Financial Market Manipulation: How to identify the Mechanisms?

by
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Abstract. The financial market responds to a variety of regulations that are meant to ensure its proper functioning. However, there are always speculations and agents who are eager to violate the trust of the investors in order to have more personal benefits. The main purpose of the present study is to identify the forms of manipulation (through information, through actions or through transactions) that alter the transparency and the good functioning of the financial market and lead to a general inadequate behaviour among the investors. The agent-based financial markets simulation models that resulted for various indexes are the key factors in interpreting the mechanisms mentioned before. Depending on the number of agents on the market, their initial wealth and the period of the simulation, the evolution of the index price is interpreted in terms of market manipulation taken into consideration the fact that the financial market evolves to a state of equilibrium using its own mechanism.

Key words: manipulation, agent-based models, efficiency, financial markets
JEL Classification: C88, D40, D84, G10

1 Introduction and literature review

The techniques of manipulation have experienced an important evolution through time. Along with the diffusion of rumors and fake information that creates a false image of the market, agents have become more eager to increase their personal benefit in the detriment of others. This has led to the development of new techniques that can be very hard identified and thus, almost impossible to be sanctioned by the regulatory mechanisms existent on the market.

While studying the market, we understood that manipulation has become a controversial subject nowadays, with many cases situated at the limit between legal and illegal. Various strategies can be analyzed and interpreted in terms of manipulation. Starting from here, a pattern might be identified and one could build scenarios that may be used in the detection of market manipulation.

Manipulation of the market has many forms. One of the most common phenomena is stock price manipulation. Allen and Gale (1992) were the ones who identified and studied the mechanism. They built a game-model with three types of agents, identical investors, informed traders and manipulators, who act on the market depending on the information they have. Through their actions, the manipulators can influence the price and the gains of the other participants. The model is based on probability theory and it determines the utility of each participant taking into account his risk aversion.

In 2006, Aggarwal and Wu further developed the model, considering investors with asymmetric information. They determined an equation for the price depending on the values expected – high or low, making a comparison between economies where the agents are informed and economies where manipulators undertake actions. They also made an anatomy of stock manipulation cases found on the market in order to categorize the schemes put into practice and to discover their characteristics.

A number of other authors have considered market manipulation and particularly forms of manipulation through price, as being the only form of manipulation that does not suppose releasing false rumors about a company. The data analyzed are diverse and show that manipulation is a technique that has been used even on the most renowned markets. Khwaja
and Mian (2005) analyze data from the Karachi Stock Exchange in Pakistan. The principal subjects are trade-based “pump and dump” price manipulation scheme and trading cycles. The model uses a regression to evaluate the impact of PRIN (the probability over time that a given broker in a given stock will behave as a principal) over ARR (annualized nominal rate of return). An important topic is the effects of the ‘closing price’ technique over the market transactions. Comerton-Forde and Putniņš (2011) focus on the closing price manipulation which describes the strategy adopted by traders who buy or sell stocks aggressively at the end of the day in order to influence the price. Using data from USA and Canada, the authors build an index of probability that determines whether or not the closing price has been manipulated and the impact that the strategy has on a long term. Furthermore, analyzing data from stock exchanges in Paris and Madrid, Hillion and Suominen (2004) use agent-based models and they show that, by introducing closing call auction, the manipulation of the price might be reduced. The call auction algorithm design was extended by Comerton-Forde and Rydge (2006) who study the ‘matching algorithm’ used to set auction prices. Through examples of call auction price manipulation (ASX, SGX) they also prove that call auctions may reduce manipulation in some cases.

There also exist a large number of papers that build experimental markets and use mathematical techniques to examine manipulation. Goldstein and Guembel (2008) discuss the importance of the price on a market. Through mathematical mechanisms, they prove that the feedback received from the market can modify the attitude of the investors towards some stocks and it determines the appearance of manipulation because speculators try to take advantage from the weaknesses existent on the market. Diaz, Theodoulidis and Sampaio (2011) adopt data mining to study trade-based manipulations and they identify preconditions of the manipulations such as closing hours, quarter-ends and year ends. Chakraborty and Yilmaz (2004) focus on the problem of inside-traders who undertake actions (trading in the wrong direction) and determine modifications of the equilibrium on the market. This situation is influenced by the number of periods of trading and the uncertainty about the existence of the insiders. It is Veiga and Vorsatz (2009) who build an experimental asset market. The authors conduct a survey in order to identify benchmark treatment, manipulation treatment and information mirages.

