by market orders. The VAR or VEC methodology has been extensively used in this area due to its flexibility, simplicity of implementation and robustness of results. The market depth is recorded as log volumes, which makes the analysis easier and robust, also reducing the impact of large orders. A similar suggestion was made by

Potters and Bouchaud (2003) when they studied some statistical properties of limit order book markets.

We believe that a good understanding of the limit order book's behaviour, especially for a small market like the Bucharest Stock Exchange, will enable policy makers to formulate relevant regulations. As a consequence, liquidity may come at lower prices, which will finally lead to a development of the way that transactions are taking place. The remainder of the paper is organized as follows: Section 2 presents the methodology, Section 3 describes the data, the results are presented in Section 4, and Section 5 concludes.

2. Methodology

We denote by t a time index, showing all order book changes, *i.e.*, the incoming of a marker or a limit order as well as a cancelation. Moreover, p_a^t and p_b^t represent the best log selling price and the best log purchasing price, respectively, recorded after the t-th order book dynamic, while $v_t^{a,j}$ and $v_t^{b,j}$ are log market depths on the j-th price level, for $j = 1,\ldots,k$. To have a better picture regarding the impact of order book activities on price formation is necessary to consider two dummy variables, BUY_t and $SELL_t$ indicating the entry of a market order on the buying side or on the selling side. Given the previous description of the data set, the resulting vector of endogenous variables with $(4 + 2k)$ dimension is given by:

$$y_t \coloneqq \left[p_a^t, p_b^t, v_t^{a,1}, v_t^{a,2}, \ldots, v_t^{a,k}, v_t^{b,1}, v_t^{b,2}, \ldots, v_t^{b,k}, BUY_t, SELL_t\right] \quad (1)$$

To study the price impact of a market order we follow Engle and Patton (2004) or Hautsch and Huang (2012) and use a cointegrated VAR model with restictions for $\Delta y_t \coloneqq y_t - y_{t-1}$ given by:

$$\Delta y_t = \mu + \alpha\beta' y_{t-1} + \sum_{i=1}^{p-1} \gamma_i \Delta y_{t-i} + u_t \quad (2)$$

where: u_t is a white noise having the covariance matrix σ_u, μ is a constant, γ_i with $i = 1,\ldots,p-1$ is a $K \times K$ matrix of model's parameters, α and β are $K \times r$ loading and cointegrating matrices with $r < K$.

If we treat BUY_t and $SELL_t$ as stationary variables, the last two columns of β will be restricted to $\beta_1 = [0,0,\ldots,1,0]'$ and $\beta_2 = [0,0,\ldots,1,0]'$. To simplify the analysis, the impulse response functions is constructed by using a restricted $VAR\ (p)$ model given below:

$$y_t = \mu + \sum_{i=1}^{p} a_i y_{t-i} + u_t \quad (3)$$

where: $a_1 \coloneqq I_K + \alpha\beta' + \gamma_1$, I_K is the identity matrix of order K, $a_i \coloneqq \gamma_i - \gamma_{i-1}$ where $1 < i < p$ and $a_p \coloneqq -\gamma_{p-1}$. To estimate Eq. (2) we follow Hautsch and Huang (2012) and use full information maximum likelihood estimation, proposed for cointegrated VAR models by Johansen (1991) and Johansen and Juselius (1990).

Before estimating the impact, it is necessary to simulate the arrival of a market order with some specific features as a shock in Eq. (3). Once a market order enters the limit order book, two possible scenarios may occur: *i)* it will definitely change the depth in the book or *ii)* it may change the best quotes, depending on its size. Specifically, we represent this order as a shock to the system having the following structure:

$$\lambda_y \coloneqq \left[\lambda_q', \lambda_d', \lambda_t'\right]' \quad (4)$$

where: λ_q is a $2x1$ dimensional vector of shocks in quotes, λ_q is a $2Kx1$ vector of shocks in depths, while λ_t is a $2x1$ dimensional vector of shocks in the trading indicator.

The market reaction produced by some incoming market orders is captured by the impulse response function (IRF) presented below:

$$f(h;\lambda_y) = E[y_{t+h}|\boldsymbol{y_t} + \boldsymbol{\lambda_y}, y_{t-1}, \ldots] - E[y_{t+h}|\boldsymbol{y_t}, y_{t-1}, \ldots] \tag{5}$$

where: h is the number of order event activities. In this way, based on IRF, we are able to estimate both short and long-term impacts of a shock induced by a market order.

To represent the impulse response function over time, we apply the moving average representation of a $VAR\ (p)$ model reported in Eq. (2). The first step is to transform $VAR\ (p)$ into $VAR\ (1)$ as follows:

$$Y_t = \boldsymbol{\mu} + \boldsymbol{A}Y_{t-1} + u_t \tag{6}$$

where:

$$\boldsymbol{\mu} = \begin{bmatrix} \mu \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \boldsymbol{Y_t} = \begin{bmatrix} y_t \\ y_{t-1} \\ \vdots \\ y_{t-p+1} \end{bmatrix}, \boldsymbol{\mu} = \begin{bmatrix} \mu \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \boldsymbol{A} = \begin{bmatrix} A_1 & \cdots & A_{p-1} & A_p \\ I_K & \cdots & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & I_K & 0 \end{bmatrix}.$$

If we iterate the above equation we get:

$$Y_t = M_t + \sum_{i=0}^{t-1} \boldsymbol{A}^i U_{t-i} \tag{7}$$

where: $M_t = \boldsymbol{A}^t Y_0 + \sum_{i=0}^{t-1} \boldsymbol{A}^i \boldsymbol{\mu}$ is a function of the initial values of the system and a deterministic trend that are irrelevant to the analysis of the IRF.

Let $J := [I_K : 0: \ldots : 0]$ be a $KxKp$ dimension matrix with $JY_t = y_t$. Multiplying with J on both sides of Eq. (6) and considering that $U_t = J'u_t$ will result:

$$y_t = JM_t + \sum_{i=0}^{t-1} J\boldsymbol{A}^i J' u_{t-i} \tag{8}$$

As a consequence, the corresponding IRF of Eq. (6) can be written as:

$$f(h, \lambda_y) = J\boldsymbol{A}^h J' \lambda_y \tag{9}$$

After converting VECM into a VAR model, we have a consistent estimator for $a := vec(A_1, A_2, \ldots, A_p)$, marked as $\hat{a}$, for which we have the following property proofed in Luthkepohl and Reimers (1992):

$$T(\hat{a} - a) \rightarrow N(0, \sigma_{\hat{a}}) \tag{10}$$

Lutkepohl (1990) shows that the asymptotic distribution of IRF is given by:

$$\sqrt{T}(\hat{f} - f) \xrightarrow{d} N(0,\ G_h \sigma_{\hat{a}} G_h') \tag{11}$$

where: $G_h := \partial \boldsymbol{vec}(f) / \partial \boldsymbol{vec}(A_1, A_2, \ldots, A_p)'$.

This expression can be written explicitly as follows:

$$G_h = \sum_{i=0}^{h-1} (\lambda_y' J (\boldsymbol{A}')^{h-i-1} \otimes J\boldsymbol{A}^i J') \tag{12}$$

where: $\otimes$ is the Kroneker product.

To estimate the long-term effect, we can apply Granger's Representation Theorem for Eq. (3), yielding:

$$y_t = C\sum_{i=1}^{t}(u_i + \mu) + C_1(L)(u_t + \mu) + V \tag{13}$$

where:

$$C = \beta_\perp\left(\alpha'_\perp\left(I_K - \sum_{i=1}^{p-1}\Gamma_i\right)\beta_\perp\right)^{-1}\alpha_\perp^{-1} \tag{14}$$

In this case, L is the lag operator and $C_1\,(z)$ is a power series which converges for $|\,z\,| < 1 + \xi$ and some $\xi > 0$. By employing the Granger Representation Theorem, we can decompose the cointegrated process into a random walk component C, a stationary process C_1, and a deterministic term, V. Since the $C_1\,(z)$ series converge, the response generated by this component will be zero on long term; the same conclusion cand be drawn for V, which is irrelevant to IRF. In this case, the permanent response of our system to certain shocks will be completely determined if we know the first term from Granger's decomposition. Thus, the permanent answer will be given by:

$$\bar{f}(\lambda_y) \coloneqq \lim_{h\to\infty} f(h,\lambda_y) = C\,\lambda_y \tag{15}$$

3. The Data

Our study uses intra-day data for five blue-chips listed on the Bucharest Stock Exchange, namely *SIF 1*, *SIF 2*, *SIF 3*, *SIF 4* and *SIF 5* during six months, *i.e.,* October 19, 2012 to May 3, 2013. For all of them, we have available data at intra-day level, best bid and best ask quotes, the associated volumes and two trading direction dummies. Those companies are very importans players on the Romanian capital market having a large number of private and institutional shareholders, such as investment funds. Their main objective is portfolio investment and permanent identification of transactions opportunities with reasonable risk level. We select these data series because all of them are currently solid financial institutions with well-established presence in the Romanian economic environment, but also with foreign market investments. Moreover, in that period, they were in the top 15 liquid companies listed on the Bucharest Stock Exchange. A descriptive statistics regarding the trading activity is presented in Table 1.