In addition, an important aspect while studying market manipulation is to take into account the importance of regulations introduced on the market. In most of the papers, the authors build their models considering the legislation needed to eradicate manipulation. Jiang, Mahoney and Mei (2005) start their paper with the idea that the “stock pools” from the 1920s conducted at the implementation of the laws against manipulation in the USA. However, the authors prove, through an econometric regression, that there is no actual evidence to demonstrate the impact of “stock pools” on the liquidity, volatility or the market price.

The main purpose of this paper is to continue the studies and to find other methods that can help in identifying market manipulation. To achieve this, we choose to analyze cases of manipulation that occurred on the market to see how the prices evolved during this time. The data characterizes the French market. Secondly, the situation is evaluated at market-level. For this effect, we studied the progress of the representative index, CAC40, to see how its evolution shows the manipulation of one of its components. This is build using agent-based models, virtual mechanisms that allow the creation of a virtual market. Through this, we can observe the difference between the actual price and the forecasted price. The objective of the research is to see whether or not the manipulation can be identified using a simulation of the market through agent-based models.

The paper proceeds as follows. Section 2 describes the simulation program used for demonstrations. The methodology offers an insight about agent-based models. Furthermore, Section 3 offers summary statistics about data specific to the French market. Besides the
benchmark index, companies that are in the composition of the index are described, together with the cases of manipulation identified. Section 4 describes the results and we can decide if the models can help when recognizing market manipulation. Section 5 concludes and offers suggestions for future investigation.

2 Methodology

When studying the financial markets, an important role should be assigned to the theory of designing economic mechanisms (Hurwicz and Reiter, 2006). According to it, the agents on the market are considered rational and they are able to make decisions in order to maximize their own profit. They send messages between each other and they act strategically, being supervised by a regulator institution.

Starting from here, the financial markets have been implemented as a game, studying the reactions of the agents (Roman, 2000). Considering a game with \( n \) rational agents who seek to maximize their own profit, a strategy \( S_i \) chosen by each agent and a gain function \( U_i \), the game will evolve to a Nash Equilibrium. This is a situation in which each agent maximizes its expected utility, taking into account how other agents would react. The Nash Equilibrium is thus represented by a number of optimal strategies \( (S_i^*, S_2^*, ..., S_n^*) \). The model can be summarized as it follows:

\[
U_i(S_i^*, S_2^*, ..., S_n^*) \geq U_i(S_i^*, S_2^*, ..., S_i, ..., S_n^*), \forall i = 1, n
\]  

(1)

When related to market manipulation, game theory has been used to represent the relations that appear between the agents on the market. By dividing those in different categories – traders, manipulators, and market regulators – the game can help determine the necessary conditions for the equilibrium on the market.

Among the firsts who employed the technique were Allen and Gale (1992). Stock price manipulation is a strategy that cannot actually be restricted by the authorities because it does not depend on the release of the false information. The actions of the agents on the market depend on the announcements about the value of the stock. Keeping in mind that the manipulators can enter on the market even if they anticipate no announcement, the situation can be represented under the form of a game structure with 3 time moments. The equilibrium can be determined in each of the 3 dates, taking into account the asymmetric information. The possibility of manipulation in this situation appears as a consequence of the type of the agent, more precisely, his aversion to risk.

All this previous work helped to develop more complex algorithms incorporated in the agent-based modeling. They are used to create artificial financial markets that simulate the activity of agents and the way they trade. The mechanisms where created through genetic programming which made them a little hard to reach for users who are not familiarized with informatics theory.

In this paper, we used specific software, Adaptive Modeler (Altreva, 2013), which allows to design the functioning of a financial market. This simulates the interactions between the agents on the market and it creates a virtual market. The model evolves step by step depending on the historical prices. Agents study the prices they receive and evaluate them according to their own trading rules. Furthermore, they make decisions to buy or to sell. The program uses adaptive genetic programming. The model learns from experience and new agents are created based on the performance of the best agents.

The data studied is related to the French market, reflecting the evolution in different sectors of the economy.

The data is implemented in the software, generating a virtual market for the stock index. The parameters included in the model are:

- The number of agents on the market: 2000 in this case, as being the maximum population allowed by the program;
- Start capital for the agents: 100000 monetary units;
- The genome size: genomes represent the trading rules of the agents. A genome is formed by a number of ‘genes’, elementary functions and values that show the trading rules;
The broker commission, spread and slippage.

After the data is processed, the model starts to evolve. It first needs a period of time to adapt and to learn and then it represents the evolution of the market through genetic programming. The main results are represented in charts showing the stock price, the forecasted price and the signal given to the agents on the market. Besides this, there is also information related to the virtual market price, the number of buy orders and sell orders. The model shows how the wealth distribution of the agents varies in time.

Using all the information provided by the software, particularly the evolution of the price, we can identify the way the real price has distanced itself from the forecasted price. This, correlated with the information existent on the real market may show signs of market manipulation.

Whenever there appears to be a difference between the real price and the forecasted price, the manipulators might have interfered on the market and thus, they modified the price for their own purposes. This is also shown in a chart representing the Right/Wrong Forecasted Price Changes. From here we can visualize the magnitude of the price changes\(^1\) that appeared on the market at a specific moment.

### 3 Data

In order to test different aspects regarding the manipulation techniques, we analysed the French capital market and its benchmark market index, CAC40. The index was created in June 1988, after the market crash from 1987. The name comes from ‘Continuous Assisted Quotation’ and it consists of 40 companies, the most traded at Euronext Paris the main component of the European stock exchange, Euronext. Among these companies there are BNP Paribas, Société Générale, L’Oréal, Danone, GDF Suez, France Telecom, Michelin, Carrefour, Renault, so that the index can reflect the evolution at a market level through multiple sectors of the economy (banking, telecommunications and energy).

Regarding the analysed companies, we took into consideration aspects about the weight of the company in the composition of the index and public information about manipulation cases. The first company discussed in the paper is BNP Paribas, the largest banking group in France that focuses its activity on retail banking, investment and insurance. It has a significant weight in the composition of CAC40, which is 5.69%. The company was accused of using techniques of manipulation that led to influencing the stock price. Unlike this, no suspicions of manipulation have been stipulated in the media about the other analysed company, L’Oréal. L’Oréal is the biggest cosmetic group in the world, with important clients in both Europe and America. The company’s weight in the composition of the index is of 4.43%.

In the creation of agent based models, we used 3277 daily observations that reflect the evolution of the stock market index for the period 1\(^{st}\) of March 2012 – 20 December 2012. For BNP Paribas, we used 3321 daily observations and for L’Oréal 3332 daily observations. The data describes the close/open/high/low price and the volume of transactions and it has been retrieved from Yahoo Finance\(^2\).

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While studying which components influenced the stock price we studied data representing the turnover, the number of stocks traded and the number of transactions executed. The daily observations were retrieved from NYSE Euronext website and they describe the period 3 January 2011 – 20 December 2012. 508 observations have been analysed for each company.

The chart in Figure 1 reflects CAC40’s evolution and thus, the investors’ reaction to risk as they adapt their actions depending on the information existent on the market. When choosing the stock index, an important aspect was the fact that CAC40 meets the main hypothesis of the efficient market concept. There are a large number of players who seek to maximize their profits. The participants on the market are rational and in their choices they take into account the risk of the stocks. The capital market in France is influenced by information that appears random on the market. This was reflected in the evolution of the index characterised by stages of sudden growth or decrease.