Table1

Trade Statistics

Equity	Average trades per day	Max Price	Min Price	Average Mid Price	BUY Trades	SELL Trades
SIF1	36	0.9913	1.3900	1.2283	2325	2424
SIF2	33	1.0501	1.5780	1.4186	2082	2247
SIF3	94	0.7585	0.5820	0.6910	6792	5683
SIF4	28	0.9695	0.6760	0.8182	1913	1749
SIF5	44	1.5400	1.3000	1.4290	2981	2928

We may see in Table 1 that SIF 3 is superior from a liquidity perspective to all the others, while achieving the highest average daily return (4.66%). During the selected months, the return for SIF 1 was -18.97%, -22% for SIF 2, 0.73% for SIF 4 and -5.18% for SIF 5.

Table2

Percentage of Trades per Time Intervals

Interval	SIF1	SIF2	SIF3	SIF4	SIF5
10:01-11:00	14.15%	13.63%	17.85%	14.55%	14.99%
11:01-12:00	13.27%	14.92%	14.57%	14.58%	14.23%
12:01-13:00	13.50%	13.24%	13.86%	13.84%	12.37%
13:01-14:00	13.86%	12.08%	12.90%	11.77%	13.10%
14:01-15:00	13.01%	14.02%	12.77%	13.00%	13.37%
15:01-16:00	16.26%	15.68%	14.51%	14.31%	15.43%
16:01-16:45	15.96%	16.42%	13.55%	17.94%	16.50%

In Table 2, one may notice the dynamics of the traded amount. It may be clearly seen a slight increase in the number of transactions in the morning and towards the end of the day. This fact might indicate the presence of some informed traders on the Romanian capital market, as Cepoi and Toma (2016) discussed, based on intra-day data from the Bucharest Stock Exchange. Informed agents tend to trade more in the opening hours as they attempt to benefit from their private information accumulated overnight and during the pre-opening session.

We further investigate whether the series used in estimation are stationary or not based on the ADF test. This is a mandatory requirement in a cointegrated VAR model framework. In order to have a valid model, it is necessary that all data series to be integrated of order 1, *i.e.,* I(1). The results are presented in Table 3.

Table 3

ADF Unit Root Test Value (p-value in Parathesis)

Equity	Best Ask Price	Best Bid Price	Best Ask Volume	Best Bid Volume
SIF1	0.508 (0.987)	0.428 (0.984)	-11.439 (0.000)	-11.537 (0.000)
SIF2	0.786 (0.993)	0.592 (0.989)	-16.658 (0.000)	-13.177 (0.000)
SIF3	-1.312 (0.660)	-1.344 (0.610)	-21.134 (0.000)	-27.189 (0.000)
SIF4	-0.740 (0.834)	-0.744 (0.833)	-18.972 (0.000)	-21.303 (0.000)
SIF5	-0.988 (0.759)	-0.981 (0.761)	-9.492 (0.000)	-15.296 (0.000)

As above, based on the Augumented Dickey-Fuller test (ADF), the price series are clearly non-stationary, but the same conclusion cannot be drawn for the acociated volumes. Our results are in line with the findings of Hautsch and Huang (2012). They recommended, based on the Johansen and Nielsen (2010) approach, to model depth as a non-stationary variable in a cointegrated VAR framework, since its components might be both stationary and non-stationary, and the last one might be possible dominant over very short horizons. However, if we apply the ADF test for the first difference we get only stationary series, which is in line with the requirements of a cointegrated VAR model.

Since all the data series are I(1), we are entitled to study, based on Johansen's co-integration test, the existence of some long-run relationships between quotes and volumes. The results are presented in Table 4.

Table 4

The Johansen Cointegration Test

Equity	No. of CE (s)	Eigenvalue	Trace Statistics	5% Critical Value	P-Value
SIF 1	None	0.103	1381.810	47.856	1.000
	At most 1	0.097	868.030	29.797	0.000
	At most 2	0.078	386.056	15.495	0.000
	At most 3	0.000	0.211	3.841	0.646
SIF 2	None	0.119	1300.594	47.856	1.000
	At most 1	0.099	750.330	29.797	0.000
	At most 2	0.067	299.030	15.495	0.000
	At most 3	0.000	0.483	3.841	0.487
SIF 3	None	0.130	3955.560	47.856	1.000
	At most 1	0.100	2223.594	29.797	1.000
	At most 2	0.070	910.189	15.495	0.000
	At most 3	0.000	1.515	3.841	0.218
SIF 4	None	0.174	1396.597	47.856	1.000
	At most 1	0.108	696.629	29.797	0.000
	At most 2	0.073	279.320	15.495	0.000
	At most 3	0.000	0.610	3.841	0.435
SIF 5	None	0.088	1376.307	47.856	1.000
	At most 1	0.072	834.414	29.797	0.000
	At most 2	0.064	390.870	15.495	0.000
	At most 3	0.000	0.717	3.841	0.397

According to Johansen's trace and rank tests, we found three cointegration relations between best quotes and and the corresponding depths. For this reason, together with the above-mentioned stationarity results, the use of the cointegrated VAR model is fully justified.

4. Results

4.1. VECM Estimation

The previous results allow us to study the impact of market orders using a VAR model with an error corection component, *i.e.,* VECM. We present in Table 5 three different tests (Akaike Information Criterion - AIC, Schwartcz Information Criterion - SIC, Hannan-Quinn Criterion – HQ) that we used in order to choose the optimal number of lags for all five equities used in this analysis.

Table 5

VAR Lag Order Selection Criteria

Equity	AIC	SC	HQ
SIF1	6	2	2
SIF2	5	3	3
SIF3	12	3	5
SIF4	6	2	3
SIF5	4	2	4

To have a symmetry of results, we choose three lags for all five cases. Once we decided about this issue, we can go further to estimate the VEC model. The estimation results based on full information maximum likelihood estimation are presented in Table 6.

Table 6

VECM Estimation Results

Equity	Variable	$\widehat{\boldsymbol{\beta_1}}$	$\widehat{\boldsymbol{\beta_2}}$	$\widehat{\boldsymbol{\beta_3}}$	$\widehat{\boldsymbol{\beta_4}}$	$\widehat{\boldsymbol{\beta_5}}$
SIF 1	P^A	0.000	0.000	-0.249	-0.085	-0.518
	P^B	0.000	0.000	0.287	-0.133	1.000
	V^A	0.000	0.000	0.851	1.000	0.040
	V^B	0.000	0.000	-1.000	0.213	0.036
	BUY	1.000	0.000	0.000	0.000	0.000
	SELL	0.000	1.000	0.000	0.000	0.000
SIF 2	P^A	0.000	0.000	0.051	0.051	0.115
	P^B	0.000	0.000	0.000	0.000	-0.063
	V^A	0.000	0.000	-1.000	-1.000	-1.000
	V^B	0.000	0.000	0.500	0.500	0.483
	BUY	1.000	0.000	0.000	0.000	0.000
	SELL	0.000	1.000	0.000	0.000	0.000
SIF 3	P^A	0.000	0.000	-0.018	0.037	-0.167
	P^B	0.000	0.000	0.006	-0.271	0.173
	V^A	0.000	0.000	-1.000	-1.000	1.000
	V^B	0.000	0.000	0.984	-0.648	0.033
	BUY	1.000	0.000	0.000	0.000	0.000
	SELL	0.000	1.000	0.000	0.000	0.000
SIF 4	P^A	0.000	0.000	0.005	0.005	-0.034
	P^B	0.000	0.000	0.188	0.188	-0.178
	V^A	0.000	0.000	1.000	1.000	-0.067
	V^B	0.000	0.000	0.000	0.000	-1.000
	BUY	1.000	0.000	0.000	0.000	0.000
	SELL	0.000	1.000	0.000	0.000	0.000
SIF 5	P^A	0.000	0.000	0.007	0.007	-0.041
	P^B	0.000	0.000	-0.016	-0.016	0.013
	V^A	0.000	0.000	1.000	1.000	1.000
	V^B	0.000	0.000	-0.699	-0.699	-0.072
	BUY	1.000	0.000	0.000	0.000	0.000
	SELL	0.000	1.000	0.000	0.000	0.000