Data was analysed using EViews. The close series for the index and for the two companies are not stationary. The stationarity was verified using Augmented Dickey Fuller test which showed the series have a unit root. The close price series for CAC40 has a Skewness of 0.634208 and it has a positive asymmetry. The series’ distribution is platykurtic with a Kurtosis smaller than 3.

4 Empirical results

4.1 Agent based model

Using Adaptive Modeler, we generated models of virtual evolution for each of the two companies and also for the index. The virtual market is formed of 2000 intelligent agents. For BNP Paribas, Figure 2 shows the virtual market where the price of the action is represented with dark blue, the forecasted price with blue and the signal given with grey. While analyzing the evolution of the price, we observed that in some situations the forecasted price is different from the actual price which can show the existence on the market of some manipulators who trade so they can influence the price.

According to the media, in 2002 a subsidiary of BNP Paribas from Japan was closed because the employees traded in order to determine an artificial price that did not reflect the real value of the market. Besides this, in 2011 BNP announced quarterly results so that it can influence market’s opinion. They presented to the public a diminution of the profit, keeping it at a positive level, without taking into account the reevaluation of its own debt that would have generated in fact a loss.

Starting from these facts, we analyzed the evolution of the virtual market for BNP Paribas for the above-mentioned periods. There can be identified moments in both 2002 and 2011 when the evolution of the price was very different from the forecasted level.

The situation can be studied using Forecast Directional Accuracy (FDA) that represents the percentage in which the forecasted price was in the same direction as the effective change in price.

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3 Source [Online]: https://europeanequities.nyx.com/en


Figure 2 Virtual market for BNP Paribas; in dark blue – the price, in blue – the forecasted price, in grey – the signal given by the market
Source: Adaptive Modeler output

Figure 3 Evolution of the virtual market for BNP Paribas
Source: Adaptive Modeler output

Figure 4. Forecast Directional Accuracy and Right/Wrong Forecasted Price for BNP Paribas
Figure 4 (a) and (c) shows that for both 2002 and 2011 there are different levels where the changes in price were not forecasted according to the subsequent evolution on the market. Furthermore, for the end of 2002 and the beginning of 2011 FDA is situated under the 50% point. The values under 50% show that in most of the cases the predictions for the price were not correct.

All these elements show that at a certain point the evolution of the stock price was different from the one forecasted based on the historical values and on the agents’ behavior. Therefore, on the market there might have been additional information and agents that used manipulation techniques to modify the price for their own behalf.

Regarding L’Oréal, the virtual model shows few significant differences between the forecasted price and the actual close price. FDA for the whole model had a value of 51.5%, above the level of 50% which demonstrates that in most of the cases the prediction was in the same direction as the closing price.

The companies mentioned above have a significant weight in the composition of CAC40. Therefore, we studied their impact on the evolution of the index.

According to the agent-based model, there are no important modifications of the forecasted price in comparison with the stock market price that would correspond to the manipulation of BNP Paribas from 2002. However, while studying the right and wrong forecasted price, the direction of the changes in price did not always have an accurate forecast. At the beginning and at the end of 2002, FDA had a value under 50%, showing that disruptive factors existed on the French market.

For 2011, the manipulation case reported for the BNP stock was not very evident at a market level. There were periods when the closing price of CAC40 index distanced itself from the forecasted price of the virtual market, which can be shown by the FDA values that are below the 50% point.

Taking into account the results of the agent-based models, the manipulation of BNP Paribas stock price did not affect too much the evolution of the stock market index. Even though the weights of the companies in the composition of the index are significant, there are also other important companies in its composition with positive evolution that annihilated the effect of the manipulation. CAC40 is formed so that it reflects the evolution of the French market as a whole and thus, the events with a greater impact.
4.2 Econometric analysis

In order to observe how certain factors influence the stock price, we included in the analysis variables related to the turnover, number of daily trades and number of traded shares. The series for BNP Paribas and L’Oréal were processed using EViews 6.

According to a study by Rahnamay Roodposhti, Falah Shams & Kordlouie (2011), a method to differentiate the companies whose stock price is manipulated is by studying the indicators Skewness and Kurtosis of the returns. If for the analysed time period the values are too small for Skewness in comparison to the normal level (0) or too big for Kurtosis in comparison to the normal level (3), then the existence of stock price manipulation is possible.