As we stated in the introduction, we include in our model two dummy variables which characterize the trade direction. The first dummy, *i.e.,* BUY, is equal to unit when a transaction was made as a result of a purchase order and zero otherwise, while the second dummy variable, *i.e.*, SELL, takes the value of one when a sale market order has led to a transaction and zero otherwise. Following the methodology proposed by Hautsch and Huang (2012), we consider the two dummy variables as stationary. In this way, the corresponding cointegration vectors, namely, $\widehat{\boldsymbol{\beta_1}}$and $\widehat{\boldsymbol{\beta_2}}$, are considered as known, with the structure: $\widehat{\boldsymbol{\beta_1}} = [\mathbf{0}, \mathbf{0}, \mathbf{0}, \mathbf{0}, \mathbf{1}, \mathbf{0}]$ and $\widehat{\boldsymbol{\beta_2}} = [\mathbf{0}, \mathbf{0}, \mathbf{0}, \mathbf{0}, \mathbf{0}, \mathbf{1}]$. Also, the components of these two dummy variables in the structure of $\widehat{\boldsymbol{\beta_3}}$ to $\widehat{\boldsymbol{\beta_5}}$ are set to zero.

4.2. Market Orders as Shocks to the System

Based on the estimates in Table 6 we quantify the impact of placing a market order based on two common scenarios. For example, let's imagine a limit order book, structured on 5 levels of depth, having at some time *t*, the architecture presented in Table 7. The best bid is 1.51; the best ask is 1.53, while the best volumes are 74 for the bid side and 70 for the ask side, respectively.

Table 7

A Limit Order Book Example

Prices	1.46	1.47	1.48	1.49	1.51	1.53	1.53	1.54	1.55	1.56
Volumes	22	18	28	55	74	70	49	42	44	17
Limit Order Book	$\underbrace{Buy\ Side}_{Structure}$					$\underbrace{Ask\ Side}_{Structure}$				

In the methodology section, we defined the effect of an order to be represented as a shock having the following structure, $\lambda_y := [\lambda_q', \lambda_d', \lambda_t']'$. As we have previously pointed out, λ_q is a $2x1$ dimensional vector of shocks in quotes, λ_q is a $2Kx1$ vector of shocks in depths, while λ_t is a $2x1$ dimensional vector of shocks in the trading indicator.

The following two very common scenarios are considered in our analysis:

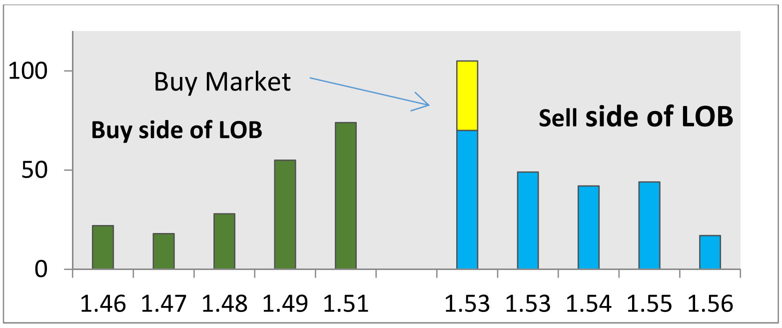
Scenario 1: Normal Market Buy Order

a) Description

In this scenario, a buy market order with half of the best asking volume size comes into the limit order book, *i.e.,* a buy order with price 1.53 and a volume of 35 units (70/2). Taking into account the fact that our prices and volumes are recorded in logarithms, the shock vector for this scenario has the following form: $\lambda_q = [0, 0]$ - the order will not affect the best bid or the best ask prices, $\lambda_d = [0, ln(0.5)]$ - the best bid volumes will remain the same, while the best ask volume will remain only a half, which in our approach is $ln(0.5)$. The shock vector caracterizing the trading indicator is in this case $\lambda_t = [1, 0]$. As a concequence, we expect that sale limit orders will be introduced at higher prices, *i.e.,* the best ask price will increase, since investors wishing to sell will estimate that other buy traders will apply the same strategy. In this way, it is possible to observe an increase in the volumes on the sell side of the limit order book. A graphical description of this scenarion is shown in Figure 1.