Table 1: Main coefficients for the return of the stocks

<table>
<thead>
<tr>
<th></th>
<th>BNP Paribas</th>
<th>L’Oréal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Skewness</td>
<td>0.203189</td>
<td>-0.036086</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>6.021138</td>
<td>3.605299</td>
</tr>
</tbody>
</table>

Source: EViews output, after data processing

Skewness value is close to 0 levels for both companies. BNP Paribas has positive asymmetry while L’Oréal has negative asymmetry. Regarding the Kurtosis, only L’Oréal has a value near 3, proving that for this company no manipulation cases have been reported. For BNP Paribas, Kurtosis level is double than the normal level, indicating the presence of possible manipulation cases. The results are in accordance with the information from media and the conclusion of the agent based modelling.

For every company we built regression models that would show what elements led to manipulation. The dependent variable is the logarithm of the return, while the independent variables are the logarithms of the turnover, number of trades and number of shares. The regression equations are shown below.

\[ \log\text{return}_{\text{BNP}} = -0.3397 + 0.0202 * \log\text{shares} - 0.0411 * \log\text{trades} + 0.0226 * \log\text{turnover} \] (2)

\[ \log\text{return}_{\text{L’Oréal}} = -0.0112 - 0.0038 * \log\text{shares} - 0.0047 * \log\text{trades} + 0.0058 * \log\text{turnover} \] (3)

The only valid model is the one of BNP Paribas. For BNP Paribas, we obtained significant values for all the coefficients. As previously discussed, in 2011, BNP confronted with manipulation cases. The regression shows that the number of daily transactions has a negative influence on the return, while the number of shares and the turnover has a positive impact.

For L’Oréal, the non-manipulated company, the model is not valid and the variables have no influence on the stock price.

5 Conclusions

A good-functioning market has always been in the centre of every economy. Studies about its efficiency have been made in order to find solutions that would improve the conditions and that would ensure a transparent and reliable environment. However, economic agents have sought to maximize their profits. Thus, they found ways in which they could obtain personal benefits from the market, without considering the activity of other participants. By manipulating the market they could achieve such results. Even if important regulations were imposed over the time, manipulation through price remains hard to identify. Rumours can easily alter the price in the direction wanted by the manipulator, before it can be identified by the regulators.

Using agent based models, we created virtual markets through which we tried to identify signs of manipulation. By following the evolution of the model for the analysed period of time, we observed the functioning of the market according to agents’ behaviour. It allowed to identify situations in which the evolution was not the one predicted by historical data; this is a sign of the presence of disruptive factors. Among these factors, there are the manipulators who interfere on the market with false information, rumours and transactions that alter the price. Most of the times, the company itself plays the role of the manipulator in order to keep the value of the company at a certain level and to make profit.

The results show that the analysis was
consistent with the information existent on the real market. The data series from the French market allowed the identification of manipulation cases. Econometric analysis was consistent with the result, showing that only for the manipulated case the model was valid. The significant factors such as the daily number of shares or the number of transaction influence the evolution of the price.

The importance of the research resides in the study of the manipulation using virtual markets. It demonstrates that manipulation might be identified while comparing price evolution with the forecasted price. This should be helpful for regulators who are trying to discover cases where the stock price was artificially influenced. Only through a better observation of the market, the attitude of the manipulators might be discouraged.

However, the study offers only an insight of the evolution of the market. The situations show only the possibility of manipulation, but they do not offer certitude about it. For future investigations, it would be interesting to develop a method to introduce certain information on the virtual market, to be able to modify the number of agents or the behaviour of a specific agent. This way, the virtual model can show at a given point a more realistic development of the market and it would reflect properly the evolution of the market and the agents’ reactions in case of manipulation.

References


Roman, M. (2000), Jocuri și negocieri, București: Ed. AISTEDA


Altreva Modeler site, available online at http://www.altreva.com/product.htm
Appendix 1 – Augmented Dickey-Fuller test for CAC40

<table>
<thead>
<tr>
<th>Augmented Dickey-Fuller Unit Root Test on CAC40</th>
</tr>
</thead>
<tbody>
<tr>
<td>Null Hypothesis: CAC40 has a unit root</td>
</tr>
<tr>
<td>Exogenous: Constant</td>
</tr>
<tr>
<td>Lag Length: 0 (Automatic based on SIC, MAXLAG=28)</td>
</tr>
<tr>
<td>t-Statistic</td>
</tr>
<tr>
<td>---------------------</td>
</tr>
<tr>
<td>Augmented Dickey-Fuller test statistic</td>
</tr>
<tr>
<td>Test critical values: 1% level</td>
</tr>
<tr>
<td>5% level</td>
</tr>
<tr>
<td>10% level</td>
</tr>
</tbody>
</table>

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CAC40)
Method: Least Squares
Sample (adjusted): 3/02/2000 12/20/2012
Included observations: 3278 after adjustments

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>CAC40(-1)</td>
<td>-0.002433</td>
<td>0.001068</td>
<td>-2.278480</td>
<td>0.0228</td>
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<tr>
<td>C</td>
<td>9.507889</td>
<td>4.646862</td>
<td>2.046088</td>
<td>0.0408</td>
</tr>
</tbody>
</table>

R-squared   | 0.001683    | Mean dependent var | -0.790473 |
Adjusted R-squared | 0.001278 | S.D. dependent var | 61.80122 |
S.E. of regression | 61.76171 | Akaike info criterion | 11.08505 |
Sum squared resid | 12488703 | Schwarz criterion | 11.08878 |
Log likelihood | -18155.32 | Hannan-Quinn criter. | 11.08639 |
F-statistic     | 5.191469   | Durbin-Watson stat | 2.089855 |
Prob(F-statistic) | 0.022762 |                     |           |

Source: EViews output, after data processing

Appendix 2 – Evolution of the virtual market for L’Oréal

Source: Adaptive Modeler output
Appendix 3 – Evolution of the virtual market for CAC40 in 2011, including Forecast Directional Accuracy and Right/Wrong Forecasted Price

Source: Adaptive Modeler output

Appendix 4 – Regression model for BNP Paribas’ log return

BNP Paribas

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>-0.339733</td>
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<td>0.0008</td>
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<tr>
<td>LOGSHARES</td>
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<td>0.008941</td>
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<tr>
<td>LOGTRADES</td>
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<td>-3.505312</td>
<td>0.0005</td>
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<tr>
<td>LOGTURNOVER</td>
<td>0.022596</td>
<td>0.007954</td>
<td>2.841030</td>
<td>0.0047</td>
</tr>
</tbody>
</table>

R-squared     | 0.026198    | Mean dependent var | -0.000202   |
Adjusted R-squared | 0.020390    | S.D. dependent var | 0.032572    |
S.E. of regression | 0.032238    | Akaike info criterion | -4.023482   |
Sum squared resid | 0.522763    | Schwarz criterion | -3.990121    |
Log likelihood   | 1023.953    | Hannan-Quinn criter. | -4.010399   |
F-statistic      | 4.510646    | Durbin-Watson stat | 1.886368     |
Prob(F-statistic) | 0.003908    |

Source: EViews output, after data processing
Appendix 5 – Regression model for L’Oréal’s log return

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>-0.011235</td>
<td>0.043768</td>
<td>-0.256688</td>
<td>0.7975</td>
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<tr>
<td>LOGSHARES</td>
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<tr>
<td>LOGTRADES</td>
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<tr>
<td>LOGTURNOVER</td>
<td>0.005857</td>
<td>0.006621</td>
<td>0.884549</td>
<td>0.3768</td>
</tr>
</tbody>
</table>

- R-squared: 0.010164
- Adjusted R-squared: 0.004260
- S.E. of regression: 0.013002
- Sum squared resid: 0.085027
- Log likelihood: 1484.349
- F-statistic: 1.721674

Source: EViews output, after data processing