Figure 1

Normal Buy Market Order Design

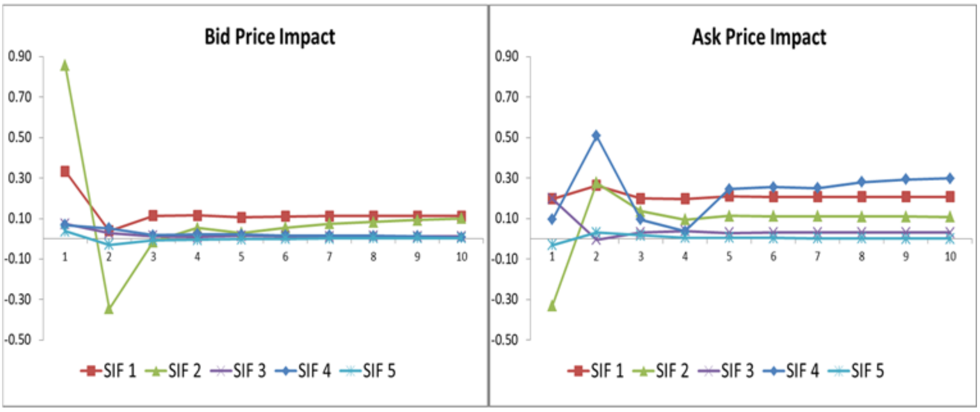


b) The Impact

Figure 2 shows the impulse response functions for a buy market order that halves the best ask depth for 10 periods ahead (a period is given by the length of time, in minutes, between two transactions).

Figure 2

Price Impact of a Normal Buy Market Order



In an entirely electric limit order book as Euronext Amsterdam, Hautsch and Huang (2012) have found that a buy market order which corresponds to 50% of the current depth would increase sharply afterwards. As expected, in our case both best bid and best ask prices increase starting with the third period. On the bid side, the impact is immediate and extremely high for a liquid stock such as SIF 3, reaching a maximum of 88 basis points in the next activity period, but vanishes starting with the third period. It must be pointed out that For SIF 2 the price correction is visible in the second period. For all the other stocks the impact is positive, ranging from 2 basis point to 32 basis points in the first period and becomes null in the following periods. However, we have a different story when we look at the ask side. The immediate impact is ranging from 9 to 51 basis poins for SIF 1, SIF 3 and SIF 4 in the first period and remains persistend afterwards.

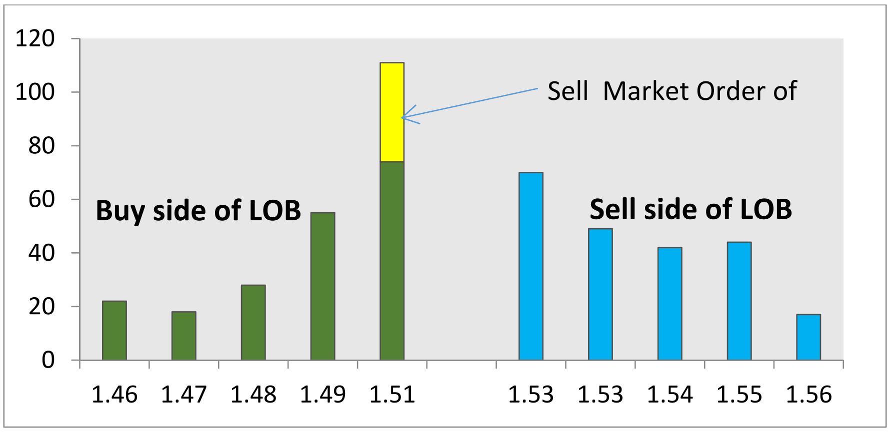
Scenario 2: Normal Market Sell Order

a) Description

In this scenario, a sell market order with half of the best asking volume size comes into the limit order book, *i.e.,* a sell order with price 1.51 and a volume of 37 units (74/2). As in the previuos case, the shock vector for this scenario has the following form: $\lambda_q = [0, 0]$ - the order will not affect the best bid or the best ask prices, $\lambda_d = [ln(0.5), 0]$ - the best ask volumes will remain the same, while the best bid volume will remain only a half, which in our approach is $ln(0.5)$. The shock vector caracterizing the trading indicator is in this case $\lambda_t = [0, 1]$. As a concequence, we expect that buy limit orders will be introduced at lower prices, *i.e.,* the best buy price will decrease, since investors wishing to buy will estimate that other sell traders will apply the same strategy. In this way, it is possible to observe decrease in the volumes on the buy side of the limit order book. A graphical description of this scenario is shown in Figure 3.

Figure 3

Normal Sell Market Order Design

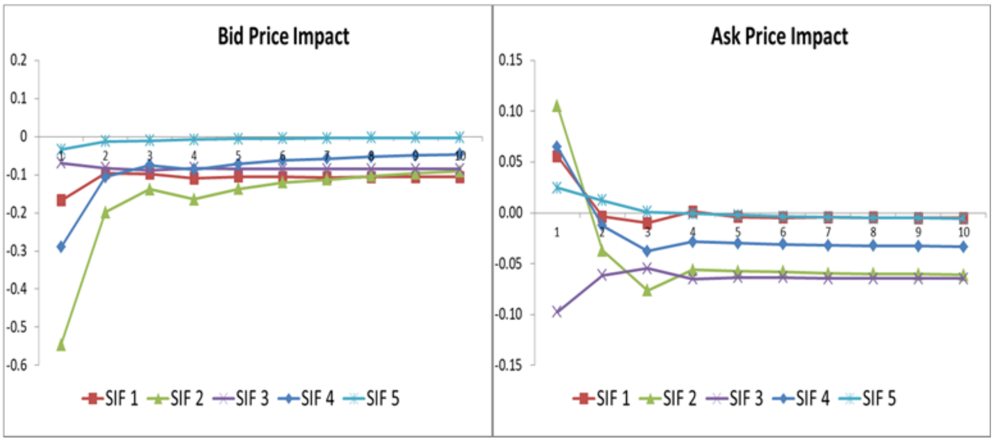


b) The Impact

Figure 4 shows the impulse response functions for a sell market order that halves the best ask depth for 10 periods ahead.

Figure 4

Price Impact of a Normal Sell Market Order



In contrast with the previous scenario, a sell market order has a significantly lower impact on both bid price and ask price. With the only exception of SIF 5, whose long-term and short-term impacts are close to zero, in the remaining situations a sell market order will decrese the best quotes starting with the second period. The drop is higher in absolut values for the bid prices in comparison with the ask prices and is robust to firm's liquidity. It must be noticed that the impact is positive in a first stage on the ask side of the limit order book, but the corrections are immediate for four out of five stocks. These results are in line with the previous findings of Hautsch and Huang (2012) for Euronext Amsterdam.

4.3. Policy Implications

We believe that our analysis is useful to traders, market makers and also to regulators. Traders are interested to know, for profitability reasons, how a market order will affect the prices. In this way, they are able to decide whether to buy or sell immediately, postpone a trade or to cancel their pending limit orders. Market makers are interested in the same issue because they want to know how to adjust their quotes when a large market order appears. Regulators are directly involved in ensuring transparency and avoiding anomalies due to large orders. From our perspective, this study is very useful in the cases of orders placed for acquisition of the majority of listed companies (Dragotă *et al*., 2013).

5. Conclusions

In this study, we assess the price impact of market orders in a limit order book environment by the means of a cointegrated VAR approach. By considering market orders as shocks to the system, we capture the interactions between market orders and price dynamics by the estimated impulse response functions. Our study uses five stocks traded on the Bucharest Stock Exchange with similar features but with different levels of liquidity on the highest intra-day frequency and reveals some interesting facts. First, we find strog empirical evidence regarding the long-run relationship between best bids and ask prices and their corresponding volumes. This is in line with the previous findings reported by Engle and Patton (2004) or Hautsch and Huang (2012) for NYSE and Euronext Amsterdam, respectively. Second, buy market orders have a positive and significant impact on the selling prices, especially for companies with low liquidity during the trading day. In comparison with the buy orders, the impact of the sell market orders is much lower in absolute values and suggests that the investors on the Romanian capital market are reacting differently to good news than to bad news. Third, high liquid companies such as SIF 3 are not affected on long term by the market orders with significant volumes. However, the impact is extremely visible immediately after order's placement, but it vanishes afterwards. This fact shows us the increased capacity of the Romanian capital market, in the case of the liquid companies, to deal with some speculative attacks with large volumes.

References

Albu, L.L. Lupu R. and Călin A.C., 2015. A Comparison of Asymmetric Volatilities across European Stock Markets and their Impact on Sentiment Indices. *Journal of Economic Computation and Economic Cybernetics Studies and Research*, 2015(3), pp. 5-20.

Biais, B. Hillion, P. and Spatt, C., 1995. An empirical analysis of the limit order book and the order flow in the Paris Bourse. *Journal of Finance*, 50, pp.1655–1689.

Cepoi C., 2014a. How Trading costs affect liquidity on Bucharest Stock Exchange?. *Procedia Economics and Finance*, 15, pp.1153-1158.

Cepoi C., 2014b. Price Leadership in Romanian Capital Market. *Procedia Economics and Finance*, 15, pp.1185-1191.

Cepoi, C.O. and Toma, F.M., 2016. Estimating Probability of Informed Trading on the Bucharest Stock Exchange. *Czech Journal of Economics and Finance*, 66(2), pp. 140-160.

Cont, R. Stoikov S. and Talreja R., 2010. A stochastic model for order book Dynamics. *Operations Research,* 58, pp.76–713.

Cont, R. Kukanov, A. and Stoikov S., 2014. The Price Impact of Order Book Events. *Journal of Financial Econometrics*, 12(1), pp. 47–88.

Damian, V.C. and Cepoi, C.O., 2016, Volatility Estimators with High-Frequency Data from Bucharest Stock Exchange. *Economic Computation and Economic Cybernetics Studies and Research*, 50(3), pp. 247-264.

Dragotă, V. Lipara C. and Ciobanu R., 2013. Agency problems and synergistic effects in Romania: The determinants of the control premium. *Czech Journal of Economic and Finance*, 63(2), pp.197-219.

Dufour, A. and Engle R., 2000. Time and the impact of a trade. *Journal of Finance*, 55, pp.2467–2498.

Eisler, Z. Bouchaud, J. and Kockelkoren, J., 2012. The price impact of order book events: market orders, limit orders and cancellations. *Quantitative Finance*, 12, pp. 1395-1419.

Engle, R. and Patton, A., 2004. Impact of trades in an error-correction model of quote prices. Journal of Financial Markets, 7, pp.1–25.

Escribano, A. and Pascual R., 2006. Asymmetries in bid and ask responses to inonovation in the trading process. *Empirical Economics*, 30, pp.913-946.

Foucault, T., 1999. Order flow composition and trading costs in a dynamic limit order Market. *Journal of Financial Markets*, 2, pp.99–134.

Foucault, T. Kadan, O. and Kandel, E., 2005. Limit Order Book as a Market for Liquidity. *Review of Financial Studies*, 18 (4), pp.1171-1217.

Goettler, R.L. Parlour, C.A. and Rajan, U., 2005. Equilibrium in a dynamic limit order Market. *The Journal of Finance*, 60, pp.2149–2192.

Griffiths, M. Smith, B. Turnbull, D. and White, R.W., 2000. The costs and the determinants of order aggressiveness. *Journal of Financial Economics*, 56, pp. 65–88.

Hasbrouck, J., 1991. Measuring the information content of stock trades. *The Journal of Finance*, 46, pp.179–207.

Hautsch, N. and Huang R., 2012. The market impact of a limit order. *Journal of Economic Dynamics and Control*, 36, pp.501-522.

Jang, H. and Venkatesh P., 1991. Consistency between predicted and actual bid-ask quote-revisions. *Journal of Finance*, 46, pp.433-446.

Johansen, S., 1991. Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models, *Econometrica*, 59, pp.1551–80.

Johansen, S. and Juselius K.,1990. Maximum likelihood estimation and inference on cointegration - with applications to the demand for money, *Oxford Bulletin of Economics and Statistics,* 52, pp.169–210.

Johansen, S. and Nielsen, M., 2010. Likelihood inference for a fractionally cointegrated vector autoregressive model. Research Paper 2010-24, CTEATES.

Lutkepohl, H.,1990. Asymptotic distributions of impulse response functions and forecast error variance decompositions of vector autoregressive models. *Review of Economics and Statistics*, 72, pp.116–125.

Lutkepohl, H. and Reimers, H., 1992. Impulse response analysis of cointegrated systems. *Journal of Economic Dynamics & Control*, 16, pp.53–78.

Naes, R. and Skjeltorp J. A., 2006. Order book characteristics and the volume-volatility relation: empirical evidence from a limit order market. *Journal of Financial Markets*, 9, pp.408-432.

Parlour, C. and. Seppi D., 2008. Limit Order Markets: A Survey. *Handbook of Financial Intermediation & Banking*. In: A.W.A. Boot and A.V. Thakor, eds. 2008.

Handbook of Financial Intermediation & Banking. Elsevier Publishing: Elsevier Science, Ch. 3.

Potters, M. and Bouchaud J.P., 2003. More statistical properties of order books and price impact. *Physica A*, 324, pp.133–140.

Radu R. and Cepoi C., 2015. Measuring trading costs and noise on Bucharest Stock Exchange. A Bayesian Approach. *Procedia Economics and Finance*, 32, pp.1459-1468.

Ranaldo, A., 2004. Order aggressiveness in limit order book markets. *Journal of Financial Markets*, 7(1), pp. 53-74.

Riordan, R. and Storkenmaier, A., 2012. Latency, liquidity and price discovery. *Journal of Financial Markets*, 15(4), pp.416 – 437.

Roşu, I., 2009. A dynamic model of the limit order book. *Review of Financial Studies,* 22(11), pp. 4601-4641.

Wuyts, G., 2012. The impact of aggressive orders in an order-driven market: a simulation approach, *The European Journal of Finance*, 18(10), pp.1015-1038.